Transportation Resilience: Behavioral Impact Analysis of Disruptions and Pandemic on Public Transit

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DISSERTATION

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To Sepideh,

my amazing wife,

Whose sacrificial care made it possible for me

to complete this work.

Partner with me on a vibrant journey,

full of life.

CONTRIBUTION OF AUTHORS

I would like to thank Ali Shamshiripour, Dr. Ramin Shabanpour, and Dr. Joshua Auld for allowing the use of our joint papers in this dissertation. Chapter 3 of the dissertation represents the following published manuscript:

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The materials of the sub-chapter 5.2.2 of the dissertation are also part of our previously published article as follows:

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All authors contributed to the conceptual development, methodology development, and model estimation and interpretation.

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SUMMARY

Most definitions for the Smart Cities paradigm have one common characteristic: being resilient. Transportation is associated with all aspects of urban life, including recreation, education, and business. Ensuring an efficacious, accessible, and integrated transportation system is vital to building resilience in our cities. Reduction in the transportation system's performance, as the heart of urban life, may compromise the city’s operations across several sectors, leading to large and costly disruptions. A resilient transportation system is crucial to avoid such incidents, and it can provide accessible service to the public even during disruptions, emergencies, accidents, and special events

Public transit disruption is becoming more common across different transit services and can have a destructive influence on the resiliency of the transportation system. Even though transit agencies have various strategies to mitigate the probability of failure in the transit system by conducting preventative actions, some disruptions cannot be avoided because of their either unpredictable or uncontrollable nature. Utilizing recently collected data of transit users in the Chicago Metropolitan Area, the current study analyzed how transit users respond to unplanned service disruption and disclose the factors that affect their behavior. The results of the analysis reveal that a wide range of factors, including socio-demographic attributes, personal attitudes, trip-related information, and built environment, are significant in passengers’ behavior in case of unplanned transit disruptions. Our findings provide insights for transportation authorities to improve the transit service quality in relation to user satisfaction and transportation resilience. These insights help transit agencies to implement effective recovery strategies.

We also focused on another threat to public transit and the transportation system, which is the COVID-19 pandemic. In this study, we investigated risk perceptions toward using shared mobility solutions during the pandemic. It is vital for policymakers to accurately characterize the different types and degrees of behavioral changes among various social groups. Risk perception of using various modes is one of the major factors which can substantially explain individuals' travel behavior changes during a health crisis. This study focused on public transit and ridesharing services since these options are the most widespread forms of shared mobility in the current transportation system. We utilized a recent multidimensional travel-behavior survey data conducted in the Chicago Metropolitan Area, focusing on the impacts of the COVID-19 pandemic on individuals' travel behavior. According to the results, a wide range of explanatory variables is found to be significant in the risk perception model, including socio-demographic variables, built environment, health condition, virus spread, and the restriction factor. Our findings provide insights into the influential factors on being risk-averse versus risk-taker with respect to use shared mobility services during the pandemic. The findings assist policymakers in two main directions. First, the results showed that minority groups, including African Americans and extremely low-income families, were more at risk of exposure to the novel coronavirus while using shared mobility options. Such findings highlight the importance of achieving "equity" in access to a safe transportation system, especially during a health crisis such as the COVID-19 pandemic. Second, the results revealed that risk perception behaviors might vary based on places' spatial characteristics, where individuals reside. Besides, the spread of the novel coronavirus might also affect the risk perception behavior in each neighbor.

1 INTRODUCTION

1.1 Background

The concept of "Smart Cities" is gaining growing attention in the world. There is no unique definition for the Smart Cities paradigm; however, being sustainable and resilient as characteristics of a smart city are in common in most definitions (Allam and Newman 2018). Recently, the development of Information and Communication Technologies (ICTs) provides an opportunity to make the critical infrastructure components and services of a city more intelligent, interconnected, and efficient, resulting in more sustainable and resilient cities.

Transportation is associated with all aspects of urban life, including recreation, education, and business. Ensuring an efficacious, accessible, and integrated transportation system is vital to sustaining social and economic development. Reduction in performance of transportation system, as the heart of urban life, may compromise the city's operations across several sectors, leading to large and costly disruptions (Arup and Siemens 2015). A resilient transportation system is crucial to avoid such incidents, and it can provide accessible service to the public even during disruptions, emergencies, accidents, and special events (Transportation Systems Resilience Section 2017).

Among all modes of transportation, public transportation plays a crucial role in evacuation and other emergency response measures. Thus, keeping the transit system operational or able to quickly recover when an incident occurs is critical for the entire community's resiliency (Golshani et al. 2019). Enhancing the resiliency of public transportation systems can also encourage people to use this green mobility option more frequently, which is aligned with the Smart Cities paradigm.

In the past several years, a sizable number of studies have been published that explore the dynamic and evolving state of the practice in the transportation sector related to the resiliency of public transit system concerning natural disasters related to extreme weather events (FTA 2017;

Amekudzi et al. 2013; Golshani et al. 2019). Such natural disasters comprise temperature extremes, severe storm events and coastal storms, sea-level rise, winter storms, earthquakes, wildfires, and droughts and dust storms (National Academies' Transportation Research Board; 2017). However, unplanned transit disruptions due to non-disaster events (e.g., crashes, system failure, cyber-attack) and health disasters (e.g., the COVID-19 pandemic) as the two significant threatening incidents to the resiliency of public transit are overlooked.

1.2 Study Framework

Public transportation has long been a matter of concern in many cities around the world. Offering affordable, efficient, and green service to the public, the transit infrastructure of every municipality acts as the veins of its transportation system. The Chicago metropolitan area is not an exception, where the Chicago Transit Authority (CTA) provides service to over 3.5 million riders in the city of Chicago and 35 suburbs surrounding the city (Chicago Transit Authority 2017). More importantly, building resilience into transportation systems is crucial at all levels of federal, state, and local government agencies (Baylis et al. 2015). Thus, this study focuses on two incidents threatening the resiliency of public transit and urban mobility: (1) Transit disruptions and (2) health disasters (e.g., the COVID-19 pandemic). The first step to mitigating such events is to investigate citizens' behaviors in response to those incidents.

To do so, we characterize the transit users' behavior during transit disruption in Chicago and discuss some potential solutions to mitigate the impacts of disruptions. Focusing on the COVID-19 pandemic as one of the major 21st-century health threats, we shed light on the dramatic transit ridership decline and explore the perceived risk of using this mobility option among people.

1.3 Transit Disruptions

Maintaining a satisfactory quality of service is a major challenge ahead of having the transit options adopted by as many customers as expected by the planning agencies. Even though transit agencies, including CTA, have various strategies to mitigate the possibilities of service disruption, some disruptions cannot be avoided due to their either unpredictable or uncontrollable nature. For instance, consider the situation that the normal operation of a bus line is interrupted due to a road closure caused by a severe traffic accident along the way or failure of a traffic signal. Such incidents can cause unpredictable difficulties to maintain the quality of service by the affected transit line, and thereby, a service disruption.

Service disruptions can cause severe damage to transit users' experience, which calls for taking a more in-depth look into the transit riders' expectations of the system. In a study in Melbourne, Currie and Muir (2017) observed that the rail disruption has the potential to increase the level of dissatisfaction of passengers by up to fourfold based on the recovery conditions. Hence, it is of great interest for transportation authorities to understand transit users' decision behavior during a disruption in order to implement efficacious recovery strategies.

Transit disruptions can be classified into two groups of pre-planned and unplanned disruptions. Pre-planned disruptions occur due to disruptive activities planned ahead of time such as labor strikes and road or rail closures for maintenance activities. On the other hand, unplanned disruptions are mostly caused by unpredictable or uncontrollable incidents such as natural disasters (e.g., earthquakes, storms, blizzards, and floods), infrastructure failures (e.g., I35W Mississippi River bridge collapse), accidents, and terrorist attacks. Studies on their decision behavior in case of unplanned disruptions in still scarce, although transit users' response behavior in case of pre-planned disruptions has been extensively investigated in the literature. In this study, we focus on the unplanned disruptions which are not caused by disasters (e.g., terrorist attack, fire), since a disaster might impose drastic disruptions to the whole city and needs to be studied from a different perspective, similar to Golshani et al. (2019).

We breakdown the decision-making process of transit users during a non-disaster, unplanned disruption into two major phases. First, the passenger would probably wait for a while before starting to think about an alternative solution. Second, reaching a waiting threshold, he/she would decide about an alternative solution, which can be canceling the trip, changing the destination, using another travel mode to reach the planned destination, etc. Obtaining a profound understanding of both of these aspects is critical for transportation authorities to devise and implementing strategies to recover from service disruptions (TYT Lin 2017).

The analyses reported in the current research are based on an intercept SP-RP survey which was designed and conducted in the Chicago metropolitan area, within which participants were asked to provide detailed information about their ongoing transit trips. They were also faced with a hypothetical scenario in which the transit service was disrupted, and they were asked to indicate how long they would be willing to wait for the service to be restored before planning for an alternative solution. A unique aspect of this web-based survey is that it is fairly comprehensive with respect to the transit options taken into account. The fact that the respondents are among users of both buses and rail services enables us to analyze the behavioral differences between the two groups.

Focusing on the first phase, the first portion of the current research (presented in section 2.2) aims to add to the literature by exploring transit users' waiting tolerance during unplanned service disruptions and disclose the factors that affect their behavior. In order to model the waiting tolerance, interval-censored accelerated failure time (AFT) models with four different distribution alternatives (i.e., Exponential, Weibull, Log-logistic, and Log-normal) are developed, compared, and the factors influencing the survival functions of the waiting tolerance are identified. Focusing on the second phase, furthermore, we estimated a random parameters multinomial logit model considering all the potential choice alternatives at the time the survey was designed (i.e., canceling the trip, changing the destination, or switching to other travel modes such as a personal vehicle, taxi, or a ride-sharing services) to gain a comprehensive understanding of people's decision behavior.

1.4 Public Transit and the COVID-19 pandemic

The novel coronavirus (SARS-CoV-2) has caused upheaval around the world and has caused our daily routines to change quickly. The World Health Organization (WHO) reported more than 60 million confirmed cases and more than 1.4 million deaths globally as of November 26th, 2020 (WHO 2020). Governments around the world are striving to fight against the pandemic by substantial diagnosis tests and enacting restrictive guidelines, including stay-at-home and social distancing. In the U.S., despite all preventive policies implemented so far, the cases are still increasing at an alarming rate, and the situation is getting worst in various states across the country. On March 14, 2020, the Illinois Department of Public Health (IDPH) announced the first confirmed COVID-19 case in the state (IDPH 2020). Currently, Illinois is among the four states with the highest number of COVID-19 cases, with 685,467 confirmed cases and 12,440 deaths as of November 26th, 2020 (Worldometer 2020).

COVID-19 spreads from person to person through sneezing, coughing, or touching contaminated surfaces. According to the Harvard Medical School, the virus can be airborne for up to several hours and can live on various surfaces for multiple days (Harvard Medical School 2020). Thus, individuals can be at risk of exposure to it when visiting different locations to fulfill their daily activities (e.g., workplace, school, shopping center, bar and restaurant, and hospitals) or when using different modes of transportation, especially the ones which are shared with other passengers.

The pandemic provokes public fear, which may result in changes in travel behavior, and more specifically, alterations in the activities people engage in and transportation modes they use to reach their activity locations. One of the major factors which can substantially explain people's behavior during a health crisis (e.g., COVID-19 pandemic) is the perceived risk of performing various activities (Hotle, Murray-Tuite, and Singh 2020). It is imperative for transportation authorities to properly identify the different types and degrees of behavioral changes among various groups of society. In this sense, investigating the inter-personal variations in the perceived risk of exposure to COVID-19 is the first step in understanding the adjustments people may make in their travel behavior to protect themselves, including canceling their trips, avoiding public transit, and avoiding public places, among others (Hotle, Murray-Tuite, and Singh 2020). These adjustments can certainly impact the behavioral process of activity planning and scheduling, destination choice, mode choice, and eventually traffic congestion patterns and emissions.

Concrete evidence could be found on the impacts of the viral pandemics and other public threats alike in the past. However, the impacts of the recent COVID-19 pandemic on travel behavior are relatively understudied. Among the limited number of studies on the impacts of COVID-19, we can refer to (Ito, Hanaoka, and Kawasaki 2020; Teixeira and Lopes 2020; Hotle, Murray-Tuite, and Singh 2020; Sobieralski 2020; Bucsky 2020; De Vos 2020). Although these studies are informative and provide invaluable insights into the changes in performing various activities and use of different modes, characterizing individuals' risk perception due to the COVID-19 pandemic has yet to be investigated. The present study is thus designed to investigate the risk that individuals perceive while using public transit and ridesharing services (as the widespread types of shared mobility solutions) during the COVID-19 pandemic. Early evidence highlights the vital role of shared mobility, and more importantly, public transit, in economic recovery after the pandemic (Sifuentes 2020).

1.5 Dissertation structure

The rest of the dissertation is organized as follows. Chapter 2 reviews the earlier studies on transit users' disruption behavior and the impacts of COVID-19 on transport mobility. Chapter 3 elaborates on the first phase of transit user's response (i.e., the waiting tolerance) to service disruptions. This is followed by Chapter 4, which provides the analysis of mode choice decisions for transit users whose service is disrupted (i.e., Phase II). Chapter 5 is devoted to characterizing the perceived risk of exposure to the COVID-19 pandemic while riding with public transit and ridesharing services. Finally, this work is concluded in Chapter 6 by providing a summary of findings as well as several directions for future research.

2 LITERATURE REVIEW

2.1 Transit Disruptions

The research on pre-planned or unplanned transit disruptions is relatively new but has been receiving growing attention over the past few years. The literature on transit service disruption consists of multiple research streams focusing on its various aspects, including transit users' response behavior, transportation network conditions, transit ridership, mitigation strategies, the effect of information provision, and service recovery duration. **Table 2-1** presents a summary of previous studies on these aspects. With respect to the focus of the current study, a review of studies on transit users' response behavior during unplanned transit disruptions is presented in what follows.

As one of the very few studies focusing on transit users' behavior during unplanned transit disruptions, Murray-Tuite et al. (2014) explored the long-term impacts of the deadly Metrorail accident, which occurred in June 2009 in Washington, D.C., on users' travel behavior. Focusing on those who had used the Metrorail in the period of six months before the accident, the authors investigated potential changes in users' travel mode and seat location decisions as a result of the incident. They found out that factors such as gender, transit type, number of delayed services in the past month, and number of children in the household could affect transit users' decision regarding either trip mode or seat location. While the results are fairly informative, this study has limited ability to provide more generalized insights due to its incident-based nature.

In another study, Currie and Muir (2017) conducted an online revealed preference (RP) survey to understand rail passengers' behavior, perceptions, and priorities in response to unplanned urban rail disruptions in Melbourne, Australia. Utilizing a statistical analysis approach, the authors found that system's ability to quickly recover after the incident is an important factor in rail users' response behavior. Moreover, the authors observed that experiencing unplanned rail disruptions is highly associated with users' level of dissatisfaction. Interestingly, the authors also reported that more than 70% of rail users would wait for either resumption of the disrupted service or arrival of shuttle bus replacements.

Most of the reviewed studies have used RP surveys to collect required data for their analysis. RP surveys typically suffer from several issues such as lack of variation in data to study all variables of interest and potential strong correlation between explanatory variables (Kroes and Sheldon 1988). Due to limitations of RP surveys, some scholars suggested use of stated preference (SP) surveys to reveal transit users' behavior during service disruptions. In an SP survey, respondents are presented with one or multiple hypothetical scenarios and are asked to indicate their decisions when facing such a situation in the real world. Conducting an SP survey from train passengers in Klang Valley, Malaysia, Bachok (2008) focused on modal shift behavior of rail users due to a service disruption. In this study, train passengers were asked to choose an alternative among a set of provided options, including other trains, shuttle bus, private vehicles, and wait for the restoration of the rail system in a hypothetical scenario.

Similarly, Fukasawa et al. (2012) investigated the effect of providing information such as estimated arrival time, arrival order and congestion level on passengers' modal shift behavior in response to unplanned transit disruption using a data from an SP survey. They found that train users, who have access to the information, generally have a higher tendency of shifting to other trains in comparison with those without access to the information. In contrast, Bai and Kattan (2014) conducted an SP survey on light rail transit passengers in Calgary, Canada, and found out that respondents without access to the information concerning possible recovery period have more willingness to switch their travel mode.

SP surveys might not necessarily represent transit users' behavior in real transit disruption incidents. One approach to address such issues is to combine RP and SP surveys. As an example of this approach, Lin (2017) proposed a combined RP-SP survey to analyze rail users' behavior in response to a subway disruption in the Toronto area. In the survey, the RP section collected information about respondents' last experience with unplanned rail disruptions. Further, in the SP section, several hypothetical disruption scenarios were included in which respondents were asked to indicate their response to the incident such as canceling the trip or switching to other available modes. Focusing on subway commuters, the authors found that household income, age, travel cost, waiting time, the length of delay, weather condition, trip purpose, and being frequent rail user affect transit users' behavior during subway service disruptions.

Previous studies provide valuable insights into transit users' preferences regarding alternative options during unplanned transit disruptions. To the best of our knowledge, there is yet no study focusing on transit users' waiting tolerance before starting to think about alternative options when an unplanned disruption occurs. Furthermore, while the literature is mostly focused on one specific transit mode, this study is designed to consider the entire transit system in the Chicago region. In addition, as an improvement to the recall SP-RP survey conducted by Lin (2017), we have designed a new SP-RP survey in which the respondents are intercepted while waiting in the transit stations. The results of such surveys can be more reliable than recall surveys particularly if they are conducted during the trip (Sudman and Bradburn 1973). The details of our conducted survey are fully described in Auld et al. (2018) and briefly presented in the following sections.

