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Investigating Mode Choice of Ridesourcing Services: Accounting for Attitudes and Market Segmentation

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INVESTIGATING MODE CHOICE OF RIDESOURCING SERVICES: ACCOUNTING FOR ATTITUDES AND MARKET SEGMENTATION

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To: Dean John L. Volakis
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This dissertation, written by Ghazaleh Azimi, and entitled Investigating Mode Choice of Ridesourcing Services: Accounting for Attitudes and Market Segmentation, having been approved in respect to style and intellectual content, is referred to you for judgment. We have read this dissertation and recommend that it be approved.

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DEDICATION

This dissertation is dedicated to my lovely parents, Yahya and Afsaneh, for their unconditional love and sacrifices, to my beloved husband, Alireza, for his unbounded support, to my wonderful sisters, Minoo and Shamim, for their endless support and encouragement.

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ABSTRACT OF THE DISSERTATION

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Professor. Xia Jin, Major Professor

The phenomenal development of ridesourcing is possibly one of the greatest revolutions that have happened to transportation networks. Ridesourcing improves mobility and mitigates traffic congestion by reducing vehicle ownership and serving as a first/last-mile feeder to public transportation. This tremendous growth created a burgeoning literature exploring ridesourcing users' characteristics, yet there is no clear picture of its market. In the absence of sufficient information, policymakers face a major challenge in planning equitable and accessible transportation systems. This dissertation presents a detailed analysis of individuals' decisions to adopt ridesourcing, focusing on three main objectives that have not been addressed previously. First, a reduced fare of ridesourcing was considered to explore its adoption beyond cost constraints. Second, the effect of attitudes on the choice of ridesourcing was explored. Lastly, the adoption of ridesourcing across various market segments was examined. Advanced economic models were applied to the data from a stated preference survey, which is a rich database of attitudes and mobility patterns.

The results indicate that attitudes play a major role in the adoption of ridesourcing and considering the impact of attitudinal factors could provide valuable insights into individuals' behavior toward ridesourcing. It was shown that attitudinal factors (e.g., technology-savviness, driving enjoyment) could explain individuals' choice behavior in a way that cannot be clarified by socioeconomic and demographic factors.

The market segment-based analysis of ridesourcing adoption demonstrated that different segments have distinct perceptions and attitudes toward ridesourcing. For instance, for regular transit users, travel time and cost perceptions are decisive factors in adopting ridesourcing. In contrast, visitors (i.e., auto users when their vehicle is unavailable) will adopt ridesourcing when it provides higher utility regarding time, cost, and convenience. Moreover, regarding the impact of ridesourcing experience on the adoption of these services, it was shown that individuals with no ridesourcing experience are more sensitive to traveling with strangers, worry about the higher travel time, and are more attached to their vehicles. Finally, considering the role of generational effects on ridesourcing adoption, it was shown that Generation Xers' choice highly depends on the perceived utility of shared mobility and their desires for mobility for non-drivers features. Contrarily, Millennials' choices are more likely to be affected by their preference toward technology and driving stress relief.

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AV	Autonomous Vehicles
AIC	Akaike's Information Criterion
APTA	American Public Transportation Association
BIC	Bayesian Information Criterion
CFA	Confirmatory Factor Analysis
DOT	Department of Transportation
DUI	Driving Under the Influence
ICT	Information and Communication Technologies
IID	Independently and Identically Distributed
GHG	Greenhouse Gas
LRT	Log-Likelihood Ratio Test
MNL	Multinomial Logit
MSA	Metropolitan Statistical Areas
NHTS	National Household Travel Survey
NL	Nested Logit
PCA	Principal Component Analysis
RP	Revealed Preference
SED	Socioeconomic and Demographic
SEM	Structural Equation Modeling
SP	Stated Preference
TAZ	Traffic Analysis Zone

TNC	Transportation Network Company
USDOT	United States Department of Transportation
VMT	Vehicle Miles Traveled

CHAPTER 1

INTRODUCTION

1.1 Background

Human society is facing the early steps of a technological revolution that transforms the current transportation system and brings unprecedented behavioral and social changes. One particular aspect of this technological revolution, the rise of shared mobility services, like Uber, Lyft, and Zipcar, has substantially changed traditional transportation networks. Shared mobility is considered a potential replacement for private vehicles. Travel cost savings, convenience, multitasking opportunities, parking issues, driving avoidance, and environmental concerns were noted as top reasons for shifting from private vehicles to ridesourcing services (Alemi et al. 2019, Rayle et al. 2016, Dias et al. 2017). The Substitution of personal cars could reduce vehicle miles traveled (VMT), greenhouse gas (GHG) emissions, traffic congestion, parking demand, and mode dependency.