Table 2-1 Literatures on different aspects of transit disruption

Study	Geographical context	Disruption type[a]		Study method									Research focus						
		Pre-planned	Unplanned	Discrete choice analysis	Statistical analysis	Qualitative analysis	Probabilistic analysis	Simulation	Complex network analysis	Survival analysis	Mathematical programming	Literature review	Network condition	Transit ridership	Mitigation	Information effect	Service recovery duration	Users ‘ response behavior	Users ‘ waiting tolerance
(Company., Authority., and Zimmermann. 1967)	New York City, U.S.	×			×													×	
(Crain and Flynn 1975)	Los Angles, U.S.	×			×													×	
(Blumstein and Miller 1983)	Pittsburgh, U.S.	×			×													×	
(N.Job A. van Exel and Rietveld 2001)	Netherlands	×										×						×	
(Walker, Snowdon, and Ryan 2005)	New Zealand	×	×								×				×				
(Lo and Hall 2006)	Los Angles, U.S.	×			×								×						
(N.J.A. van Exel and Rietveld 2009)	Netherlands	×		×														×	
(Zeng, Durach, and Fang 2012)	Munich, Germany	×	×								×				×				
(Murray-Tuite, Wernstedt, and Yin 2014b)	Washington D.C.		×	×														×	
(Pender et al. 2014)	Australia		×									×				×			
(Pnevmatikou, Karlaftis, and Kepaptsoglou 2015)	Athena, Greece	×		×														×	
(Papangelis et al. 2016)	United Kingdom	×	×			×										×		×	
(H. Sun et al. 2016)	Beijing, China	×	×			×	×						×	×					
(Jacob Louie, Shalaby, and Habib 2017)	Toronto, Canada	×	×							×							×		
(Currie and Muir 2017)	Melbourne, Australia		×		×													×	
(Ghaemi, Cats, and Goverde 2017)	Netherlands	×	×								×	×			×				
(Srikukenthiran and Shalaby 2017)	Toronto, Canada	×	×					×					×		×				
(Teddy Lin et al. 2018)	Toronto, Canada		×	×														×	
(Saberi et al. 2018)	London, U.K.	×			×				×									×	
(Nazem et al. 2018)	Montreal, Canada	×			×													×	
(Yap, Nijënstein, and van Oort 2018)	Hague, Netherlands	×					×							×					
(Nguyen-Phuoc et al. 2018)	Melbourne, Australia	×		×														×	
(Hua and Ong 2018)	Singapore	×	×								×					×			
Current study	**Chicago, U.S.**		×	×						×								×	×

[a] Both types are marked for studies focused on the general nature of disruption.

2.2 The COVID-19 pandemic and mobility

The association between travel behavior and perceived risk of exposure to a public health crisis similar to the COVID-19 pandemic has received little attention in the literature, despite the fact that the risk perception significantly characterizes individual travel behavior (Hotle, Murray-Tuite, and Singh 2020). In a recent study, Elias, Albert, and Shiftan (2013) investigated the changes in travel behavior caused by a terror threat in Israel and showed that fear and risk perception are vital in understanding travel behavior with respect to public transportation. In this study, women were found to perceive more risk than men, and thus, such impacts on women's travel behavior are found to be more exhaustive. As a result, an undesired modal shift from public transportation to personal cars might occur.

Focusing on the effect of perceived risk of viral outbreaks on travel behavior, Rittichainuwat and Chakraborty (2009) conducted a study in Thailand and found that people did not completely discontinue traveling during the outbreak caused by SARS; instead, they selected different options from less dangerous destinations. Moreover, the authors showed that although all travelers perceived risk of diseases, the level of risk might be different from person to person, depending on whether one is either a first-time or repeatedly traveler. In another study, Wen, Huimin, and Kavanaugh (2005) analyzed the impact of SARS (Severe Acute Respiratory Syndrome) on the travel behavior of Chinese domestic tourists focusing on their leisure travel. Running a survey among those who were affected, the authors found that SARS has dramatically changed people's life, work, and traveling during the SARS period; however, the level of the impacts on people's preference to travel and the preference of leisure trips might be different. Besides, the decrease in travel was caused by a combination of internal motivation (e.g., perceived risks) and external enforced measures (e.g., travel bans, stay-at-home orders).

Moreover, Liu, Moss, and Zhang (2010) studied the effects of the SARS outbreak on travel between the U.S. and three destinations: China, Hong Kong, and Taiwan. The authors found that although frequency of trips was decreased in all countries, the level of risk was perceived differently among those countries, highlighting the influence of lifestyles on travel behavior during an outbreak. Hotle, Murray-Tuite, and Singh (2020) investigated risk perception and risk mitigation of travel-related decisions concerning influenza to characterize the risk perceptions. The authors highlighted that being female and self-experience of having influenza-like symptoms significantly increased risk perception at the locations that people perform mandatory and health-related activities (e.g., doctor's office and hospitals). Furthermore, their results showed that high perceived risks of exposure to an influenza virus do not lead people to travel to their workplaces less frequently.

There are a limited but growing number of studies focusing on the impacts of the COVID-19 pandemic on individuals' travel behavior. Bucsky (2020) analyzed the demands for various modes of transport such as public transport, personal vehicle, and bike during the COVID-19 pandemic in Budapest, Hungary. The author observed that usage of public transit decreased dramatically by 80%, while the overall mobility was reduced, at least by 51% and maximally by 64%. On the other hand, modal shares of personal vehicles and bikes increased to 65% and 4% from 43% and 2%, respectively.

In another study conducted in Netherland, de Haas, Faber, and Hamersma (2020) found that approximately 80% of people engaged in out of home activities less frequently. Moreover, seniors are turned out to be less active than before the pandemic. The authors also observed that the number of trips and VMT are reduced by 55% and 68%, respectively, as compared with the fall of 2019. The demand for public transit is impacted severely with a decrease of over 90% of ridership; Most people preferred individual modes compared to public or shared modes of transport. Teixeira and Lopes (2020) focused on the usage of bike-sharing and subway system during the COVID-19 pandemic in New York and observed that Citi Bike (i.e., the bike-sharing system operating in New York) was revealed to be more resilient than the subway system, with a less significant ridership reduction and an increase on its trips' average duration. Moreover, the author found a potential modal transfer from some subway users to the bike-sharing system.

3 PHASE I OF TRANSIT USERS' DISRUPTION BEHAVIOR: WAITING TOLERANCE

3.1 Introduction

This chapter sheds light on transit users' waiting tolerance, defined as the length of time that transit users are willing to wait for a disrupted transit service to be restored before starting to think about switching to another mode or canceling/adjusting the trip. According to our recent survey in the Chicago region, about 33% of the transit users reported that they would wait more than 20 minutes for the system to be restored, and more interestingly, about 8% of them would wait more than 45 minutes. The heterogenous behavior of riders can be attributed to several factors including their personal attitudes and preferences, trip characteristics, and accessibility to other modes, among others. Yet, there is limited empirical evidence on how these factors affect riders' decision behavior.

3.2 Survey Design and Data Descriptions

The main source of data used in the current study is a survey recently designed and conducted by a research team from Argonne National Laboratory, University of Illinois at Chicago, and University of Chicago. Full information about design of various parts of the survey, implementation process, and summary statistics of the collected data can be found in Auld et al. (2018). Here, we only elaborate on the sections that are related to the scope of the current study.

The survey was designed as an in-station intercept survey with the objective of analyzing transit riders' decision behavior in case of facing an unplanned service disruption in the Chicago metropolitan area. Passengers were intercepted by the survey implementation team at each of the four major transit systems in the Chicago area: CTA bus, CTA rail, Metra, and PACE suburban bus. Stations and stops were sampled employing a Probability Proportional to Size (PPS) sampling approach, with the size represented by the average daily ridership as well as the boarding information of each agency (Auld et al. 2018). As a result, around 100 separate stations were selected belonging to all major operators of the transit network.

With respect to the survey operation, trained interviewers were positioned in or near stations, considering rights that were granted by each transit agency (Auld et al. 2018). For CTA buses, passengers were intercepted at stations. For CTA trains and Metra, interviewers were positioned right after the turnstiles to intercept riders who are either boarding or alighting multiple lines at each station (Auld et al. 2018). Interviewers were instructed to 1) select all passengers entering or exiting the station, 2) provide a short description of the research, and 3) offer a tear-off sheet that includes all the information necessary for completing the online survey (Auld et al. 2018). Besides, interviewers explained that a $5 Amazon E-gift card would be offered when the passenger completed the survey. We ensured that the entire interaction between the interviewer and the passenger lasted about 3 minutes (Auld et al. 2018).

Around 15,500 invitation cards were printed to be handed out to passengers at the selected stations, and ultimately, a total of 6,377 transit passengers were approached and given the invitation card. Among those who received the invitation, 892 passengers logged in to the online survey and 659 of them completed the full survey in an average time of 21.9 minutes. Accordingly, the rate of participation for the survey was turned out to be 10.3 percent of the intercepted passengers.

The survey was designed using a web-based surveying platform and it was accessible through a survey link and PIN distributed to the intercepted respondents. Passengers who agreed to participate in the study were given a contact card with a unique PIN which identified the service, contact time, and station. Through entering the PIN, respondents were directed to the online questionnaire. In the survey, a full set of individual- and household-level socio-demographic information as well as comprehensive information about the intercepted transit trip including fare, time, origin, destination, access/egress, ride quality, time use, and trip purpose among others were collected. Further, passengers' preferences and attitudes towards transit and other mobility options such as taxi, ridesharing, and bike-sharing programs were collected.

This survey uses Google Maps API to collect information regarding the origin and destination of transit trip, display transit routes, and calculate travel time (**Figure 1**). Taking advantage of Google Map APIs, travel-related information such as travel times, waiting times, and the number of transfers is automatically stored.

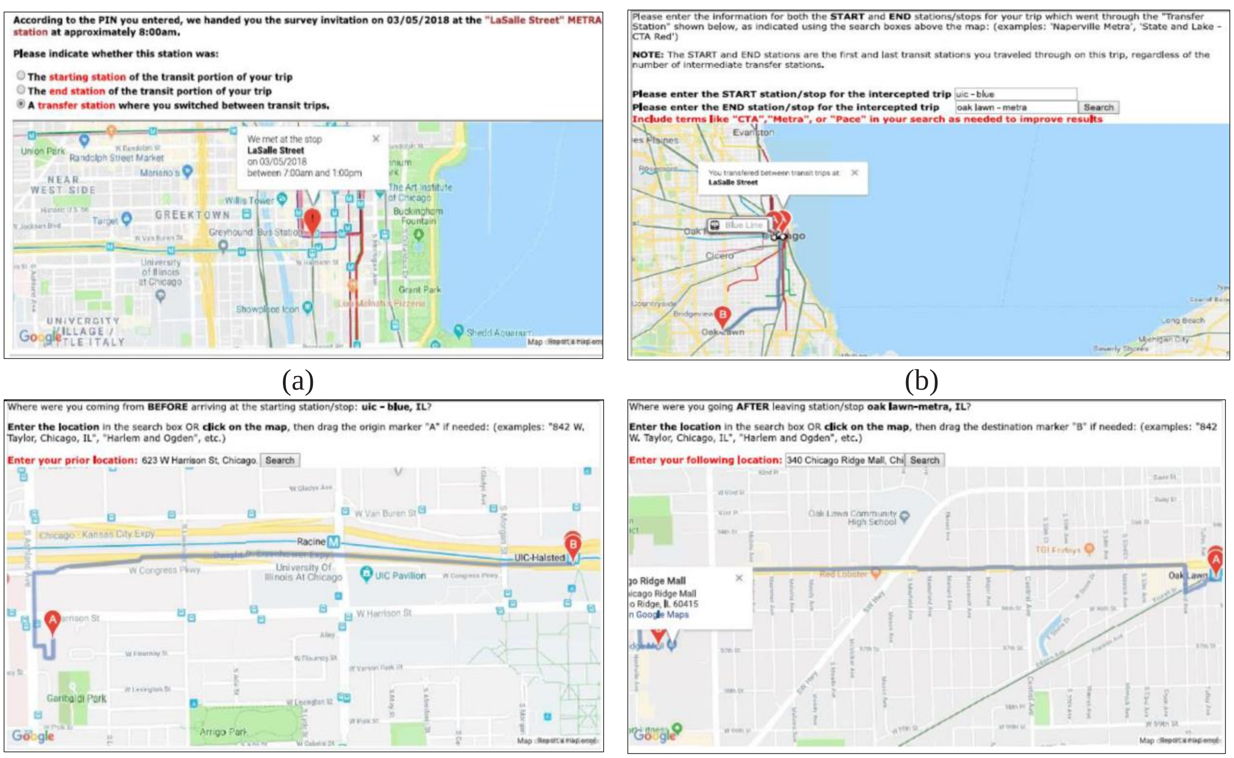


Figure 1. Collecting the intercepted transit trip information using Google Maps API: a) Identifying the intercepted station, b) Choosing the start/stop stations, c) Choosing the location before arrival to the station, d) Choosing the location following the departure from the station (Adapted from (Auld et al. 2018)).

In the current study, the outcome variable is derived from a question in the survey which asks the riders to indicate how long they are willing to wait for the service to be restored before planning for an alternative solution (i.e., waiting tolerance). The frequency of the observations is shown in **Figure 2**.

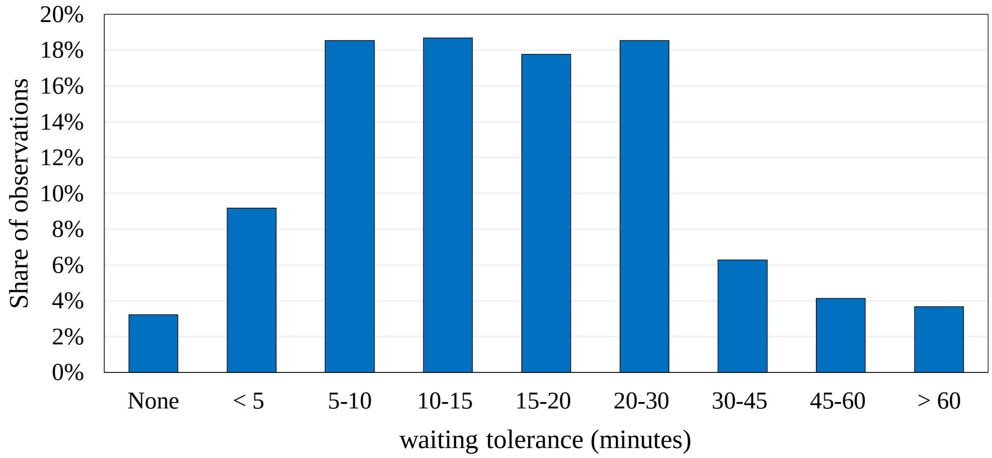
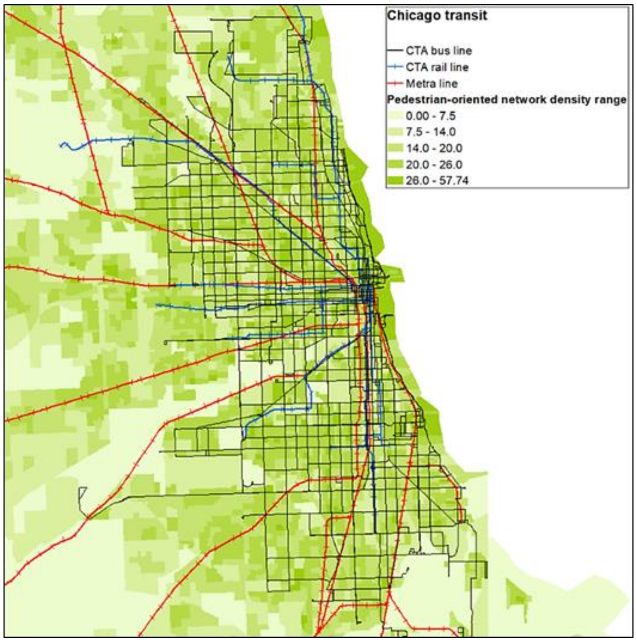


Figure 2. Waiting tolerance for the transit system to be restored.

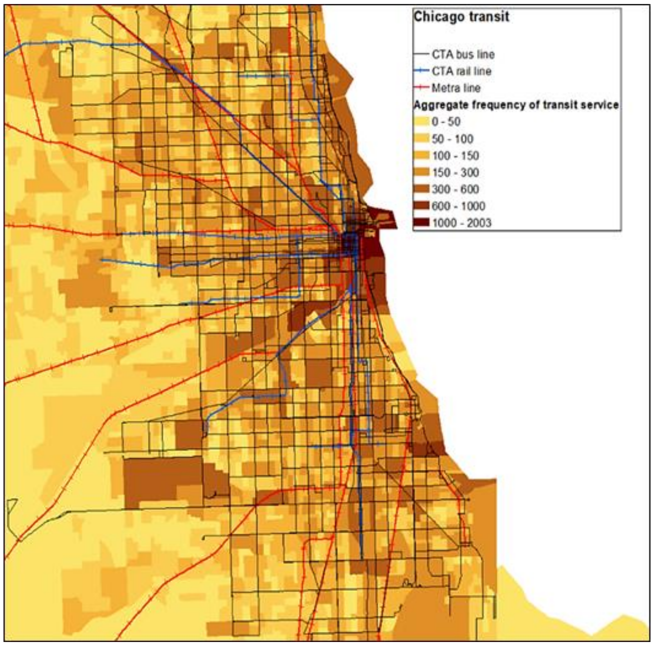
We have also complemented the data from the survey with built-environment information from the Smart Locations provided by the Environmental Protection Agency (EPA). This information is provided at the census block group level and could provide insights into understanding the effect of built-environment settings at the block-group, where the origin station is located, on transit user's waiting tolerance during a disruption.

Figure 3 illustrates Chicago transit system mapped on the color scheme of two variables (that are turned to be significant in the final model as will be discussed in the next sections) including pedestrian-oriented network density and aggregate frequency of transit service at block groups. Pedestrian-oriented network density defines as a walkability criterion and is calculated by summing pedestrian-oriented links within a block group dividing by the area of that block group (Ramsey and Bell 2014). The aggregate frequency of transit service for each block group is calculating by summing the frequency of transit routes with service that stops within 0.25 miles from the block group's boundary (Ramsey and Bell 2014).

The final sample comprises of 630 observations, each for a separate transit trip. **Table 3-1** outlines the definition of independent variables introduced into the models, along with their summary statistics. As can be seen, the independent variables can be categorized into 4 groups of socio-demographics, attitudes, trip characteristics, and built-environments.



a) Pedestrian-oriented network density at a block group level



b) Aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period

Figure 3. Chicago transit system at a glance

Table 3-1. Variables used (found to be significant) in the Log-Normal AFT model

Category	Name	Definition	Mean	Std. Dev.
Demographics	Senior	1: If the age of transit user is more than 65 years old/ 0: Otherwise	0.030	0.171
	Younger boomer	1: If the age of transit user is between 55 and 65 years old/ 0: Otherwise	0.118	0.323
	Millennial	1: If the age of transit user is between 25 and 34 years old/ 0: Otherwise	0.329	0.470
	GRADUATE	1: If the transit user has a master degree and more/ 0: Otherwise	0.336	0.473
Attitudes	COMPETITIVENESS	1: The transit mode is selected because there is a lack of other options/ 0: Otherwise	0.193	0.395
	TRAFFIC	1: The transit mode is selected because there is no need to pay attention to the traffic/ 0: Otherwise	0.374	0.484
	PRIVACY	1: If the transit user believes that privacy is restricted in the transit/ 0: Otherwise	0.316	0.465
	TRUST	1: If the transit user trusts and follows the instructions releasing by the transit authority/ 0: Otherwise	0.915	0.280
	FRND_TRNST	1: If the person uses transit as a travel mode almost every day/ 0: Otherwise	0.513	0.500
	TNC	1: If the person has the experience of using ride-hailing (e.g., Uber, Lyft) in the past as a travel mode/ 0: Otherwise	0.335	0.472
	DIVVY	1: If the person has the experience of using the bike-sharing program in the past as a travel mode/ 0: Otherwise	0.191	0.394
Trip characteristics	DISTANCE	The distance between the trip origin and destination in miles (Ranged between 0.39 and 59)	15.29	26.44
	DIST_L5	1: If the distance between origin and destination is less than 5 miles/ 0: Otherwise	0.264	0.441
	DIST_5_10	1: If the distance between origin and destination is less than 10 miles and more than 5 miles/ 0: Otherwise	0.286	0.452
	MANDATORY	1: If the purpose of the trip is work or school/ 0: Otherwise	0.510	0.500
	FLEXIBLE	1: If the transit user has time flexibility for arrival at the destination/ 0: Otherwise	0.703	0.457
	DURATION_O	The activity duration at the origin before going to a transit station (Ranged between 0 and 23 hours)	7.164	5.069
	ALONE	1: If the transit user is traveling alone/ 0: Otherwise	0.863	0.345
	WAIT_TIME	The waiting time at the origin's transit station (Ranged between 0 and 45 min)	7.556	6.334
	CTA_BUS	1: If the person is waiting for CTA bus/ 0: Otherwise	0.164	0.371
Built environment	FRQ. TRANSIT	The aggregate frequency of transit service within 0.25 miles of block group (where the origin station is located) boundary per hour during the evening peak period (Ranged between 1 and 2003)	295.7	412.2
	FRQ.TRANSIT_L50	1: If FRQ.TRANSIT < 50/ 0: Otherwise	0.188	0.391
	NDNSTY_PED	Network density of block group (where the origin station is located) regarding facility miles of pedestrian-oriented links per square mile (Ranged between 1.42 and 50.5)	19.19	9.539
	NDNSTY_PED_L20	1: If NDNSTY_PED < 20/ 0: Otherwise	0.645	0.479

3.3 Modeling Approach

In this study, we are interested in understanding the transit users' waiting tolerance before planning for an alternative solution in case of unplanned transit disruptions; that is, the interval from the time that the rider arrives at a station and the time he/she starts to make a decision about the alternative options. This period of time, *T*, is the survival variable of interest and can be thought of as a non-negative random variable. Let us assume this variable has a cumulative distribution function, denoted by *F(t)*, and a probability density function, denoted by *f(t)*. In survival analysis, *F(t)* is also interpreted as the failure function and provides the probability of occurrence of an event before any specific value of interest *t*. Also, the survival function, denoted by *S(t)*, gives the probability that the random variable *T* being higher than a specific value of interest *t*. (J. Sun 2006)

$$S(t) = P(T > t) = 1 - F(t), \quad 0 < t < \infty \qquad \textbf{Eq. 1}$$

The hazard function, *h(t)*, can be defined as the conditional probability of occurrence of an event between time *t* and $t+\Delta t$, provided that the survival time is greater than *t*.

$$S(t) = \int_t^\infty f(s)ds \qquad \textbf{Eq. 2}$$

$$h(t) = f(t)/S(t) = \lim_{\Delta t \to 0^+} \frac{P(t<T<t+\Delta t \mid T>t)}{\Delta t} \qquad \textbf{Eq. 3}$$

Therefore, it can be proved that (J. Sun 2006):

$$S(t) = \exp\left[-\int_0^t h(s)ds\right] \qquad \textbf{Eq. 4}$$

The form of hazard function in **Eq. 4** should be assumed to define the survival function. Three basic types of hazard functions are common including non-parametric, semi-parametric, and parametric (Kleinbaum and Klein 2012). In this study, we utilized a fully parametric approach which allows using different distributional alternatives for the survival function such as Exponential, Log-logistic, Weibull, and Log-normal. Besides, parametric survival models are more consistent with the theoretical definition of survival (Kleinbaum and Klein 2012).

Proportional hazard (PH) and accelerated-failure time (AFT) are two alternative modeling approach for parametric survival analysis (Greene 2003). The critical assumption for an AFT model is that the effect of explanatory variables is proportional with respect to survival time, while the critical assumption for a PH model is that the effect of explanatory variables is proportional with respect to the hazard (Kleinbaum and Klein 2012). We adopted AFT formulation due to several reasons: 1) The structure directly includes the effects of explanatory variables on the survival time, 2) It facilitates the interpretation of results, and 3) the objective of this study is developing a model to predict duration itself, rather than the probability of occurrence over time (Rashidi and Mohammadian 2011; Haque and Washington 2015).

In an AFT model, a linear relationship is considered between the logarithm of the survival time and the vector of explanatory variables (J. Sun 2006):

$$\log T = X'\beta + \varepsilon \qquad \textbf{Eq. 5}$$

where X' is the vector of explanatory variables, β is the vector of coefficients to be estimated, and ε is the error term with a known distribution. Define $\varepsilon^* = \exp(\varepsilon)$ and let $h_w(t)$ denote the hazard function of ε^*, which is independent of β. Then, $T = \exp(X'\beta)\,\varepsilon^*$, and the survival function of T given X' would be (J. Sun 2006):

$$S(t, X') = \exp\left[-\left(te^{-X'\beta}\right)\int_0^t h_w(s)ds\right] \qquad \textbf{Eq. 6}$$

In estimating **Eq. 6**, four commonly used distributions for T were considered, including Exponential, Weibull, Log-normal, and Log-logistic to find the best fit for the waiting tolerance data. The distributions and corresponding survival functions are listed in **Eq. 7** to **Eq. 10**.

Exponential: $S(t) = e^{-\lambda t}$ **Eq. 7**

Weibull: $S(t) = e^{-(\lambda t)^p}$ **Eq. 8**

Log-normal: $S(t) = \Phi[-p. \ln(\lambda t)]$ **Eq. 9**
$\ln t$ is normally distributed with mean $-\ln \lambda$ and standard deviation 1/*p*

Log-logistic: $S(t) = 1/[1 + (\lambda t)p]$ **Eq. 10**
$\ln t$ has a logistic distributed with mean $-\ln \lambda$ and standard deviation $\pi^2/(3p)^2$

Where λ is the location parameter, p is the scale parameter, and $\Phi(.)$ is the standard normal cumulative distribution function.

A standard approach to estimate the coefficients and parameters is using a maximum likelihood estimator, which is shown in **Eq. 11**.

$$L = \prod_{i=1}^{n} L_i = \prod_{i}^{n} h(t_i)^{d_i} S(t_i)$$ **Eq. 11**

Where, d_i is the failure indicator for individual $i = 1, 2, \dots, n$.

As explained in the previous sections, the data used in this study records the length of time in which the failure occurs rather than the exact value. Thus, the models need to be corrected for the so-called interval and right censorship (Kleinbaum and Klein 2012). Interval censorship occurs if an individual's exact survival time is within a known time window in the follow-up period. Similarly, the right censorship occurs when the failure does not happen during the study period due to ending the follow-up period or losing the observation. Different methods have been suggested in the literature to address this issue. One popular approach proposed for an AFT model suffering from interval and right censorship is to adjust its likelihood function (Finkelstein 1986; Lindsey and Ryan 1998; Odell et al. 1992; J. Sun 2006). Let T_i denote the survival time of the outcome for individual i, and consider the survival function of a AFT model, $S(t, \boldsymbol{\delta})$, where $\boldsymbol{\delta} = (\delta_1, \delta_2, \dots, \delta_p)'$ denotes unknown parameters. Also, suppose that $[L_i, R_i]$ is the period that T_i is given. Then the adjusted log-likelihood function would be (J. Sun 2006) :

$$\log L(X', \boldsymbol{\delta}) = \sum_{j=1}^{n} S_j(L_i, \boldsymbol{\delta}) - \sum_{j=1}^{n} S_j(R_i, \boldsymbol{\delta}) \qquad \textbf{Eq. 12}$$

3.4 Estimation Results

This section is devoted to elaborating on modeling and results, and is organized as follows: First, different model specifications are tested to find the outstanding model. Next, the best-fitted model and its results are presented. Last, the survival function is illustrated in different scenarios and based on the results, several policy implications of this study are discussed.

3.4.1 Model specification

As described in Section 3.3, four different AFT models are fitted to the data, using the Exponential, Weibull, Log-Logistic, and Log-Normal distributions. Also, following the underlying literature (Machin, Cheung, and Parmar 2006; B. Lee and Timmermans 2007; Tavassoli Hojati et al. 2013; J Louie, Shalaby, and Habib 2016; Rashidi and Mohammadian 2011), we employed different techniques to robustly compare the models.

First, the general goodness of fit of the AFT models is compared with each other using the BIC index (Rashidi and Mohammadian 2011). BIC is a criterion for choosing a well-fitting model among a set of parametric models with different number of explanatory variables (Rashidi and Mohammadian 2011) complexity (i.e., number of explanatory variables). The lower the value of

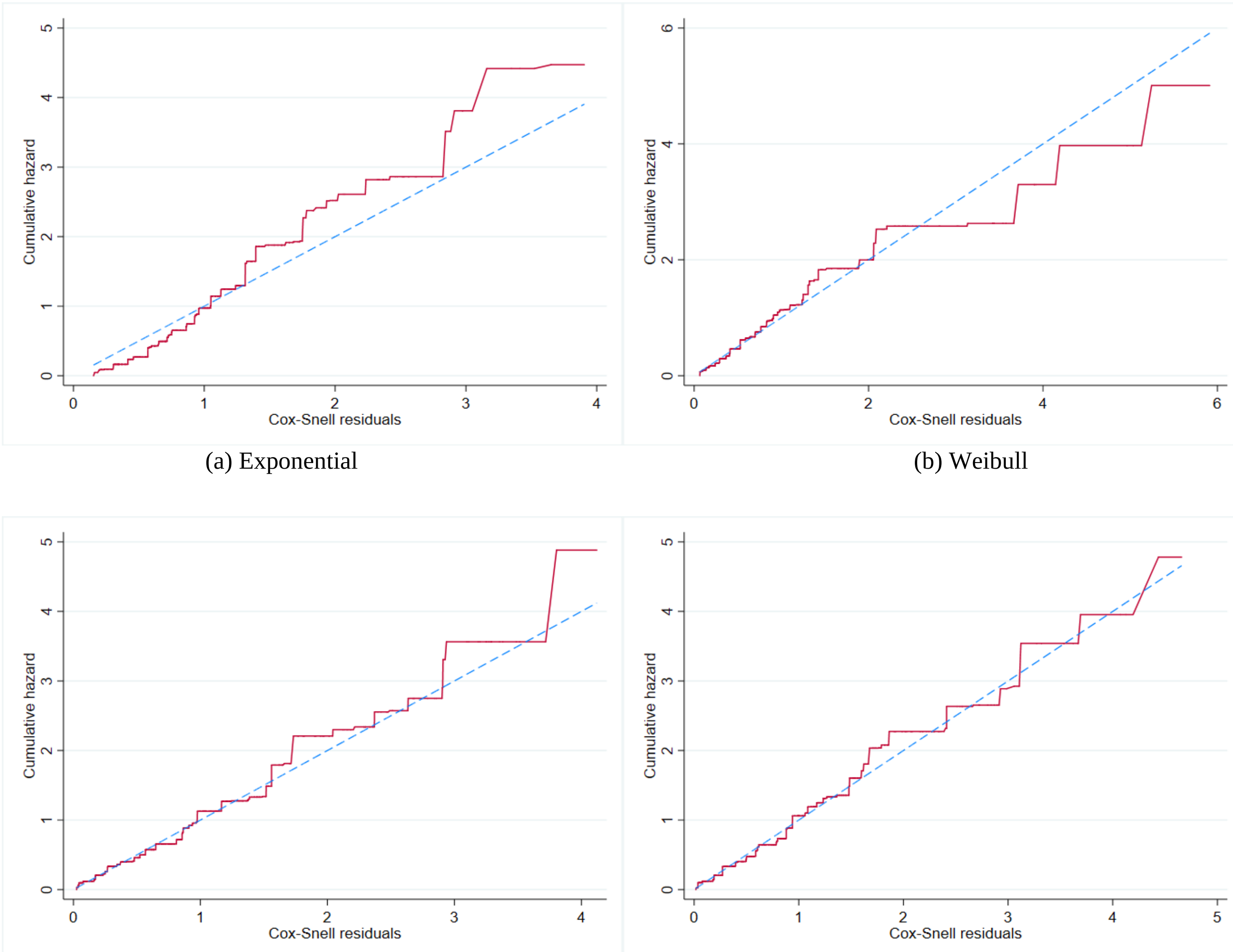
BIC, the better is the fitted model. The BIC values for the AFT models' specifications are presented in **Table 3-2**. As can be verified from **Table 3-2**, AFT models with Log-Logistic and Log-Normal distributions provide a better fit than the rest. However, the values of BIC for Log-Normal and Log-Logistic AFT models are very close and thus proposing the best one might need further investigations.

Table 3-2. BIC analysis for the Exponential, Weibull, Log-Logistic, and Log-Normal AFT models

Model Type	**Log-Likelihood at the convergence**	**Number of variables**	**BIC**[a]
Exponential	-1231.24	17	2572.14
Weibull	-1172.54	21	2480.44
Log-Logistic	-1159.5	23	2467.25
Log-Normal	-1165.42	21	2466.20

[a] BIC $= -2\ln[L(\beta)] + k.\ln(N)$, Where $\ln[L(\beta)]$ is the log-likelihood value at convergence, k is the number of variables, and N is the number of observations.

Another approach used to compare the models' specifications is based on the Cox-Snell residuals (Cox and Snell 1968; Machin, Cheung, and Parmar 2006). In this approach, the Cox-Snell residuals are plotted against the cumulative hazard function to assess the overall fit of models. A Cox-Snell residuals plot for the most well-fitting model specification should closely align with a slope of 1 and an intercept of 0. **Figure 4** shows Cox-Snell residuals plots for the AFT models with four distributional alternatives. According to **Figure 4**, Log-Normal specification remains the best out of the four AFT models, since its slope of Cox-Snell residuals plot is closest to 1. Interestingly, this visualization could justify the outcome of BIC approach as well.



(a) Exponential (b) Weibull

(c) Log-Logistic (d) Log-Normal

Figure 4. Cox-Snell residuals plot for the Exponential, Weibull, Log-Logistic, and Log-Normal AFT models

3.4.2 Lessons from the best-fitted model

The explanatory variables that are found to be significant (with at least 80% confidence level) in the best-fitted model (i.e., the Log-Normal AFT model) are discussed in this section, in four categories of 1) socio-demographics, 2) attitudes, 3) trip characteristics, and 4) built environments. **Table 3-3** presents the estimated parameters, along with their level of significance. To interpret the results, an estimated parameter with positive sign reveals an increase in the duration of transit users' waiting tolerance.

Table 3-3. Results for the Log-Normal AFT model

Variable Category	Explanatory Variable	Lognormal AFT model	
		Coefficient	***p*-value**
Demographics	Senior	0.284	0.115
	Younger boomer	0.214	0.026
	Millennial	-0.146	0.031
	GRADUATE	-0.0778	0.161
Attitudes	COMPETITIVENESS	0.214	0.005
	TRAFFIC	0.189	0.003
	PRIVACY	-0.140	0.038
	PRIVACY * TNC	-0.326	0.078
	FRND_TRNST	0.130	0.035
	DIVVY	-0.164	0.036
	TRUST	0.289	0.008
Trip characteristics	DISTANCE * DIST_L5	-0.079	0.002
	DISTANCE * DIST_5_10	-0.026	0.007
	MANDATORY	-0.108	0.100
	FLEXIBLE	0.128	0.005
	ALONE	0.217	0.014
	WAIT_TIME	0.015	0.002
	CTA_BUS	-0.248	0.003
Built environment	FRQ. TRANSIT * 10^{-3}	-0.159	0.041
	FRQ. TRANSIT * FRQ.TRANSIT_L50 * 10^{-2}	0.428	0.195
	NDNSTY_PED_L20	0.097	0.139
Constant		2.111	0.000
Ln (P)		-0.327	0.000
P		0.721	
LL (β)		-1165.42	
LL (c)		-1233.52	
LL (0)		-1368.53	
Number of observations		630	
Right-censored		23	
Left-censored		0	
Interval-censored		607	

3.4.2.1 Attitudes

In terms of individual attitudes toward transit, our results indicate that those who have selected the transit option to avoid the hassle of traffic congestion might have more willing to wait at the station during a disruption. This could be because such individuals could take advantage of the waiting time to either socialize with others or do other activities such as reading a book or newspaper. This finding is in line with Beirão and Sarsfield Cabral (2007) where the authors argued that for some individuals who have selected the transit as a worry-free option, the time spent on public transit would be an opportunity to relax, read a book or talk to others.

Moreover, the availability of alternative modes to the riders is found as an influential factor on transit users' waiting tolerance at the station. In-line with the intuition, we found that those who have selected the transit due to the lack of other alternatives might have more tendency to wait at a station during unplanned disruptions.

Our results also show that those transit users who trust and follow the information provided by transit authorities stay at stations more than others. This finding is consistent with the literature arguing that passengers prefer to have some information about the disruption, and such information significantly impacts their decision-making process in such situations (TYT Lin 2017; Fukasawa et al. 2012). Moreover, the results indicate that although transit users prefer to receive information regarding an unplanned disruption, such information is not expected to have the same effect on each passenger; this effect might vary depending on how transit users trust authorities.

As can be seen in **Table 3-3**, interestingly, the experience of using the ride-hailing and bike-sharing program in the past could accelerate leaving the station during an unplanned disruption, especially for those who have concerns about their privacy while traveling by transit. This is possibly because privacy concerns regarding public transit, as one of the most important factors of transit dissatisfaction (Tyrinopoulos and Antoniou 2008), encourage the transit user to decrease the duration of waiting time at the station and choose ride-hailing as an alternative transport mode. This is in line with the literature arguing that ride-hailing option theoretically has a complementary relationship with public transit (Stillwater, Mokhtarian, and Shaheen 2008). Our finding, also, is justifiable with respect to Murphy and Feigon (2016) who revealed that ride-hailing users consider transit as the most preferred alternative mode to perform their trips. Thus, if a ride-hailing user select transit and the system become disrupted, he or she might probability shift the mode sooner than others.

Another attitudinal attribute is the frequency of public transit usage. Supported by the intuition, our results reveal that those individuals, who are more dedicated to transit, have more tendency than others to wait during unplanned disruptions.