Furthermore, shared mobility can facilitate door-to-door travel (Jittrapirom et al., 2017), providing an integrated network of transportation and enhancing mobility for the disadvantaged population (e.g., people with disabilities, seniors, low-income individuals). In interconnected networks, shared mobility modes often serve as a first/last mile connector to fixed-route transit services (Jittrapirom et al., 2017), playing a crucial role in facilitating public transit use. This impact could be especially beneficial for areas with poor transit service or low and medium-density land-use patterns (Lavieri. 2018). In addition, shared mobility services can be integrated into existing paratransit services or directly serve persons with disabilities who cannot drive (Feigon and Murphy 2016). However, unlike public transit services that all buses must be fully accessible to riders who require mobility assistance (e.g., wheelchairs), shared mobility services can be a fleet with a mix of accessibility levels (Feigon and Murphy 2016). There are different types of shared mobility services, including shared micromobility, carsharing, ridesharing, and ridesourcing. Shared micromobility provides a platform for sharing small, lightweight, and low-speed travel modes that primarily serve short-distance trips or provide first/last mile solutions. Shared micromobility modes include bikesharing (traditional bikes or electronic bikes), electronic scooter sharing, and other emerging lightweight transportation means. Carsharing is a service that provides access to a vehicle, usually for a period that is less than one day (Feigon and Murphy 2016). In this type of service, vehicle (fleet) owners give the authorization to others to use their cars when available. Examples of these services include Zipcar and car2go.

In view of ridesharing services, when passengers and drivers have the same destination or their destinations are close to each other, they share a private ride. Traditional forms of ridesharing include carpooling or vanpooling (Feigon and Murphy 2016), for which the trip is pre-arranged often between family members, friends, or colleagues. In the past few years, the advances in information and communication technologies (ICT) enabled a new form of ridesharing services called dynamic ridesharing, which provides the opportunity of sharing a ride on short notice among strangers and without the need for pre-arrangement (Feigon and Murphy 2016, Shaheen et al. 2015).

Ridesourcing, as a form of dynamic ridesharing, uses an online platform to link passengers and drivers via an automated reservation and payment system. With this type of shared mobility service, passengers are provided with various vehicle options, including personal vehicles, traditional taxicabs, and premium services with livery drivers. Examples of ridesourcing services include Uber and Lyft. Ridesourcing services have experienced remarkable growth in recent years. For instance, Uber served one billion trips in 2015, six years after its introduction to the market, then reached five billion trips one year later (Uber 2017), which showed exceptional growth in the number of riders. Statistics show that ridesourcing has the largest market share among all shared mobility services in the U.S. In 2017, Uber's number of active subscribers (as one ridesourcing company) was more than ten times and four times the total number of active subscribers of all carsharing and bikesharing companies, respectively (Statista 2018a, 2018b, 2018c).

As the most popular type of shared mobility, there is widespread interest in understanding the mode choice behavior in light of ridesourcing services. However, currently, there is limited knowledge on factors that impact the adoption of these services. This partial knowledge is primarily due to limited data about the characteristics of the users and the reasons they adopt ridesourcing, as well as the high level of ambiguity over the development and evolution of these services. Due to the resistance of ridesourcing companies to share their data, as well as their unclear regulations and privacy protection policies, local and national officials actively challenge the promotion of these services, holding back their continuous growth and making the future of these services vague and uncertain. To compensate for this lack of data, some studies designed travel behavior surveys to gather information from respondents about their socioeconomic and demographic (SED) attributes and travel behavior (Rayle et al. 2014, Lavieri 2018, Asgari et al. 2018, Jin and Asgari 2019). The collected data were used to investigate individuals' mode choices between conventional modes and ridesourcing. Besides individuals' SED characteristics and mobility profiles, another factor that substantially impacts individuals' mode choice behavior is psychological constructs, such as attitudes (Hagman, 2003;

Verplanken et al., 2008; Domarchi et al., 2008; Kuppam et al., 1999). Individuals' preferences for attributes of travel modes and their perceptions of available alternatives are among some critical attitudes that should be considered in mode choice behavior analysis. Previous studies showed that the public's perceptions of reliability, safety, security, convenience, and availability of a specific could make them highly motivated or hesitant to use that mode and have unquestionable roles in individuals' travel behavior (Loa and Khan, 2021; Lavieri and Bhat, 2019; Alemi et al., 2019).