3.4.2.2 Socio-demographics

Compared to individuals aged between 44 and 54 (as the base group), millennials (i.e., 24-34 years old) are found to have lower tolerance to wait at the station during a disruption. One possible reason for this finding is that millennials are more tech-savvy than older groups (Clayton, Jain, and Parkhurst 2017; Lyons, Jain, and Weir 2016), which leads them to be adept at finding information on the alternative travel modes such as ride-hailing services. They are also physically and mentally more open to switching to active modes such as shared bicycles and walking. Furthermore, this group might have tighter activity-travel schedule compared to older generations. On the other hand, seniors (this variable found to be significant at 85% level of confidence) might prefer to stay at stations longer than millennials and younger boomers (i.e., 55-65 years old) because they are most probably retired (Burris and Pendyala 2002) and have more flexible activity-travel schedules (Frei, Hyland, and Mahmassani 2017).

Moreover, the results reveal that highly educated individuals might stay at the station less than others during a disruption. This is possibly because this group of society is more likely to be knowledgeable about alternative options such as ride-hailing due to their greater propensity to use information and communication technologies (Dias et al. 2017). This group also might have tighter activity-travel schedules compared to others.

3.4.2.3 Trip characteristics

With respect to the influence of trip distance, per the results, short-distance transit users intend to decide about alternative modes in a shorter period while the service is disrupted. In fact, the more the distance, the more is the transit users' waiting time at the station. This is probably because, in short-distance trips, walking could be a preferred alternative of transit (Rodríguez and Joo 2004) and thus short-distance transit users might consider this free mode in a shorter period of time. Moreover, since ride-hailing options are already competitive with public transit on short distances (New York Public Transit Association 2018), this alternative could be utilized rapidly by short-distance users when transit service is disrupted.

The results also indicate the significant associations of trip purpose and arrival time flexibility at destination. It is found that those who are traveling to work or school (i.e., performing a mandatory trip) prefer to stay at the station less than others. This effect might be because mandatory trips have less arrival time flexibility than other trips. Furthermore, intuitively appealing, our results suggest that having flexibility for arrival time at destination increases the duration of the transit users' waiting tolerance at the station while a transit service is disrupted.

As can be seen in **Table 3-3**, we found that transit users who are accompanied by others have less waiting tolerance at stations during an unplanned disruption. This could be because group travelers might have more constraint on their activity-travel scheduling. In addition, the possibility of sharing the cost of the alternative modes for group travelers could encourage them to leave the station ahead of others.

Our findings also suggest that those transit users who are used to wait more at the transit station in the normal (undisrupted) situations have the intention to stay more than others in case of unplanned disruptions. This is possibly because the waiting time in a normal situation, over time, increases the transit user's overall expectation for the transit service operation. This is in line with

Murray-Tuite, Wernstedt, and Yin (2014a) where the authors argued that transit users' experiences regarding their past transit trips is an influential factor on their future decisions about transit services.

Also, our results reveal that the type of transit service (i.e., bus or rail) is a significant factor in transit users' waiting tolerance during an unplanned disruption. Per the results, compared to rail transit users, those who travel by bus have less intention to stay at the station when an unplanned disruption occurs. This is might be due to the ease of accessibility to other options from bus stations compared to rail.

3.4.2.4 Built environment

With respect to transit accessibility, the results indicate that the frequency of transit services within the block group, where the trip is originated, accelerates transit users' decision making about alternative modes at the station during a disruption. This is possibly because individuals who are affected by an unplanned disruption in a block group with the high frequency of transit service might have shorter-time access to another transit service to get to their destinations.

The density of pedestrian-oriented roadways at the block group, where the trip is originated, are negatively associated with transit users' waiting tolerance during an unplanned disruption. Per the results, the low density of pedestrian-oriented facilities within the block group could decelerate the survival function of waiting tolerance. Since the density of pedestrian-oriented facilities is positively correlated with the percentage of sidewalks within the block group, these findings might be because the higher density of pedestrian-oriented links increases the utility to choose walking in a shorter period as a less expensive alternative of transit. This finding is in line with (Rodríguez and Joo 2004) where the authors showed that the frequency of sidewalks has a positive impact on the utility of walking in short-distance trips.

3.5 Policy implications

To compare the influence of explanatory variables on the waiting tolerance during a transit disruption, survival curves were plotted using estimated parameters of the Log-normal AFT model. The probabilities of waiting tolerance could be estimated using the survival function of the Log-normal AFT model presented in **Eq. 9**. In this approach, the reference curve is evaluated at the mean values of all explanatory variables, and by assuming specific values for explanatory variables, the new curve could represent a specific scenario.

Figure 5 presents the survival curves in different scenarios during a disruption where transit users are performing a mandatory or non-mandatory trip, and they have either flexibility in their arrival time or not. According to the curves, although having flexibility in arrival time regardless of trip purpose increases the probability of survival at a specific amount of time, trip purposes (i.e., mandatory or non-mandatory) could either accelerate or decelerate this effect. For instance, as can be seen in , the probability of survival at the upper bound average value of waiting tolerance variable (i.e., 20 minutes) when a transit user is performing a mandatory trip without flexibility (the worst case) would be 40% less than when he/she is performing a non-mandatory with flexibility (the best case). Consequently, since the most portion of trips during morning rush hours might be mandatory trips without flexibility, disruptions occur in that time should be given more priority in recovery strategies.

Figure 6 depicts the effect of having experience of using ride-hailing services on the survival function of waiting tolerance period during an unplanned disruption for those transit users who have privacy concerns about transit service. As can be seen, the probability of survival at the upper bound average value of waiting tolerance for transit users who have ride-hailing experience is 34% less than other transit users. This finding highlights the potential of collaboration between transit authorities and transportation network companies in providing recovery options for transit users who are facing a service disruption. This collaboration can significantly help transit authorities to mitigate affected users' dissatisfaction. Moreover, it can also improve the overall transportation resilience since ride-hailing services can transfer transit users to their planned destinations or closest operational transit service in a significantly shorter period compared to shuttle bus replacements provided by transit authorities. A suitable platform to facilitate such collaboration can be provided through mobility-as-a-service (MaaS), which is recently introduced to the transportation market. This innovative concept combines various transportation modes to offer a personalized mobility package which includes other complementary services such as trip planning, booking, and payments (Jittrapirom et al. 2017). The results of this study suggest considering the possibility of collaboration between transportation service providers in the MaaS concept, which can result in enhancing both systems resiliency as well as users' satisfaction.

The relationship between the density of pedestrian-oriented links within a block group where a trip is originated and the survival function of waiting tolerance is illustrated in **Figure 7**. As can be seen, the probabilities of survival within a block group with a high density of pedestrian-oriented links are lower in comparison with a block group with a low density of pedestrian-oriented links. For instance, at the upper bound average value of waiting tolerance, the survival probability within block groups with a low density of pedestrian-oriented links would be 10% more than other block groups. Focusing on the resiliency of the system, these findings indicate that transit users living in the areas with low density of pedestrian-oriented facilities (e.g., suburban areas) are probability more reliant on the transit mode due to the lack of accessibility to other transport options (e.g., active modes, other transit lines). Thus, these areas should be given a higher priority when a transit service is disrupted.

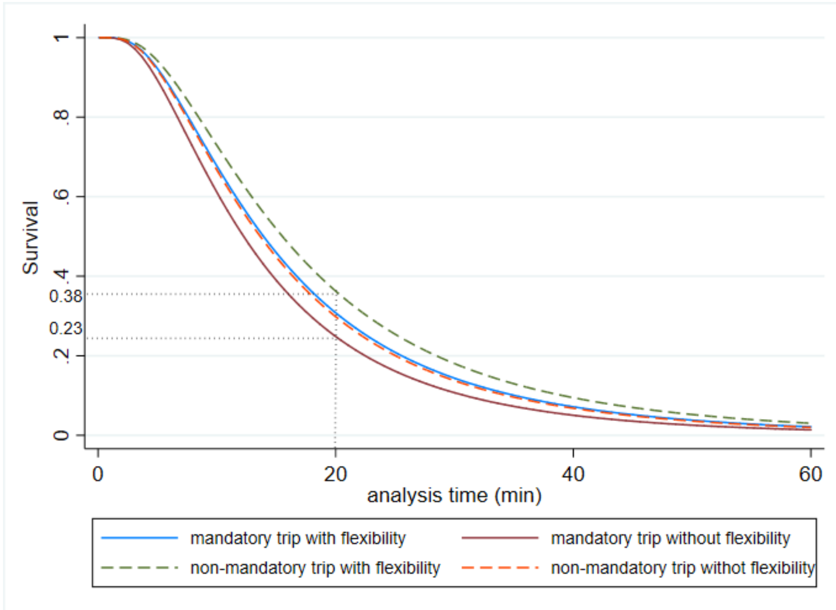


Figure 5. The effect of trip purpose and flexibility of arrival time on the survival function of waiting tolerance during a disruption

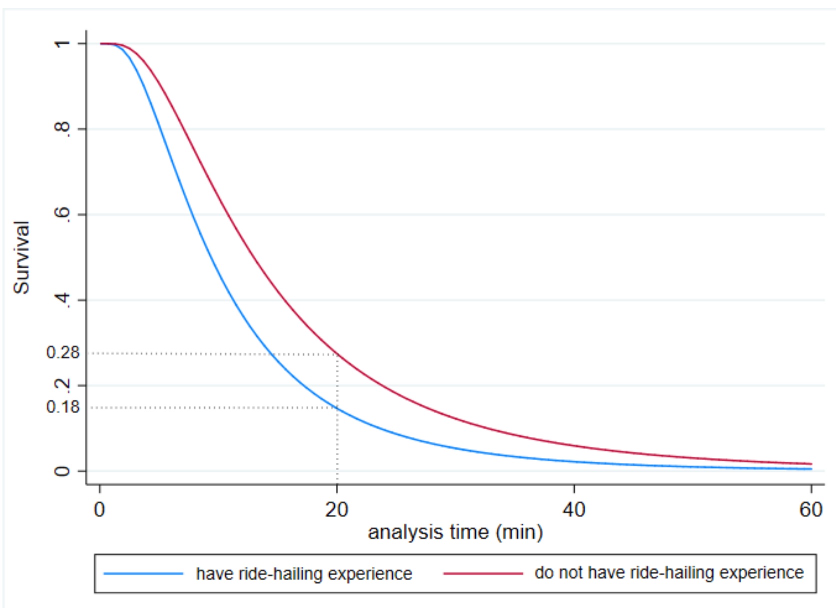


Figure 6. The effect of having ride-hailing experience on the survival function of waiting tolerance during a disruption

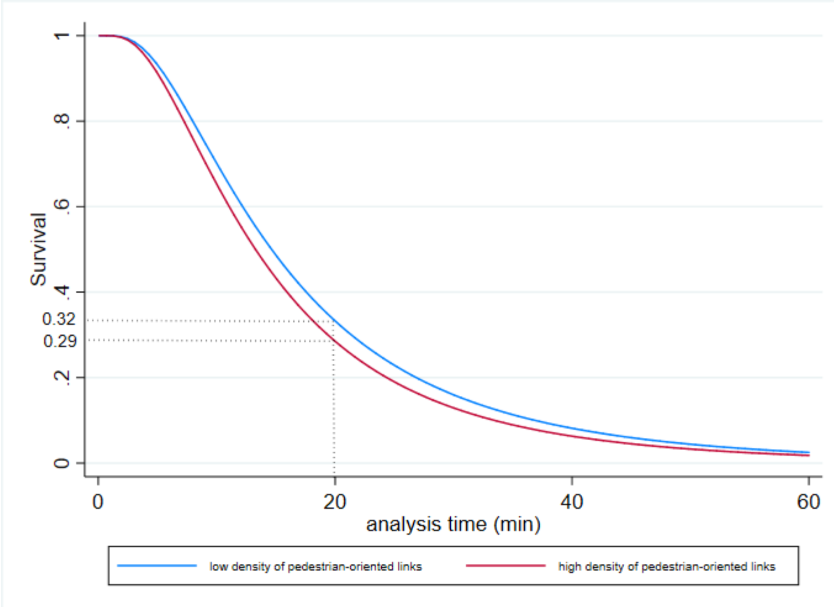


Figure 7. The effect of walkability level within the block group where the trip is originated on the survival function of waiting tolerance during a disruption

3.6 Summary and Conclusions

This study presents the results of a recent web-based SP-RP survey about transit users' response to an unplanned transit disruption. In this survey, respondents were intercepted in the field at the CTA bus, CTA rail, Metra, and PACE stations based on a sampling plan, and they were given a survey link and unique PIN to access to the questionnaire. Focusing on transit users' waiting tolerance for a disrupted transit service to be restored, we utilize interval-censored accelerate failure time models including Exponential, Weibull, Log-logistic and Log-normal. In this approach, a hypothetical disruption scenario with respect to the intercepted trip was provided to a transit user and he/she was asked to choose their waiting threshold for the disrupted transit service to be restored before thinking about other alternative options. We aim to identify which explanatory variables either accelerate or decelerate the survival function of waiting tolerance. Our results find variables such as socio-demographics, having experience of using ride-hailing services or the bike share program, the availability of alternative options, trip purpose, distance, arrival time flexibility, transit service type, and the density of pedestrian-oriented links within the block group where the trip is originated to be influential in the waiting tolerance. The findings of this paper can be used to understand the response of transit users when transit service is disrupted. The results, also, could improve the transit service quality in terms of user's satisfaction and transportation resilience and could help transit agencies in order to implement most efficacious recovery scenarios.

This study has several suggestions for future research directions. First, the structure of interval-censored AFT model can be improved by adding attitudinal variables into the model as latent. Second, the waiting time tolerance can be analyzed in different scenarios. For example, transit users might have a specific amount of waiting tolerance based on their travel-scheduling or past experiences. However, they can extend this time after figuring out the characteristics of alternative options such as price, waiting time, etc.

4 PHASE II OF TRANSIT USERS’ DISRUPTION BEHAVIOR: MODE CHOICE DECISION

4.1 Introduction

Using an intercept stated preference (SP)-revealed preference (RP) survey recently conducted in the Chicago metropolitan area, the present chapter contributes to the literature by looking deep into the diverse aspects of transit users’ response behavior to understand how a non-disaster unplanned disruption in the transit system affects their travel preferences. To the best of our knowledge, the present study is among the first to scrutinize the decision behavior of transit riders in Chicago in case of facing a non-disaster, unplanned service disruption, while accounting for the various alternatives that a user of the interrupted service could consider. In case of facing a disrupted service, one may cancel the trip, change the destination, or switch to other travel modes such as a personal vehicle, taxi, or a ride-sharing services. We estimated a random parameter multinomial logit model considering all these choice alternatives to gain a comprehensive understanding of people’s decision behavior. The random parameter multinomial logit formulation also enabled us to account for the underlying heterogeneity in the behavior.

4.2 Dependent variables

For this study, we utilized the data described in Section 3.2. In the survey, respondents were presented with multiple hypothetical disruption scenarios based on the intercepted transit trip and were asked to indicate which action they would likely take while the intercepted transit service is disrupted (**Figure 8**). Their response to this question has been considered as the variable of interest (dependent variable) in the current study. In the survey design, it is assumed that passengers have full information about the alternative options and their characteristics.

In each scenario, seven potential actions were listed including waiting for a back-up shuttle bus, asking for a ride from family/friend, picking up his/her own auto (if any), taking a taxi, using ride-sharing services, changing the trip destination, and canceling the trip. Each option, if applicable, was further described in terms of waiting time, travel time, arrival time, and cost. Alternative-specific attributes were generated considering the characteristics of the intercepted trip as the basis for a set of SP questionnaires with randomly altered modal characteristics set according to an experimental design which is fully described in Auld et al. (2018). The information displayed to the respondents all pivots off of the exact transit and driving trip characteristics as determined by the Google Direction API router at the actual time of departure, so real-time traffic congestion, transit schedule, etc. are accounted for when setting the scenario values. For instance, the waiting time attribute for shuttle bus was determined as a portion of travel time of the undisrupted journey. Further, a set of piece-wise functions was used to generate travel cost and waiting times. **Figure 8** illustrates an example of an SP transit disruption scenario presented to each respondent.

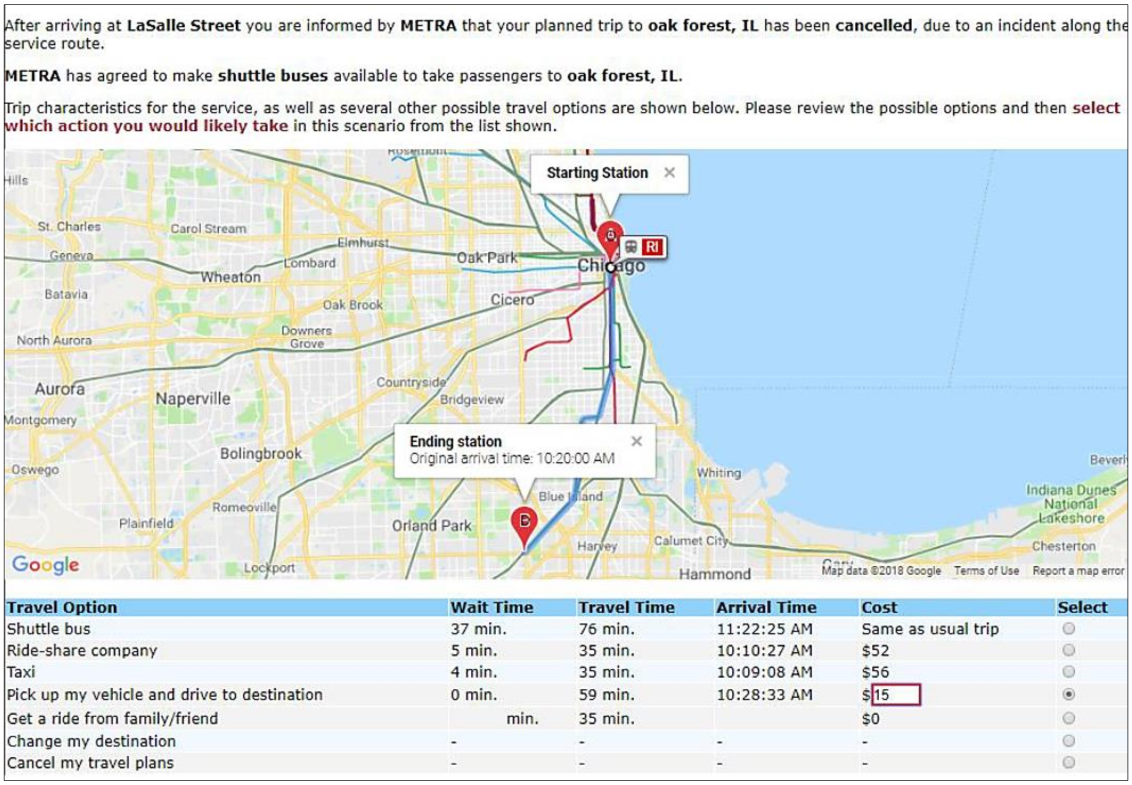


Figure 8. An example of an SP transit disruption scenario (Adapted from (Auld et al. 2018)).