In spite of the considerable impact of attitudes on travel behavior, only a few studies incorporated these factors in their surveys to collect data for investigation on the effects of attitudes on individuals' mode choice in the era of ridesourcing services (Shabanpour et al. 2018, Bansal et al. 2019, Alemi et al. 2018, Asgari et al. 2018, Asgari and Jin 2019, Asgari and Jin 2020).

1.2 Problem Statement

The problem statement is divided into three sections. Each section describes the existing knowledge gap in the literature and how it may influence the current understanding of the mode choice in the era of ridesourcing.

1.2.1 *Role of Travel Cost in Adoption of Rideosourcing Services*

While ridesourcing provides a convenient and reliable transportation service that might encourage people to consider it their primary travel mode, regular use of these services can impose considerable costs on individuals. At its' current price, not everybody can afford the expenses for everyday use of the service. To unearth the full spectrum of attitudes that can affect one's decisions on using ridesourcing, observing how people view ridesourcing services compared to other modes when the cost constraint is relaxed can provide valuable insights. In this context, stated preference (SP) experiments are ideal for revealing the decision-making process and identifying the tradeoffs between ridesourcing and conventional modes beyond cost considerations. In addition, with the upcoming introduction of Autonomous Vehicles (AV) into the ridesourcing fleet, the cost of ridesourcing could drop significantly, supporting the necessity of studying mode choice behavior with SP scenarios (Compostella et al. 2020, Walker Johnson, 2016, Stocker and Shaheen 2018, Spieser et al. 2014, Karamanis wt al. 2018).

1.2.2 *Impact of Attitudinal Factors on Mode Choice Behavior*

The second major element of shared mobility research that has not received much attention in the existing studies is the role of attitudes in mode choice behavior. Previous studies have shown that attitudes have considerable impacts on individuals' mode choice behavior. However, these studies mainly focused on traditional modes (Hagman 2003, Jensen 1999, Verplanken et al. 2008, Vredin Johansson et al. 2006, Paulssen et al. 2014, Domarchi et al. 2008, Verplanken et al. 1994). While the impacts of SED variables on the adoption of ridesourcing services have been well studied, only a few papers have investigated the effects of attitudinal factors on travelers’ mode choice in the context of ridesourcing services (Dias et al. 2017, Shabanpour et al. 2018, Bansal et al. 2019, Alemi et al. 2018, Alemi et al. 2019). Taking into account the role of attitudes in the propensity toward or against ridesourcing services might be beneficial for planners and legislators to better address the needs and concerns of the public.

1.2.3 *Mode Choice Analysis Based on Market Segments*

The third major element in studying the impacts of ridesourcing is the consideration of distinct behaviors of various market segments (e.g., users of different traditional modes) toward these services. This section outlines multiple market segments and discusses the factors that may influence their desire for ridesourcing services.

1.2.3.1 The Choice Between Public Transit and Ridesourcing

Although ridesourcing services probably affect the market shares of traditional modes, such as personal cars or public transit, their impacts on mode shares can be subject to change by the distinct characteristics, attitudes, and preferences of various user markets. Consequently, it is vital to take into account these differences in studying the adoption of ridesourcing services.