After rejecting observations with either missing or invalid information, the final database for this study includes 628 respondents who were faced with 2498 disruption choice situations. The collected dataset consists of 45.2% male and 54.0% female participants who live in Chicago metropolitan area. As for the age, 17.6% are less than 24 years old, 32.8% are between 25 and 34, 19.6% are between 35 and 44, and the rest are older than 45 years old. As for the employment status, the data contains 72.1% full-time workers, 10.6% part-time workers, and the rest consists of unemployed and retired people. **Table 4-1** presents summary statistics of respondents' key demographic attributes in the collected sample. In addition, **Figure 9** presents a comparison between our sample and weighted estimates from the last Chicago Metropolitan household travel survey (CMAP) for transit riders 18 and over (CMAP 2008).

Table 4-1. Summary statistics of the respondents' key characteristics.

Variable	**Category**	**Share (percentage)**
Household size	1	28.53
	2	47.80
	3	13.66
	4	5.92
	5 or more	3.49
Household income	Under $15K	6.37
	$15K - $35K	8.95
	$35K - $50K	11.99
	$50K - $75K	12.90
	$75K - $100K	14.72
	$100K or more	30.80
Gender	Male	45.22
	Female	54.02
Age	≤ 24	17.60
	25-34	32.78
	35-44	19.58
	45-54	15.02
	55-64	11.99
	≥ 65	2.89
Race	White/Caucasian	56.90
	African American	16.54
	Hispanic/Latino	10.47
	Asian	8.50
	Two or more ethnicities	4.10
	Native American	0.61
	Other	1.97
Education	Less than high school	0.91
	High school graduate	5.31
	Some college credit	13.96
	Vocational school certificate	1.06
	Associate degree	6.53
	Bachelor's degree	37.94
	Graduate degree	33.38
Employment status	Full time	72.08
	Part time	10.62
	Other	17.30

Note: The sum of the percentages may not equal 100 due to observations with missing values

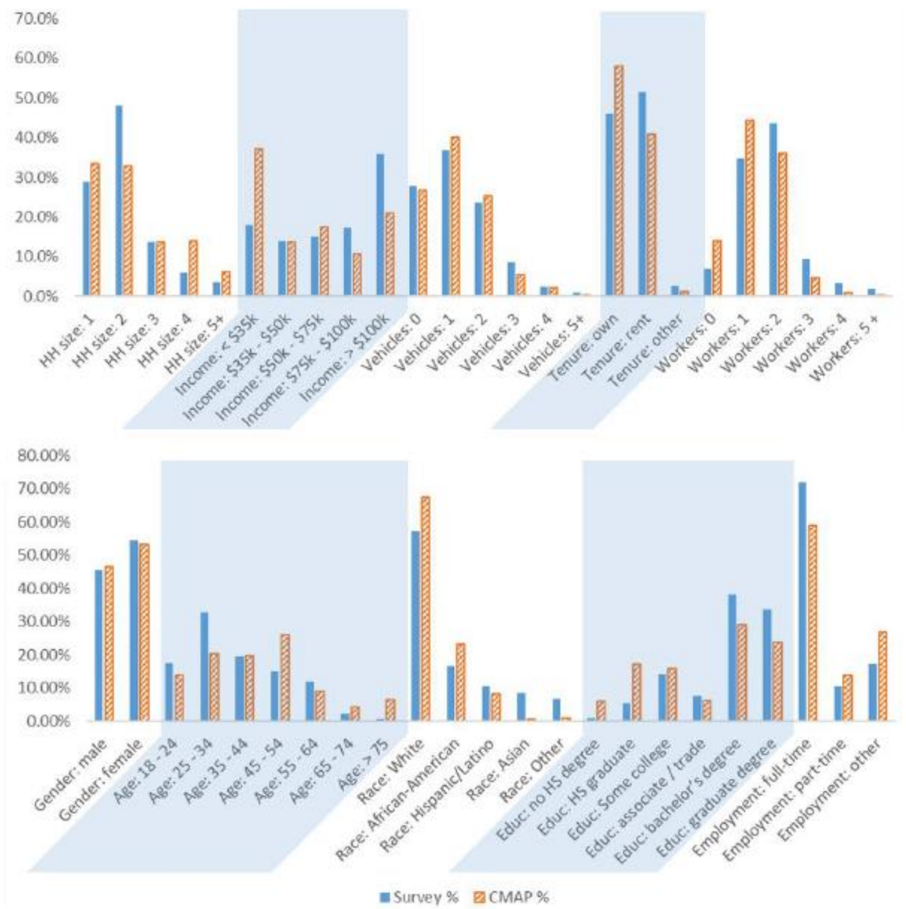


Figure 9. A comparison between our sample and CMAP transit riders (adapted from Auld et al. (Auld et al. 2018)).

It should be noted that the personal vehicle option was not available for those who either had no vehicle or had no access to their vehicle at the time of the disruption. **Figure 10** presents the distribution of selected actions with respect to the personal vehicle availability. As can be seen in the figure, waiting for the back-up shuttle and using ride-sharing services are the first and second most frequent selected actions in the data. It is also interesting to note that, respectively, in about 10% and 5% of scenarios, people decided to cancel their trip or change their destination.

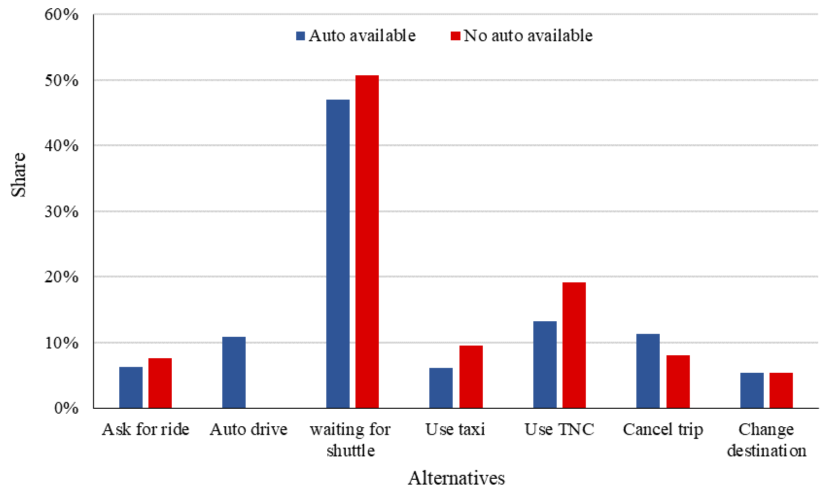
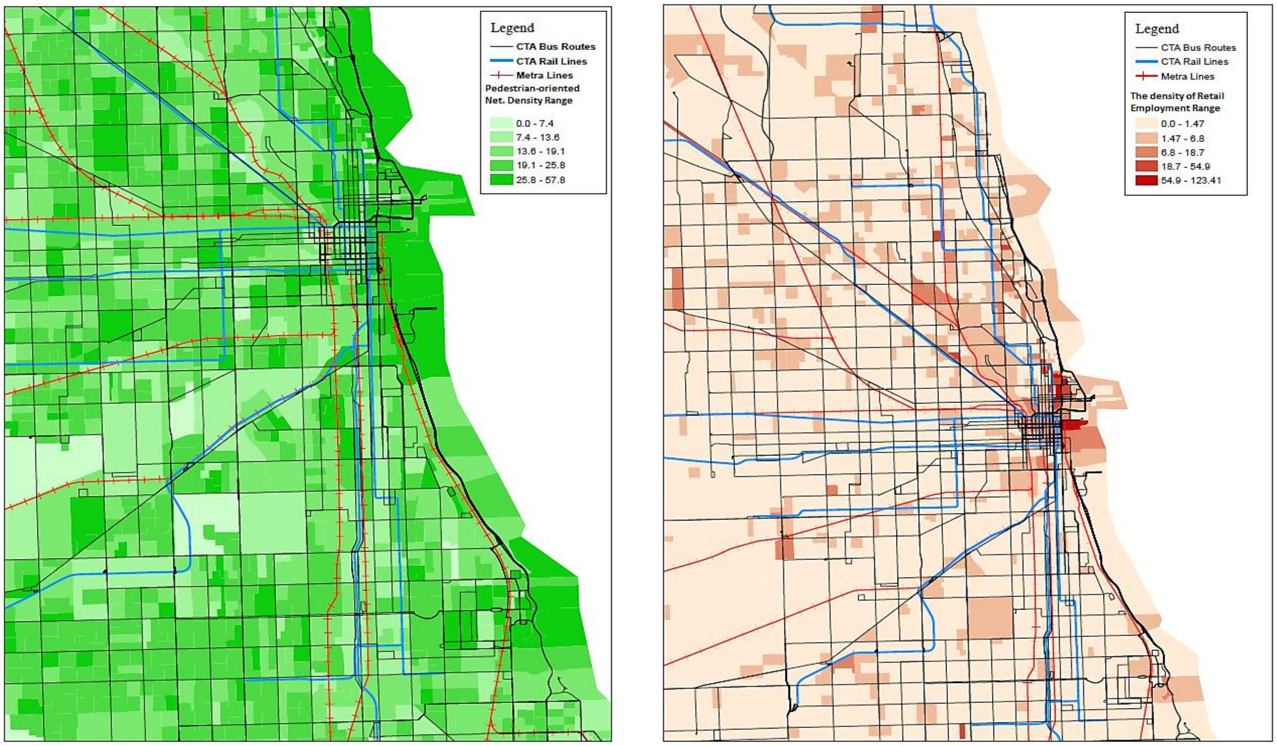


Figure 10. The distribution of alternatives in the sample with respect to auto availability

We have also complemented the survey data with the Smart Location Database provided by the Environmental Protection Agency (EPA). The Smart Location Database is a nationwide geographic data which includes population density, land use density, neighborhood design, destination accessibility, transit service, employment, and demographics (Ramsey and Bell 2014). This information is provided at the census block group level and can provide insights into understanding the effect of built-environment settings on transit users' travel behavior. **Figure 11** depicts the Chicago transit system mapped on the color scheme of two variables: retail employment density and pedestrian-oriented network (that are found to be significant in the final model as will be discussed in the next sections).



a) Pedestrian-oriented network density at block-group level b) Retail employment density at a block-group level

Figure 11. Chicago transit system at a glance.

Pedestrian-oriented network density represents the level of walkability within a block-group and is calculated by summing pedestrian-oriented links within a block group dividing by the area of that block group (Ramsey and Bell 2014). The retail employment density for each block group is calculating by summing the total retail jobs within a block-group dividing by the unprotected area of that block-group (Ramsey and Bell 2014). **Table 4-2** summarizes the descriptive statistics of the variables used (found to be significant) in the final model.

4.3 Modeling approach

In this study, the random parameter multinomial logit (RPMNL) model is applied to understand transit users' decision behavior in case of an unplanned service disruption. This model is highly flexible which obviates the three limitations of multinomial logit (MNL) model by relaxing the independence of irrelevant alternatives (IIA) assumption, allowing for random taste variations, and potential correlation in unobserved factors over time (Greene 2012; Train 2009; Boggs, Arvin, and Khattak 2020; Rahimi, Shamshiripour, Samimi, et al. 2020; Mansourkhaki, Karimpour, and Yazdi 2017; Mansourkhaki, Karimpour, and Sadoghi Yazdi 2017; Karimpour, Kluger, and Wu 2020; Mousavi et al. 2019). Consider U_{int} as the utility function of alternative i for decision-maker n in choice situation t as follows (Nazari, Rahimi, and Mohammadian 2019; Train 2009):

$$U_{int} = \alpha_{in} + \beta_{in} X_{int} + \varepsilon_{int} \qquad \textbf{Eq. 13}$$

Where, α_{in} is the constant term for alternative i, β_{in} represents the estimable coefficients, X_{int} is the vector of explanatory variables of alternative i for decision-maker n in choice situation t, and ε_{int} is the error term that is Type I Extreme Value. The probability functions of RPMNL model are the integrals of standard logit probabilities over a density of parameters (Train 2009):

$$P_{nit} = \int \left(\frac{e^{\alpha_{in} + \beta_{in} X_{int}}}{\sum_j e^{\alpha_{jn} + \beta_{jn} X_{jnt}}} \right) f(\alpha, \beta | \theta) d\beta \qquad \textbf{Eq. 14}$$

here, $f(\alpha, \beta | \theta)$ is the probability density function of coefficients, and θ would be the parameters that describe the density of β. Denoting T_n as the number of choice situations observed for decision-maker n, the likelihood function for RPMNL would be (Train 2009):

$$L_n(\theta) = \prod_{t=1}^{T_n} \prod_{j=1}^{J} \left[\int \left(\frac{e^{\alpha_{in} + \beta_{in} X_{int}}}{\sum_j e^{\alpha_{jn} + \beta_{jn} X_{jnt}}} \right) f(\alpha, \beta | \theta) d\beta \right]^{y_{nit}} \qquad \textbf{Eq. 15}$$

where, y_{nit}= 1 if decision-maker n chooses alternative i in choice situation t.

Since, in general, the integrals cannot be solved analytically, the maximum simulated likelihood estimator (MSLE) is suggested to estimate the parameters. In this study, we employed NLOGIT 6.0 to develop the RPMNL model. Also, 200 simulated Halton draws for the model turned to be enough in terms of model stability and accuracy as it is also suggested by the literature

(Bhat 2003). Moreover, the model was run assuming several distribution functions including Normal, Log-logistics, and Log-normal; however, the normal distribution provided better results in terms of model stability as well as the goodness of fit to the data.

Table 4-2. Definition of variables used in the model.

Category	Name	Definition	Mean	Std. Dev.
Demographics	BACHELOR	1: If the transit user has a bachelor degree/ 0: Otherwise	0.386	0.487
	GRADUATE	1: If the transit user has a master's degree and more/ 0: Otherwise	0.340	0.474
	FULL_TIME	1: If the transit user has a full-time job / 0: Otherwise	0.723	0.447
	MILLENNIAL	1: If the age of transit user is between 24 and 35/ 0: Otherwise	0.330	0.470
	SENIOR	1: If the age of transit user is more than 64/ 0: Otherwise	0.030	0.173
	LOW_INCOME	1: If the household income of transit user is less than $30K	0.091	0.289
Attitudes	RIDESHARE	1: If the person has the experience of using TNCs (e.g., Uber, Lyft) in the past as a travel mode/ 0: Otherwise	0.339	0.473
	TECH_ACCESS	1: If the person has access to a smartphone and data/ 0: Otherwise	0.957	0.201
Trip characteristics	DISTANCE	The distance between the trip origin and destination in miles	16.23	26.12
	DIST_M15	1: If the distance between origin and destination is more than 15 miles / 0: Otherwise	0.315	0.465
	ALONE	1: If the transit user is traveling alone/ 0: Otherwise	0.863	0.345
	MANDATORY	1: If the purpose of the trip is work or school/ 0: Otherwise	0.510	0.500
	SHOP	1: If the trip purpose is shopping/ 0: Otherwise	0.033	0.178
	CTA_RAIL	1: If the person is waiting for CTA rail/ 0: Otherwise	0.529	0.499
	CTA_METRA	1: If the person is waiting for Metra rail/ 0: Otherwise	0.267	0.442
	PACE	1: If the person is waiting for PACE/ 0: Otherwise	0.042	0.201
	SHUTTLE_WAIT	Waiting time for a shuttle bus in minutes	46.61	59.60
	TNC_WAIT	Waiting time for TNC in minutes	9.55	2.84
	TNC_COST	Trip cost for TNC in dollar	51.53	88.85
	DRIVE_TIME	The auto travel time between the trip origin and destination in minutes (Auto, TNC, taxi)	35.81	29.00
	TAXI_WAIT	Waiting time for a taxi in dollar	21.90	15.68
	LONGDIST_MNDT	1: If the distance between the trip origin and destination is more than 15 miles and the purpose of the trip is work or school./ 0: Otherwise	0.266	0.441
	SHUTTLE _WAIT_METRA	Waiting time for shuttle bus if the disrupted service is Metra transit	61.56	68.47
	SHUTTLE _WAIT_CTA_RAIL	Waiting time for shuttle bus if the disrupted service is CTA rail	35.87	49.18
Built environment	RETAIL_DENSITY	Gross retail employment density in a block group	3.61	9.43
	RET_SHOP	Gross retail employment density in a block group if the trip purpose of transit user is shopping	0.088	0.65
	NDNSTY_PED	Network density regarding facility miles of pedestrian-oriented links per square mile in a block group	18.98	9.46
	NDNSTY_PED_L10	1: If NDNSTY_PED < 10/ 0: Otherwise	0.158	0.365

4.4 Model estimation results

The results of the RPMNL model to analyze transit users' behavior in response to an unplanned service disruption are presented in **Table 4-3** and **Table 4-4**. Various variables and variable interactions are tested for each option, and the statistically significant variables at 90%, 95%, and 99% levels of confidence are shown in the table. Based on the results, a wide range of socio-demographic attributes, personal attitudes, trip-related information, and built-environment factors are significant in passengers' response behavior in case of transit service disruptions.

Table 4-3. Estimation results of random parameter multinomial logit model.

Explanatory Variable	Coefficient	*p*-value
CONSTANT (**Auto**)	00689	0.570
Std. dev.	3.261***	0.000
CONSTANT (**Shuttle bus**)	4.044***	0.000
Std. dev.	2.575***	0.000
CONSTANT (**TNC**)	0.697	0.890
Std. dev.	1.803***	0.000
CONSTANT (**Taxi**)	0.690*	0.079
Std. dev.	1.947***	0.000
CONSTANT (**Change destination)**	-3.631***	0.000
Std. dev.	4.802***	0.000
CONSTANT (**Cancel trip**)	-3.057***	0.000
Std. dev.	5.275***	0.000
Ask for ride: base		
Auto		
LONGDIST_MNDT	1.477**	0.038
Shuttle bus		
SHUTTLE_WAIT	-0.016***	0.000
ALONE	0.475*	0.088
SHUTTLE _WAIT_METRA	-0.039***	0.000
Std. dev.	0.0478***	0.000
SHUTTLE _WAIT_CTA_RAIL	-0.040***	0.000
Std. dev.	0.091***	0.000
RET_SHOP	-0.376*	0.066
NDNSTY_PED_L10	1.059**	0.017
PACE	0.985*	0.095

*** 99% level of confidence, ** 95% level of confidence, * 90% level of confidence

Table 4-4. Estimation results of random parameter multinomial logit model (continued)

Explanatory Variable	Coefficient	*p*-value
TNC		
MILLENNIAL	1.099***	0.000
SENIOR	-1.850*	0.063
BACHLOR	0.598*	0.071
GRADUATE	1.096***	0.001
TNC_WAIT	-0.119***	0.000
TNC_COST	-0.015***	0.000
DRIVE_TIME	-0.022***	0.006
TECH_ACCESS	1.280*	0.062
RIDESHARE	0.777***	0.007
Taxi		
SENIOR	-1.173*	0.090
FULL_TIME	0.676*	0.051
LOW_INCOME	-0.593*	0.088
DRIVE_TIME	-0.030***	0.000
TAXI_WAIT	-0.014***	0.000
RIDESHARE	0.802**	0.013
Change destination		
RIDESHARE	-4.852***	0.000
Std. dev.	4.991***	0.000
Cancel trip		
SENIOR	1.041*	0.087
MANDATORY	-0.486*	0.100
Number of observations	2495	
Loglikelihood value at convergence	-2747.52	
McFadden Pseudo R-squared	0.21	
McFadden Pseudo R-squared (multinomial logit model)	0.08	

*** 99% level of confidence, ** 95% level of confidence, * 90% level of confidence

Regarding the auto option, as the results in **Table 4-3** indicate, long-distance commuters are more likely to use their own vehicle (if accessible) to reach the destination in the case of a transit service disruption. This is possibly because the generalized cost of personal vehicle can be more reasonable compared to TNC or taxi for long-distance travels. This finding is in line with Limtanakool, Dijst, and Schwanen (2006), who argued that auto is the dominant mode for long-distance commutes. Moreover, due to less flexibility of mandatory trips with respect to the arrival time, choosing personal vehicle can decrease the uncertainty level of arrival time to the planned destination.

With respect to the back-up shuttle bus, it was found that waiting time has a negative impact on the utility of this option. This intuitive finding has been supported by several other studies (e.g., (Miller, Roorda, and Carrasco 2005; Chen, Gong, and Paaswell 2008) who indicated that higher waiting time can decrease the utility of public transit as travel mode. Moreover, Lin (2017) found that increasing the waiting time for the shuttle bus encourages more transit users to shift to other modes when a service disruption occurs. Our findings, also, add that the influence of waiting time for back-up shuttle bus on passengers' decision is different across various types of transit services.

The variables reflecting the waiting time at the CTA-rail station and the waiting time at the Metra station are both found to be significant with normally distributed random parameters. More specifically, the parameter of waiting time at Metra station and the parameter of waiting time at CTA-rail station are associated with the higher likelihood of switching to other options for the vast majority of observations. It is possibly because rail users have more concerns about the service to be on-time compared to bus users (Currie and Muir 2017). Moreover, the average and standard deviation values of the parameter of waiting time at Metra station which is normally distributed revealed that the parameter is negative for 80% of the individuals, while it is positive for 20% of them. Also, the results showed that the parameter of waiting time at CTA-rail station would be negative for the 77% of individuals, while it is positive for 33% of them. These findings further support the idea that the waiting time is not necessarily perceived as a disutility by everyone, provided that one can engage in other activities while he or she is waiting for the transit (i.e., performing multitasking). This is in-line with a growing body of literature on the positive utility of travel (Pawlak et al. 2016; Mokhtarian 2019; Malokin, Circella, and Mokhtarian 2019; Circella, Mokhtarian, and Poff 2012). Besides, the heterogeneity in individuals' travel behavior in different incidents was reported in the literature (Ebnali et al. 2020, 2019; Ebnali, Lamb, and Fathi n.d.).

Per the results, Pace users are found to have more tendency to wait for the back-up shuttle bus. As Pace provides bus service to suburban neighborhoods in the Chicago region, people will have less accessibility to other alternatives to reach their destinations or they would be much more expensive compared to Pace service. Thus, Pace users prefer to wait for the back-up shuttle bus in case of an unplanned disruption. Further, as Pace provides special paratransit services for people with physical disabilities, a considerable portion of its users are among such people ("Pace Bus" 2019). Obviously, such people have less flexibility to shift their mode due to their physical constraints.

Also, the indicator parameter of traveling alone is turned out to be significant with a positive and fixed parameter across observations. Per the result, transit users who are accompanied by others have less tendency to select the shuttle during a disruption. This is probably because they will have more constraints in scheduling their joint activity-travel compared to an individual traveler. Furthermore, group travelers have the possibility of sharing the cost of the alternative modes which can encourage them to shift to other modes rather than waiting for the recovery shuttle bus.

With respect to the built-environment variables, we found that the higher density of retail employment in a block group decreases transit users' likelihood to choose shuttle bus, when their trip purpose is shopping. Also, it is found that within a block group, where the density of pedestrian-oriented links is low, transit users have more tendency to wait for the shuttle bus while a service is disrupted. This result might be because the lower density of pedestrian-oriented links increases the disutility of walking to other destinations or to access other modes (Rodríguez and

Joo 2004; Shamshiripour et al. 2019), and waiting for shuttle bus could remain the only option with a reasonable disutility. Focusing on the resiliency of the transit system, this finding highlights that transit users living in the areas with low density of pedestrian-oriented facilities (e.g., suburban areas) might be more reliant on the transit mode due to the lack of accessibility to other transport options (e.g., active modes, other transit lines) (Rahimi et al. 2019). Such results support the importance of accessibility in transportation network (Samimi et al. 2019; Samimi, Rahimi, and Amini 2018; Bargegol et al. 2017; Y.-J. Lee and Nickkar 2018; Mahmoudzadeh et al. 2019; Mahmoudzadeh and Wang 2020).

Turning to the variables that affect the use of ride-sharing services, it is found that millennials have more tendency to choose TNCs while a transit service is disrupted. This finding might be because they are more tech-savvy and familiar with such services compared to older adults (Rayle et al. 2016; Vivoda et al. 2018). In terms of the education level, our results indicate that having a bachelor or graduate degree increases the probability of using ride-sharing services as an alternative to a disrupted transit service. This might be because these people have more knowledge about such services (Vivoda et al. 2018) or they have higher value of time that discourages them to wait for the recovery shuttle bus.

Per the results, the experience of using ride-sharing services in the past can enhance the probability of choosing this mode as an alternative to disrupted transit services. This is possibly because experiencing ride-sharing services, as a relatively new technology in the transportation market, not only could increase the awareness about this mode, but also could improve people's technology acceptance (Wang et al. 2018). Supported by intuition, our results reveal that having access to a smartphone and data positively affects the probability of using TNCs in case of transit disruptions. We also found that, as expected, the trip-related characteristics of TNCs including waiting time, trip cost, and travel time are negatively significant in the model. Mode choice literature supports this finding (Chen, Gong, and Paaswell 2008; Miller, Roorda, and Carrasco 2005; TYT Lin 2017). Besides, comparing the waiting time parameter in the TNC's utility function with the parameter in other utilities revealed that waiting for TNC causes more disutility for individuals during unplanned disruption.

With respect to the factors that affect the use of taxi, our results indicate that seniors have less tendency than others to use taxi in case of a transit service disruption. This could be because this group of people have generally more flexibility in scheduling their daily activities and travels, and thus, they might not prefer to choose taxi which is an expensive alternative compared to other modes. This finding is in line with Rayle et al. (2016) who reported that share of taxi usage among seniors is very low. The results, also, show that low-income passengers are less likely to choose taxi as an alternative to a disrupted transit service. Moreover, the indicator parameter of having a full-time job is turned out to be positively significant in the model. This might be because passengers who have a full-time job have a higher value of time and less flexibility in their activity-travel scheduling.

As expected, our results reveal that waiting time for taxi negatively affects transit users' willing to use this mode during a service disruption. This is in line with Yang et al. (2000) who argued that passengers consider waiting time for taxi as an important factor of service quality in their decision.

With respect to the variables that affect the decision of changing the destination of the trip, the indicator parameter representing having experience of using a ride-sharing service is found to be random in the probability of this decision. Per the model, the majority of passengers (i.e., about

70% of observations) who experienced ridesharing services in the past have less tendency to change their pre-planned travel destination when a transit service disruption occurs.

As **Table 4-4** indicates, seniors are more likely to cancel their trip when a service disruption occurs. This parameter is found to be fixed across observations. It might be because seniors are most probably retired (Burris and Pendyala 2002), and have more flexibility in their daily activity-travel scheduling (Frei, Hyland, and Mahmassani 2017). We also found that the indicator variable of mandatory trips has a significant and negative effect on the utility of canceling the trip. Supported by intuition, our result indicates that transit riders who are traveling to conduct a mandatory activity (e.g., to workplace or school) have less flexibility to cancel their trip.

4.5 Summary and Conclusions

This study presents the results of a new SP-RP survey framework in the Chicago Metropolitan Area about transit users' behavior in response to an unplanned service disruption. In this approach each respondent was faced with four different disruption scenarios in which seven potential actions were listed including waiting for a back-up shuttle bus, asking for a ride from family/friend, picking up his/her own auto (if any), taking a taxi, using ride-sharing services, changing the trip destination, and canceling the trip. Each option, if applicable, was further described in terms of waiting time, travel time, arrival time, and cost. Accounting for heterogeneity across observations as well as panel effects, the random parameter multinomial logit (RPMNL) model is utilized to understand transit users' decision behavior in case of an unplanned service disruption.

According to the results, a wide range of socio-demographic attributes, personal attitudes, trip-related information, and built-environment factors are significant in passengers' response behavior in case of transit service disruptions. Interestingly, our results showed that the effect of service recovery time on passengers is not the same among all types of disrupted services; rail users are more sensitive to the recovery time as compared to bus users. Moreover, although providing information about a service disruption is crucial, our results suggested that the passengers' response to disruption is associated with the fact that how they trust and follow the information. This can provide insights for transit authorities to prepare efficient communication strategies during a service disruption. The findings of this paper can be used to understand the response of passengers when a service is disrupted. The results also could provide insights for transportation authorities to improve the transit service quality in terms of user's satisfaction and transportation resilience. These insights could help transit agencies in order to implement effective recovery strategies.

Like any other research, this study has some limitations and could be further improved in future works. For instance, future research could contribute to our study by considering rerouting in the existing public transit network as a choice alternative in the implementation of the survey. We did not consider this option since rerouting is not available for majority of the pairs of origins and destinations in the context of the present study; yet, we acknowledge that not providing this option may overestimate the "waiting for shuttle service" option. Moreover, crowding might be an important attribute when individuals are deciding about alternative options during a disruption. In this study, we could not investigate the effect of this factor due to the lack of data; however, this factor should be incorporated in future surveys. Furthermore, in the survey design, it is assumed that passengers have full information about the alternative options and their characteristics which may not be realistic. Also, in the survey, the option "call a friend or family to give a ride" is always assumed to be available which may cause the dominance of the alternative. Although, we did not face the issue in this study. Furthermore, the highly educated respondents are relatively overrepresented in our sample which may cause biasedness toward switching the transit system with other options including TNC. For future studies, one might investigate to which extent mode choice effects are temporary (only during disruptions), or if some passengers do not return to public transit after (several) disruptions and experiencing an attractive alternative transport mode. Moreover, it would be helpful if the travel time values provided to respondents in SP survey in "HH:MM" format instead of in minutes.

5 PERCEIVED RISK OF USING SHARED MOBILITY DURING THE COVID-19 PANDEMIC

5.1 Introduction

In this chapter, we used the data collected through a multidimensional travel behavior survey instrument conducted in the Chicago region from April 25 to June 2, 2020. The online survey collected a rich set of data regarding the residents' socio-demographic details, their health-related background, as well as an extensive set of information about their daily activity-travel behavior. Specifically, two questions of the survey were designed to inquire about individuals' risk perception toward using public transit and ridesharing services during the COVID-19 pandemic. To characterize individuals' perceived risk of exposure to COVID-19, we utilized the bivariate ordered probit model which characterizes the influential factors affecting the risk perception of using those modes while accounting for the potential correlation between their unobserved factors. Our findings help policymakers better understand changes in people's travel behavior during a health crisis such as COVID-19 pandemic.

5.2 Survey Design & Data Description

5.2.1 Survey design and general demographics

We designed and performed a stated preference-revealed preference (SP-RP) survey in the Chicago metropolitan area (including the counties of Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will) to understand the dynamics of daily travel behavior, as well as multiple aspects of people's long-term travel habits, attitudes, and preferences during the COVID-19 pandemic. For the RP part of the survey, the respondents were asked to provide their travel behaviors before and during the pandemic. For the SP part, they were asked to indicate their expected behavior for the future when the pandemic is over.

The survey was structured to collect a rich set of information in the following major areas: 1) socio-demographic information such as residential location, age, gender, ethnicity, as well as the economic factors such as job status and household income; 2) health-related factors including disability status, having a pre-existing condition, and physical exercise habits, as well as COVID-19 exposure risk factors such as smoking and having obesity; and 3) an extensive set of questions regarding perceived risk of exposure to the SARS-CoV-2 virus while using shared mobility, including public transit and ridesharing services.

We used Qualtrics online platform to distribute the survey from late April to early June of 2020 in the Chicago metropolitan area. In order to consider the variation of the spread of COVID-19 within the study area, we incorporated the Google Maps API to collect respondents' approximate residential locations (i.e., the nearest intersection to their home address) in the questionnaire. **Figure 12** shows a screenshot from our survey. Furthermore, multiple quality checks were utilized in the questionnaire to identify the respondents who have not devoted sufficient attention to the survey. In this way, we excluded those who failed to correctly pass the quality checks, overly fast responses (i.e., less than 15 min), and responses with missing information. Full information about design of various parts of the survey, implementation, and summary statistics of the data can be found in authors' previous work (Shamshiripour et al. 2020b).

Although the final and cleaned data contains 915 responses, due to the scope of this study, we utilized 398 observations in which respondents indicated they had an experience of using public transit as well as ridesharing services before. **Table 5-1** reports a summary of respondents' key characteristics such as age, gender, ethnicity, household income, education employment status, and having a personal vehicle. As can be seen in this table, the collected dataset consists of 54% male and 45% female respondents who live in the Chicago metropolitan area. With respect to the annual household income, 27% of households have less than $50K, 39% earn between $50K and $100K, 17% earn between $100K and $150K, and the rest earns more than $150K. As for the employment status, the data comprises 45% full-time workers, 14% part-time workers, and the rest consists of unemployed and retired people.

Moreover, we incorporated the survey data with built environment information from the Smart Location Database (SLD) prepared by the Environmental Protection Agency (EPA) (EPA 2014). This information is provided at the census block group level and could provide insights into understanding the effect of built environment settings on the perceived risk of exposure to the SARS-CoV-2 virus. To better account for the effect of spreading the virus on the perceived risk of exposure to it, we also used the frequency of confirmed COVID-19 cases at a zip code-level resolution throughout the study area provided by Illinois Department of Public Health (IDPH) (IDPH 2020). **Figure 13** presents the respondents' approximate residential locations mapped on the zip code boundaries of the Chicago metro area, which are color-coded based on the number of confirmed COVID-19 cases. As can be seen in Figure 2, the respondents were decently scattered across the study area.

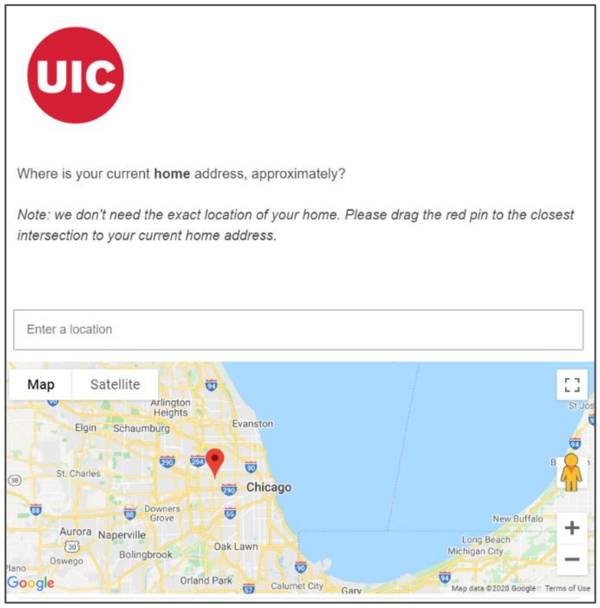


Figure 12 a screenshot of the online survey (using Google Map API to specify residential location)

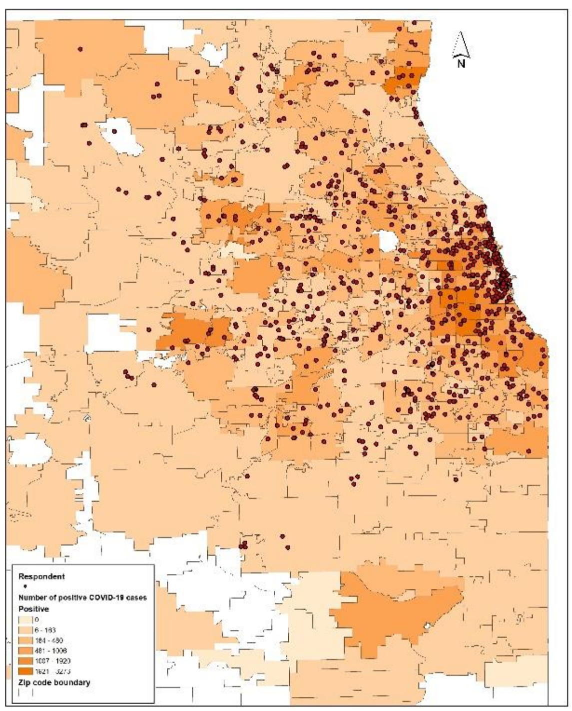


Figure 13 Respondents' residential locations mapped on the number of positive COVID-19 cases (as of June 6, 2020) in each zip code within the study area

Table 5-1. Summary statistics of the respondents' key characteristics

Variable	Category	Share (percentage)
Household income	Under $50K	29.92
	$50K - $100K	42.42
	$100K - $150K	16.67
	$150K or more	10.98
Gender	Male	60.30
	Female	39.70
Age	18-24	19.35
	25-34	21.11
	35-44	18.34
	45-54	12.31
	55-64	17.09
	65-74	9.80
	75 and above	2.01
Ethnicity	White/Caucasian	64.97
	African American	12.69
	Hispanic/Latino	9.39
	Asian	7.61
	Two or more ethnicities	3.81
	Other	1.52
Education	Less than high school	6.28
	High school graduate	27.14
	Some college credit	21.86
	Associate degree	8.29
	Bachelor's degree	22.11
	Graduate degree	14.32
Employment status	Full time	72.14
	Part time	21.07
	Other	6.79
Household vehicle ownership	No vehicles	11.56
	One to three vehicles	84.17
	More than three vehicles	4.27

5.2.2 Risk perception variables in the survey

Perceive the risk of exposure to the virus underlies many of the dynamics of travel behavior during the COVID-19 pandemic, including working from home, online shopping, mode choice, and airplane travels. This section is dedicated to exploring the perception of people towards the exposure risk given a variety of travel choices.

Figure 14 summarizes the perceived risk of using various travel modes. According to the results, personal vehicles turned out to be associated with the lowest perceived risk of exposure. ranked after personal vehicles, biking with private bicycles and walking are found to have the second- and third-lowest perceived risks of exposure – respectively, 29% and 23% categorized as medium to high risk of exposure. This shows the notable role of active transportation and micro-mobility during the pandemics in preventing the users of transit, taxi, and ride-hailing services from switching to personal vehicles. Similarly, (Teixeira and Lopes 2020) found evidence on a possible modal shift from the subway to the bike sharing system in New York, U.S.

Furthermore, transit, taxi and ride-hailing services (e.g., UberX), as well as pooled ride-hailing (e.g., Uberpool) are the first three highest risky modes in people's view. Around 93% of the respondents indicated that they associate transit with medium to extremely high risk of exposure to the novel coronavirus. This finding is in line with Bucsky (2020) who observed that usage of public transit decreased dramatically by 80%, while the overall mobility was reduced maximally by 64%. However, out of this 93% portion, more than 26% either reported that their household owns no personal vehicles or someone else in their household is the main driver of the vehicles owned. Moreover, around 14% were found to be senior citizens older than 65 (who probably have difficulty substituting transit with active modes), over 13% are from lower income households (i.e., annual income of $50K or less) who neither own a bike nor have a bike-sharing membership. As mentioned in the previous section, we collected the nearest intersection to the home address of the respondents via Google Maps API. Linking this information to the Smart Locations database (cite), we also noticed that over 24% out of the 93% portion of the observations belong to those who live in low pedestrian-oriented neighborhoods (i.e., where the density of pedestrian-oriented facilities is lower than the 25th percentile).

These results, collectively, shed light on the importance of pro-actively planning for a more "equitable" future transportation system to minimize the disparities in accessibility among various socio-demographic groups and residents of various urban settings. Explaining the sensitivity of the demand for using transit, Taxis and, ride-hailing services to the pandemics, the results also highlight the need to expand the concept of "resiliency" beyond its current domain of service disruptions (Rahimi et al., 2020; Rahimi et al., 2019). The recent pandemic experiences showed us that there should also be a longer-term aspect to "resiliency of the transportation systems" to focus on the resiliency during the prolonged pandemics.

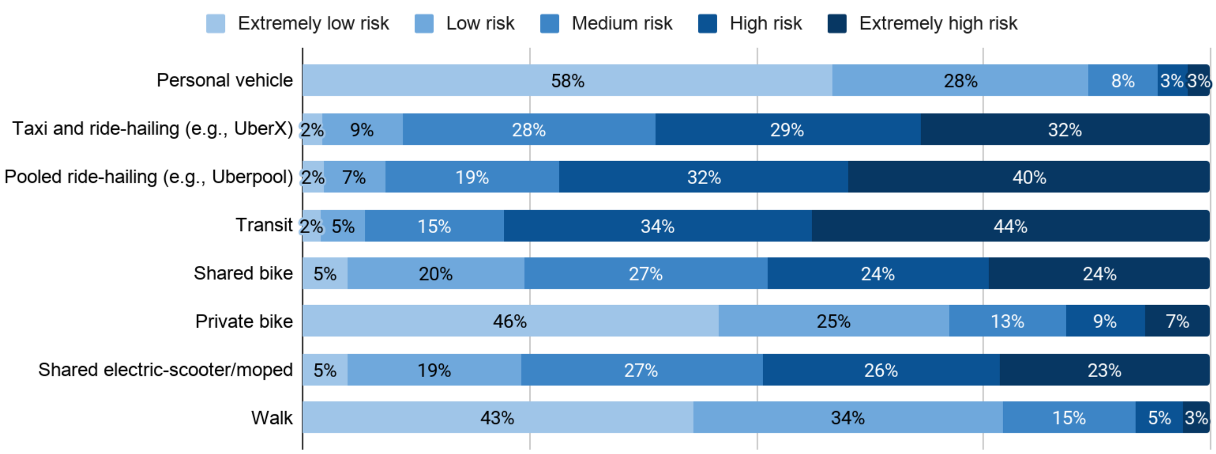


Figure 14. Perceived risk of traveling with different modes during the COVID-19 pandemic

In addition to the risk of using various modes of transportation, we also included a question asking about the perceived risk of visiting various locations and participating in various activities during the pandemic. The results are summarized in **Figure 15**. The results indicated that the risk of indoor activities is generally considered to be more than outdoor activities. Interestingly, also, going to gyms or fitness centers are found to be almost as risky as going to the hospitals in people's view—around 91% of the respondents associated medium to extremely high risk of exposure to these activities. In-store shopping and restaurants stand at the second and third ranks, respectively, with 86% and 83% categorizing as a medium to extremely high-risk activity.

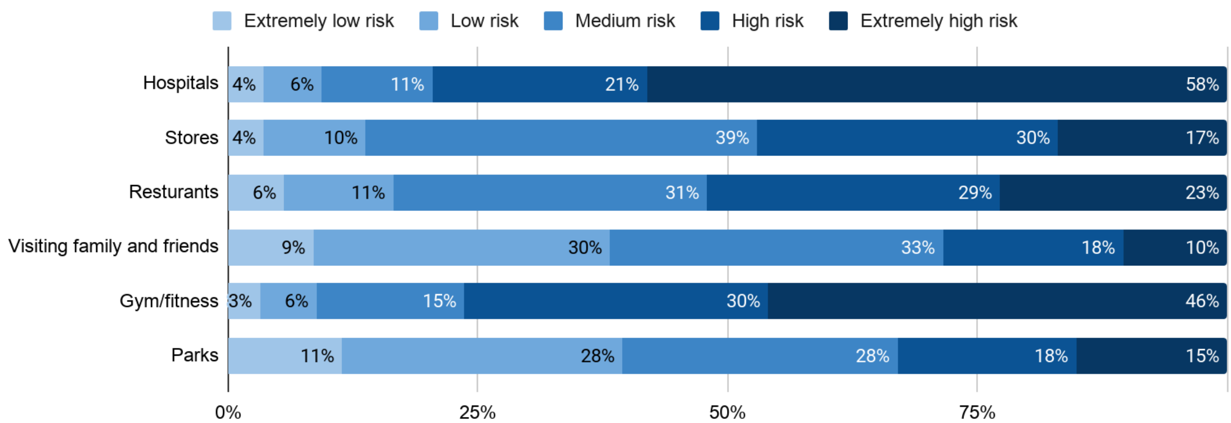


Figure 15. Perceived risk of visiting different locations *during* the COVID-19 pandemic

5.2.3 Defining the dependent variable

Our dependent variables are derived from questions focusing on people's perceived risk of exposure to the SARS-CoV-2 virus when using shared mobility options. As mentioned earlier, we asked respondents to indicate how they perceive the risk of being exposed to the SARS-CoV-2 virus while using public transit (i.e., bus system) or ridesharing services (e.g., Uber, Lyft) during the COVID-19 pandemic. For this question, we provided each respondent with a five-point Likert scale ranging from "extremely high risk" to "extremely low risk" to choose based on their experience of using these options. **Figure 16** shows the distribution of responses in our sample. For the sake of comparison, we also presented the perceived risk of exposure to the virus while driving a personal vehicle in this figure. As can be seen, more than 90% of the respondents indicated that they associate transit and ridesharing services with medium to extremely high risk of exposure to the SARS-CoV-2 virus, while this value is around 15% for personal vehicle. **Table 5-2** also defines explanatory variables turned out to be significant in the final model.

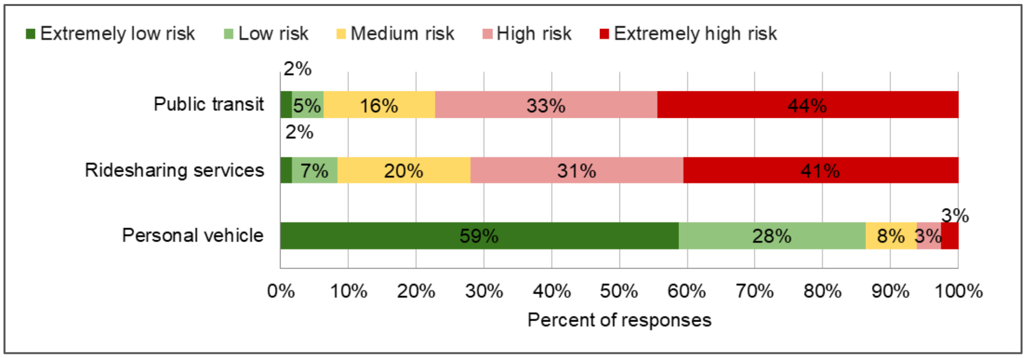


Figure 16. Perceived risk of traveling with public transit and ridesharing services as compared with personal vehicle during the COVID-19 pandemic

Table 5-2. Definition of explanatory variables turned out to be significant in the model

Explanatory variable	Definition	Mean	Std. Dev.	Frequency (%)
Socio-demographic: AfricanAmerican	1: If the respondent's ethnicity is African American/ 0: Otherwise			14.57
Socio-demographic: LowIncome	1: If the respondent is less than $20K/ 0: Otherwise			3.77
Socio-demographic: Female	1: If the respondent's gender is female/ 0: Otherwise			39.70
Socio-demographic: Senior	1: If the respondent's age is 65 years old or more/ 0: Otherwise			11.81
Socio-demographic: MainDriver	1: If the respondent is the main driver of household's vehicle/ 0: Otherwise			79.40
Socio-demographic: Job_Transportation	1: If the occupation of the respondent is transportation services/ 0: Otherwise			3.27
Socio-demographic: LivingWithGrandparent	1: If the respondent is living with their grandparent(s)/ 0: Otherwise			1.76
Health: Covid_Positive	1: If the respondent has been a confirmed case of COVID-19 in the past 14 days/ 0: Otherwise			1.76
SARS-CoV-2 virus spread: ConfirmedCaseDensity	The number of confirmed COVID-19 cases within a zipcode divided by the publulation of the zipcode, where the respondent is living	0.012	0.007	
Built environment: SLD_D3aao	Network density in terms of facility miles of auto-oriented links per square mile in a census block group, where the respondent is living	1.05	2.96	
Built environment: SLD _D4b050	Proportion of census block group employment within ½ mile of fixed-guideway transit stops in a block group, where the respondent is living	0.37	0.43	
Built environment: SLD _D4d	Aggregate frequency of transit service per square mile in a block group, where the respondent is living	1930.41	4344.48	
Built environment: SLD _D3apo	Network density in terms of facility miles of pedestrian-oriented links per square mile in a block group, where the respondent is living	15.05	6.75	
Law: OverActingBasedOnLaw	1: if the respondent is following restrictive measures (i.e., self-quarantine) on the top of the official restrictions enacted/ 0: Otherwise			49.75

5.3 Method

Since the dependent variables in this study are ordinal in nature, we utilized an ordered probit structure to characterize the factors affecting the risk perceptions. Ordered probit models assume a normal distribution for error terms and prevent the estimation difficulties related to the logit structure; thus ordered probit models is preferred as compared with ordered logit models in the literature (Washington, Karlaftis, and Mannering 2010).

The model structure has an underlying random utility or latent regression component, in which the probabilities of ordinal outcomes in the ordered probit model is driven by considering a continuous latent utility (i.e., measure), y^*(Greene 2003; Greene and Hensher 2010; Washington, Karlaftis, and Mannering 2010). This measurement variable is typically specified as a linear function for each observation (Greene 2003; Washington, Karlaftis, and Mannering 2010), as in Eq. (1), where, **X** is a vector of explanatory variables, $\boldsymbol{\beta}'$ is a vector of parameters to be estimated, and $\varepsilon \sim N(0,1)$ is the error term which is normally distributed across observations.

$$y^* = \mathbf{X}\boldsymbol{\beta}' + \varepsilon \qquad \textbf{Eq. 1}$$

The dependent variable (y) that is observed in discrete form through a censoring structure as in Eq. (2) (Greene 2003; Washington, Karlaftis, and Mannering 2010; Greene and Hensher 2010), where $\mu_1, \dots, \mu_{J-1}$ are threshold parameters which are estimated jointly along with $\boldsymbol{\beta}'$.

$$y = 0 \quad if \quad y^* \leq 0 \qquad \textbf{Eq. 2}$$

$$y = 1 \quad if \quad 0 \leq y^* \leq \mu_1$$

$$y = 2 \quad if \quad \mu_1 \leq y^* \leq \mu_2$$

…

$y = J \quad if \quad \mu_{J-1} \leq y^*$

In this chapter, we aim to model people's perceived risk of exposure to the SARS-CoV-2 virus during travel with two types of shared mobility options: 1) public transit and 2) ridesharing. Accordingly, there might be a correlation between unobserved factors of the models. To account for the potential correlation, we implemented a bivariate mechanism of ordered probit approach instead of a univariate one. The bivariate ordered probit model is an extension of traditional ordered probit model, in which two measurement variables, $y_1{}^*$ and $y_2{}^*$, are estimated simultaneously while error terms are assumed to be correlated (Greene and Hensher 2010).

$$y_1^* = \mathbf{X_1}\boldsymbol{\beta}_1' + \varepsilon_1, \qquad \varepsilon_1 \sim \mathrm{N}[0,1], \qquad y_1^* = J \text{ if } \mu_{J-1} \leq y_1^* < \mu_J \qquad \textbf{Eq. 3}$$

$$y_2^* = \mathbf{X_2}\boldsymbol{\beta}_2' + \varepsilon_2, \qquad \varepsilon_2 \sim \mathrm{N}[0,1], \qquad y_2^* = K \text{ if } \gamma_{K-1} \leq y_1^* < \gamma_K$$

$$\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\end{pmatrix} \sim N[\begin{pmatrix}0\\ 0\end{pmatrix}\begin{pmatrix}\rho & 0\\ 0 & \rho\end{pmatrix}], \text{ Cor } (\varepsilon_1, \varepsilon_2) = \rho.$$

The joint probability for $y_1 = J$ and $y_2 = K$ are presented in Eq. 4, where $\Phi(.)$ is the cumulative density function of the standard normal distribution.

$P(y_1 = J \text{ and } y_2 = K \mid \mathbf{X_1}, \mathbf{X_2})$ **Eq. 4**

$$= \Big[\Phi_2\big[(\mu_J - \mathbf{X_1}\boldsymbol{\beta'}_{\mathbf{1}}), (\gamma_K - \mathbf{X_2}\boldsymbol{\beta'}_{\mathbf{2}}), \rho\ \big]$$

$$- \Phi_2\big[(\mu_{J-1} - \mathbf{X_1}\boldsymbol{\beta'}_{\mathbf{1}}), (\gamma_K - \mathbf{X_2}\boldsymbol{\beta'}_{\mathbf{2}}), \rho\ \big]\Big]$$

$$- \ \Big[\Phi_2\big[(\mu_J - \mathbf{X_1}\boldsymbol{\beta'}_{\mathbf{1}}), (\gamma_{K-1} - \mathbf{X_2}\boldsymbol{\beta'}_{\mathbf{2}}), \rho\ \big]$$

$$- \Phi_2\big[(\mu_{J-1} - \mathbf{X_1}\boldsymbol{\beta'}_{\mathbf{1}}), (\gamma_{K-1} - \mathbf{X_2}\boldsymbol{\beta'}_{\mathbf{2}}), \rho\ \big]\Big].$$

Having the joint probabilities from Eq. (4), the log-likelihood function is calculated to estimate the parameters.

5.4 Results and discussion

Table 3 presents the estimation results for the bivariate ordered probit model. The results include the estimated parameters, t-statistics, and the log-likelihood values at both convergence and zero. We assured that the coefficients in the model are statistically significant at least within a 90 percent confidence level. More importantly, the correlation of error terms turned out to be significant with a positive sign. This indicates that the unobserved factors increasing the perceived risk of exposure to the SARS-CoV-2 virus while riding public transit might also increase the perceived risk of exposure to the virus during use of ridesharing services.

Table 5-3. Estimation results of the bivariate ordered probit model

Parameters	Public transit		Ridesharing services	
	Coefficient	t-stat	Coefficient	t-stat
constant	0.830***	12.50	0.830***	12.50
Explanatory variables				
Socio-demographic: AfricanAmerican	-0.331**	-2.05	-0.308**	-1.97
Socio-demographic: LowIncome	0.477*	1.70		-
Socio-demographic: Female	0.395***	3.25	0.271**	2.39
Socio-demographic: Senior	–	–	0.372***	2.62
Socio-demographic: MainDriver	0.156*	1.75	–	–
Socio-demographic: Job_Transportation	-0.634***	-2.52	–	–
Socio-demographic: LivingWithGrandparent	–	–	0.422*	1.68
Health: Covid_Positive	-0.584*	-1.69	-0.654*	-1.69
SARS-CoV-2 virus spread: ConfirmedCaseDensity	–	–	15.108**	2.45
Built environment: SLD_D3aao	0.038**	2.17	–	–
Built environment: SLD _D4b050	-0.159*	-1.69	–	–
Built environment: SLD _D4d	–	–	-0.00013*	-1.68
Built environment: SLD _D3apo	–	–	0.0197***	2.69
Law: OverActingBasedOnLaw	0.229**	2.01	0.137*	1.68
Thresholds				
μ_1	-1.733***	-9.10	–	–
μ_2	-1.328***	-7.81	–	–
μ_3	-0.600***	4.00	–	–
μ_4	0.397***	2.60	–	–
γ_1	–	–	-1.570***	-7.51
γ_2	–	–	-0.684***	-4.09
γ_3	–	–	0.296*	1.86
γ_4	–	–	1.065***	6.66
Model Statistics				
Number of observations	398			
Log-likelihood at zero	-922.038			
Log-likelihood at convergence	-907.87			
Joint parameter				
Correlation of error terms (ρ)	0.680***			

Note: *, **, and *** mean 90%, 95%, and 99% level of confidence, respectively.

5.4.1 Socio-demographics

As shown in **Table 5-3**, the model indicates that ethnicity might be an important factor influencing the perceived risk of exposure to the SARS-CoV-2 virus while using shared mobility options. Per the results, African Americans are more likely to be risk-takers with respect to shared mobility use. This finding is in line with the early evidence, showing the rate of confirmed COVID-19 cases among African Americans is much higher than other groups in Chicago (Goudie et al. 2020; NPR 2020).

Also, the annual household income is found to be significant in the risk perception associated with the usage of public transit. Based on the model, individuals living in extremely low-income households (i.e., who earn less than $20K per year) are more likely to be risk-averse than others. This finding supports the idea that as people's income levels increase, their overall perceptions of the world as a risky place decrease (Dosman, Adamowicz, and Hrudey 2001). One possible explanation is that high-income individuals can spend more on minimizing their exposure to (or mediate the level of) the risks. This is in good agreement with Dosman, Adamowicz, and Hrudey (2001) and Hotle, Murray-Tuite, and Singh (2020).

With respect to gender, the results indicate that females are more risk-averse than males with respect to using shared mobility options during the COVID-19 pandemic. Overall, the literature evidenced that males usually tend to perceive lower levels of risk as compared to females in similar circumstances (Flynn, Slovic, and Mertz 1994; C.-T. J. Lin 1995; Gustafsod 1998; Davidson and Freudenburg 1996; Dosman, Adamowicz, and Hrudey 2001; Hotle, Murray-Tuite, and Singh 2020). For instance, Davidson and Freudenburg (1996) highlighted that the traditional gender role of females, who are care providers within a household, might lead them to perceive higher health risks. Furthermore, Hotle, Murray-Tuite, and Singh (2020) showed that females are more likely than males to avoid public transit due to the threat of outbreaks.

According to **Table 5-3**, the age of respondents is found to affect the risk-perception behavior associated with choosing ridesharing services as a transport mode. Specifically, seniors are more likely to perceive the exposure to the SARS-CoV-2 virus as higher risk than younger respondents. Several possible reasons might explain this finding. First, seniors are more likely to have underlying health conditions, increasing the risk of dying from coronavirus. According to the CDC, the highest risk for severe illness from COVID-19 is among older adults, including seniors (CDC 2020).. As another reason, seniors have experienced previously the possible effects of health issues associated with viral diseases similar to the COVID-19; thus, they perceive similar crises as high-risk incidents (Dosman, Adamowicz, and Hrudey 2001). Besides, seniors are less knowledgeable than younger individuals about the risk, as a result, they perceive the risk to be more threatening to their life (Dosman, Adamowicz, and Hrudey 2001)

We found that being the main driver of a household's vehicle affects the perceived risk of exposure to the COVID-19 during the use of the public transit system. This variable can be a proxy for having highly auto-oriented lifestyles. Auto-oriented individuals might be more risk-averse while using public transit during the COVID-19 pandemic. Moreover, we also found that individual's occupation might impact the perceived risk of exposure to the virus. Specifically, individuals who work in transportation service industries (e.g., bus drivers) are more likely to be risk-taker than others. Supported by intuition, such individuals might have more experience in dealing with such health-related issues, thus they perceive less threat than others.

5.4.2 Virus spread

The perceived risk of exposure to the SARS-CoV-2 virus, also, varies by being a confirmed case of COVID-19. More specifically, respondents who have experienced the novel coronavirus disease in the past 14-days are more likely to be risk-takers than others to use shared mobility options. One possible reason is that such individuals trust the early evidence, showing that levels of neutralizing antibodies against the SARS-CoV-2 virus remain relatively high for a few weeks after infection, but then usually begin to decline (Callaway, Ledford, and Mallapaty 2020). In line with our finding, moreover, Hotle, Murray-Tuite, and Singh (2020) studied the risk perception associated with visiting public places during an influenza outbreak for individuals, who had experienced the flu symptoms in the past 6 months. They found that having such experiences might to some extent lead individuals to be more risk-taker than others in terms of visiting public places during an outbreak.

Another variable that turned out to be significant in the model is the density of confirmed COVID-19 cases within a zip code (i.e., the number of confirmed COVID-19 cases within a zip code divided by the population of the zip code) where the respondent resides. Per the model, the more the novel coronavirus spreads among the population of a specific zip code where an individual is living, the more he or she might perceive the risk of exposure to the virus during the use of ridesharing services. This finding is in good agreement with the literature (Davidson and Freudenburg 1996; Dosman, Adamowicz, and Hrudey 2001), emphasizing the effect of surroundings on shaping risk perceptions.

5.4.3 Built environment settings

Our results show that the transportation network density in terms of facility miles of auto-oriented links per square mile in the census block group where respondents reside, might lead them to become more risk-averse regarding the use of public transit system during the COVID-19 pandemic. In line with the literature, highlighting the effect of the built environment on shaping individuals' modality styles (i.e., the lifestyle associated with long-term mode choice decisions) (Shamshiripour et al. 2020a) and risk perception (Davidson and Freudenburg 1996), this finding provides another implication of built environment settings in forming people's travel behavior. Arguably, those who live in such areas are more prone to personal vehicles than shared mobility.

Thus, they might perceive higher levels of risk while using public transit during a health crisis like the COVID-19 pandemic, since they are less acquainted with this mode. This result also further supports our findings on the effect of being the main driver of a household vehicle (as the proxy of being auto oriented). With a similar argument, our results reveal that individuals who live in transit-oriented areas are more likely to be risk-taker than others in terms of using public transit during the COVID-19 pandemic.

Another transit-related built environment variable that turned out to be significant in the model is the aggregate frequency of transit service per square mile in a block group where the respondent resides. Living in such transit-oriented areas leads people to be less risk-averse and more prone to use shared mobility options. Furthermore, the results show that individuals who live in areas with a higher level of access to active-transportation infrastructure might be more risk-averse to use ridesharing services as compared with active modes. This finding is in good agreement with the (Bucsky 2020) who observed that people are more inclined to substitute shared mobility options such as public transit with active transport modes such as walking and biking as safer options.

5.4.4 Laws and restrictions

In the survey, we asked the respondents to indicate which types of official restrictions associated with the COVID-19 pandemic currently exist in their residential area. Then, we compared individuals' responses with the official guidelines available during the time of the survey according to the specific guidelines put forth by the governor of the state of Illinois (State of Illinois 2020). An indicator variable (i.e., *Law: OverActingBasedOnLaw*) was created for individuals who selected more restrictions than the ones that were already put in place. Therefore, if an individual selected more restrictions than those already in place (i.e., the indicator variable takes 1), it could be concluded by the rationale that the individual is voluntarily imposing more limitations to his/her way of life, which could be due to perceiving higher levels of risk. Accordingly, our results reveal that such individuals are likely to be more concerned than others about using shared mobility options, including public transit and ridesharing services.

5.4.5 Simulation of the perceived risks

To demonstrate the spatial distributions of perceived risk of using public transit and ridesharing services, we simulated the proposed model for individuals who live in the Chicago metropolitan area at a census block-group level resolution. **Figure 17** and **Figure 18** present the perceived risk of exposure to the novel coronavirus while riding public transit and ridesharing services, respectively. We also aggregated the risk levels into three categories of (1) low risk, (2) medium risk, and (3) high risk. Overall, the perceived risk of exposure to the novel coronavirus while using the public transit system is significantly higher, as compared with using ridesharing services in the region. More interestingly, the simulation results reveal a distinction between individuals who live in the suburbs and those who live in the city for the perceived risk of exposure to the virus while using ridesharing services. According to **Figure 18**, individuals who live in the suburbs perceive less risk when using ridesharing services, as compared with those who live in the city. Accounting for the perceived risk of using public transit, however, we found no distinction between the two groups of the population. In other words, the use of public transit system is perceived to be associated with high levels of risk in most census block groups in the Chicago metro area.

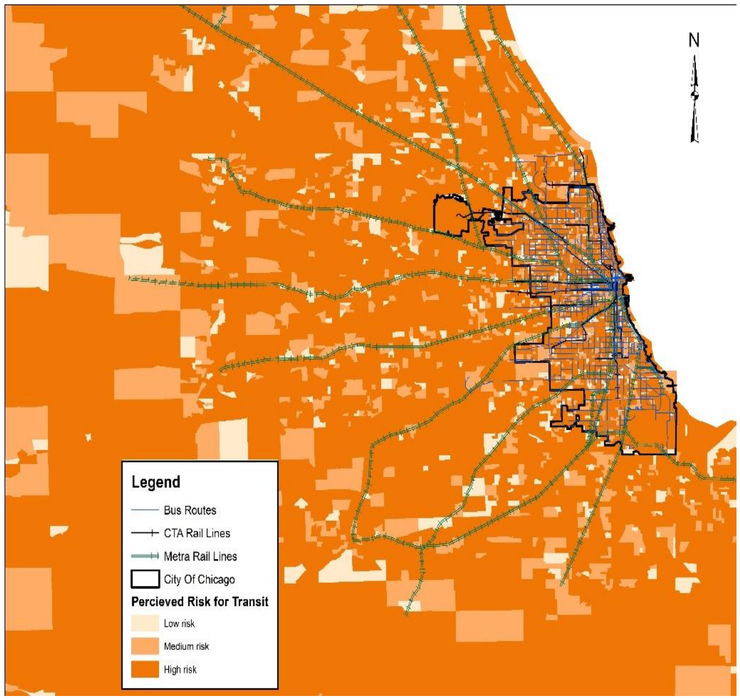


Figure 17. Perceived risk of exposure to the novel coronavirus for using public transit

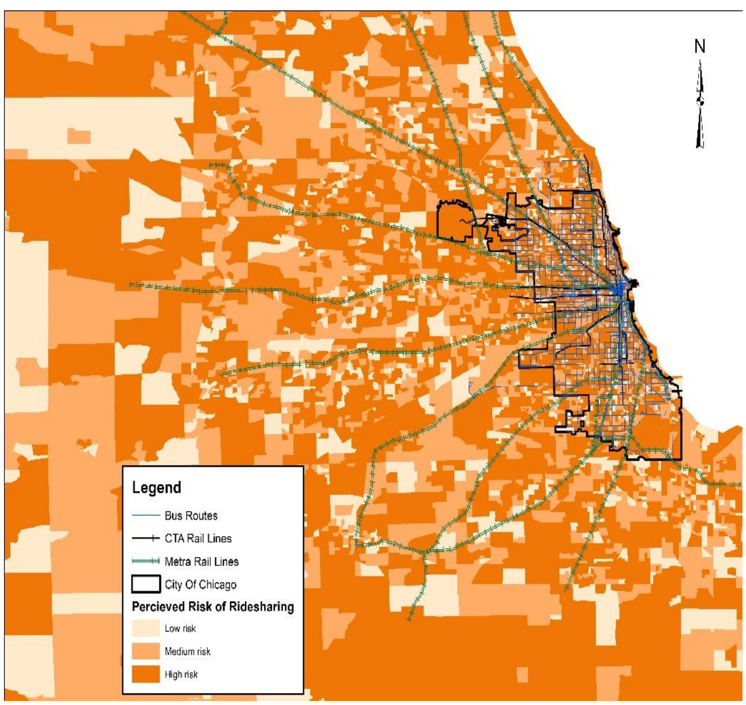


Figure 18. Perceived risk of exposure to the novel coronavirus for using ridesharing services

5.5 Summary and Conclusion

In this chapter, we aimed to investigate risk perceptions toward using shared mobility solutions during the pandemic. It is vital for policymakers to accurately characterize the different types and degrees of behavioral changes among various groups of society. Risk perception of using various modes is one of the major factors which can substantially explain individuals' travel behavior changes during a health crisis. The focus of this study is on public transit and ridesharing services since these options are the most widespread forms of shared mobility in the current transportation system. We utilized a bivariate ordered probit modeling approach in order to consider the correlation among unobserved factors while accounting for the ordinal nature of risk perception outcomes. The data used in this study is provided by a recent multidimensional travel-behavior survey instrument in the Chicago Metropolitan Area focusing on the impacts of COVID-19 pandemic on individuals' travel behavior. We launched the online survey in the Chicago region from April 25 to June 2, 2020, and collected a rich set of data regarding the residents' socio-demographic details, their health-related background, as well as an extensive set of information about their daily activity-travel behavior.

According to the results, a wide range of explanatory variables is found to be significant in the risk perception model, including socio-demographic variables, built environment, health condition, virus spread, and the restriction factor. Our findings provide insights into the influential factors on being risk-averse versus risk-taker with respect to use shared mobility services during the pandemic. The findings assist policymakers in two main directions. First, the results showed that minority groups, including African Americans and extremely low-income families perceived to be more at risk of exposure to the SARS-CoV-2 virus while they use shared mobility options. Such findings highlight the importance of achieving "equity" in access to a safe transportation system, especially during a health crisis such as the COVID-19 pandemic. The considerable economic and demographic diversity, along with the racial segregation in the Chicago Metropolitan Area, have created challenges in ensuring transportation equity in the region. Thus, policymakers should focus on the minority groups' needs and specific behavior when planning for recovering the shared mobility options, including public transit and ridesharing services. Second, the results revealed that risk perception behaviors might vary based on the special characteristics of places, where individuals reside. Besides, the spread of the novel coronavirus might also affect the risk perception behavior in each neighbor. These findings highlighted the idea that mitigating strategies should be adaptive based on the specific characteristics of each neighbor. In other words, a common strategy will not be able to mitigate the risks associated with the use of shared mobility options throughout the area.

6 CONCLUSION AND FUTURE RESEARCH

6.1 Summary and Conclusion

Public transit not only provides an affordable, efficient, and green service but also plays a critical role in the development of resilient transportation systems in urban areas. Transit disruption as a common incident in transit service operations can severely affect the resiliency of the transportation system and users' satisfaction. While it is of great interest to transportation authorities to understand passengers' decision behavior during unplanned transit disruptions to implement efficacious recovery strategies, little is known about users' behavior in case of such incidents. The scarcity of available data is a major underlying factor for this gap. Utilizing recently collected data of transit users in the Chicago metropolitan area, the current work investigates transit users' behaviors during unplanned service disruptions and discloses the factors that affect their behavior. For the first phase of the behavior (i.e., waring tolerance), a set of interval-censored accelerated failure time models using different survival distributions are developed, compared, and the factors influencing the survival functions of the waiting tolerance are identified. The results of the analysis reveal that, for instance, having experience of using ridesharing services decreases users' waiting tolerance during a disruption. Further, built-environment attributes (such as the density of pedestrian-oriented links and transit service frequency), availability of alternative modes, transit service type, user's attitudes, and trip characteristics turn to be significant in users' decision behavior.

For the second phase of the transit users' behavior during unplanned disruptions (i.e., mode choice decision), a random parameter multinomial logit model is employed to consider heterogeneity across observations as well as panel effects. The results of the analysis reveal that a wide range of factors, including socio-demographic attributes, personal attitudes, trip-related information, and built environment, are significant in passengers' mode choice behavior in case of unplanned transit disruptions. Moreover, the effect of service recovery time on passengers is not the same among all types of disrupted services; rail users are more sensitive to the recovery time as compared with bus users.

We also investigated the impacts of COVID-19 pandemic on the transit and shared mobility options. The COVID-19 pandemic has caused our daily routines to change quickly. The pandemic provokes public fear, resulting in changes in what modes of transport people use to perform their daily activities. It is imperative for transportation authorities to properly identify the different degrees of behavioral change among various groups of society. A major factor that can substantially explain individuals' behavior changes is the personal risk perceptions toward using shared mobility solutions. Thus, we aimed at exploring the risk that individuals perceive while using public transit and ridesharing services (as the most widespread forms of shared mobility) during the COVID-19 pandemic. To do so, we designed and implemented a multidimensional travel-behavior survey in the Chicago metropolitan area that comprises socio-demographic information, retrospective questions related to attitudes, and travel behavior before and during the pandemic. Utilizing a bivariate ordered probit modeling approach to better account for the potential correlation between unobserved factors, we simultaneously modeled the perceived risk of exposure to the novel coronavirus in case of riding transit and using ridesharing services. A wide range of factors is found to be influential on being risk-averse or risk-taker users, including the socio-demographic attributes, built environment settings, and the virus spread. Further, our results indicate that the mitigation strategies to increase the ridership of shared mobility services should not only be focused on equality among minority groups but also adaptive considering the spatial variations.

6.2 Future directions of research

In the previous chapters, we found the potential of collaboration between transit authorities and transportation network companies in providing recovery options for transit users who are facing a service disruption. This collaboration can significantly help transit authorities to mitigate affected users who are facing such incidents. Moreover, it can also improve the overall transportation resilience since travels can be directed to another alternative through a platform as quickly as possible. A suitable platform to facilitate such collaboration can be provided through mobility-as-a-service (MaaS), which is recently introduced to the transportation market.

In the last few years, the Mobility as a Service (MaaS) concept has gained growing attention in the mobility sector. Several countries (e.g., Finland, UK, Australia) have stated their intentions to implement this new mobility solution, which restructures the mobility sector that would satisfy users' every transportation need through a single digital platform. This innovative concept combines various transportation modes to offer a personalized mobility package which includes other complementary services such as trip planning, booking, and payments (Jittrapirom et al. 2017). Depending on the local environment, the plans include the various public transport options, which in many cities are already offered in monthly subscriptions and a taxi, TNCs, new micro-mobility options such as shared E-scooters and bike-sharing. These plans would conceptually be similar to cellphone plans, where users pay for a specific amount of services (calls, texts, and data) each month (Matyas and Kamargianni 2019).

However, there is still a vast gap in knowledge about the ideal design of mobility plans. Accounting for the heterogeneity of travelers' needs, the plans need to cater to all the sociodemographic user groups' different preferences. Further, with careful design, MaaS mobility plans can be used as a travel demand management tool to assist during emergencies. Thus, future research should investigate users' preferences toward the MaaS solution and guiding the developments and best practices of MaaS plans. Future research should also further explore how MaaS can improve the transportation system's resiliency in the context of the Smart Cities paradigm.

Furthermore, we characterized the perceived risk of exposure to the COVID-19 virus while riding with shared mobility (i.e., public transit and ridesharing). The next step is to investigate how the perceived risks might lead to individuals' mode choice decisions during and after the COVID-19 pandemic. Moreover, most activity-based travel behavior frameworks overlook the perceived risk of using various modes associated with long-term disasters, including outbreaks. Therefore, future research should incorporate the mode choice decisions while accounting for the perceived risk of using different modes during an outbreak (e.g., COVID-19 pandemic).

APPENDIX

The materials of chapter 3 are previously published as:

"Rahimi, E., Shamshiripour, A., Shabanpour, R., Mohammadian, A., Auld, J. 2019. Analysis of Transit Users' Waiting Tolerance in Response to Unplanned Service Disruptions. Transp. Res. Part D Transp. Environ".

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The materials of chapter 4 are previously published as:

"Rahimi, E., Shamshiripour, A., Shabanpour, R., Mohammadian, A., Auld, J. 2020. Analysis of Transit Users' Response Behavior in Case of Unplanned Service Disruptions. Transp. Res. Rec. J. Transp. Res. Board".

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The materials of the sub-chapter **5.2.2** are part of a previously published article as follows:

"Shamshiripour, A., Rahimi, E., Shabanpour, R. and Mohammadian, A.K., 2020. How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. Transportation Research Interdisciplinary Perspectives, 7, p.100216. https://doi.org/10.1016/j.trip.2020.100216".

The above article was published by Elsevier, and it is allowed to re-use it either in part or full as is stated in the publisher guidelines (please refer to **APPX 1** for the guidelines).

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