In view of the potential impacts of ridesourcing on the transit market, both substitution (Rahimi et al. 2019, Mahmoudifard et al. 2017) and complement effects (Rayle et al. 2014, Babar and Burtch 2017, Zhang et al. 2015, Yan et al. 2019) have been reported. In the former case, transit users switch to ridesourcing for its convenience, flexibility, and broader spatial and temporal coverage (Golshani et al., 2019). In the latter case, ridesourcing serves as the first/last mile connection for transit services. Although the magnitude of substitution or supplement depends on population density, vehicle ownership, the level of service of existing transit services (Rayle et al. 2016, Lavieri et al. 2018, Zhang et al. 2015, Murphy 2016), it was found that ridesourcing tends to compete with local transit while complementing subway and commuter rail services (Babar and Burtch 2017, Clewlow and Mishra 2016). Interestingly, ridesourcing users share many similar characteristics as transit riders; they are younger, live in denser areas, and have a lower percentage of vehicle ownership (Rayle et al. 2016, Lavieri et al. 2018, Zhang et al. 2015, Circella and Alemi 2018). Another potential market of ridesourcing services is visitors or those who temporarily have no access to a private vehicle. These people could be very auto-dependent, but in situations without access to a private vehicle, such as visiting other places or traveling to or from the airports, they may find ridesourcing more attractive than transit. This could be due to convenience, higher travel time reliability (especially for areas with low public transportation coverage), and more resemblance to private vehicles. A previous study showed that visitors and transit riders exhibited very different patterns in their mode choice behavior (Asgari et al. 2018). These differences could be highly influential in their choice between transit and ridesourcing services.

Therefore, it is crucial to investigate the choice behavior for regular transit users and visitors to illustrate their fundamental differences. Focusing on the detailed market analysis can help us understand their distinct attitudes and preferences toward various mobility options, which will result in more effective and practical planning and policy decisions.

1.2.3.2 The Role of Experience in Individuals' Mode Choice of Ridesourcing

Another essential element of ridesourcing research is the association between the experience of using ridesourcing and the future adoption of these services (Namgung and Jun 2019, Bruce et al. 2014, Franke et al. 2012, Thøgersen and Møller 2008, Brown et al. 2003, Rauh et al. 2015, Fujii and Kitamura 2003, Fujii et al. 2001). Previous studies showed that experienced people were more confident and comfortable using a mode than inexperienced ones or those who have not used the mode at all (Rauh et al. 2015, Namgung and Jun 2019, Franke et al. 2012, Dill and McNeil 2013, Bunce et al. 2014). Similarly, ridesourcing experience could substantially impact individuals' attitudes, beliefs, and perceptions, affecting their mode choice behavior. People with experience using ridesourcing services are probably less worried about the potential drawbacks and are more aware of the advantages. While previous studies explored the impact of experience on individuals' mode choice behavior, their focus was mainly on traditional travel modes.

Given the above discussion, understanding how ridesourcing experience affects individuals' attitudes toward mobility choices is useful for policy-making purposes.

1.2.3.3 Generational effects on Ridesourcing Adoption

Lastly, another major factor for ridesourcing adoption is the generational effects (beyond the impact of age or socioeconomic status). Previous studies showed that younger generations are more interested in using ridesourcing services than older cohorts (Circella et al., 2016, Rayle et al. 2014, Dias et al. 2017, Alemi et al. 2018, Clewlow and Mishra 2017). However, they did not provide evidence on their potential differences in attitudes and mobility preferences and how these factors may affect their inclinations toward ridesourcing services. The fact that younger individuals use ridesourcing services more than their older counterparts might be related to their familiarity and openness with ICT apps and new technologies, preferences for non-motorized modes, and environmental awareness (Blumenberg et al., 2016, Kuhnimhof et al., 2012). From this perspective, there is a need to examine how different generations may exhibit different attitudes and preferences toward mobility choices and identify an approach to incorporate this into the analysis framework.

1.3 Goals and Objectives

Given the above discussions, this dissertation proposes a comprehensive framework to investigate the mode choice behavior in the era of ridesourcing services, with three main objectives:

1. Understand the choice behavior and trade-off considerations between ridesourcing and conventional modes (private vehicle and transit) beyond cost constraints.
2. Explore the impacts of attitudes in terms of how they influence the choice of ridesourcing services.
3. Examine the choice behavior for different market segments.

The last objective focuses on three main research topics, which are illustrated in

Figure 1-1. As shown, the first topic investigates the choice between transit and ridesourcing for regular transit riders and visitors. The second topic explores the impact of shared mobility experience on the propensity toward or against adopting ridesourcing services. The last topic analyzes the choice behavior of two generations: Millennials, born between 1981 and 2000 (Rainer and Rainer, 2011; Galdames and Guihen, 2020; Laurie et al. 2019; Gong et al., 2018) and Generation Xers, born between 1965 and 1980. It should be noted that there is no agreed-upon definition for Millennials. There are 28 various definitions for this generation in the literature (Galdames and Guihen, 2020). The earliest and latest birth year assigned to the Millennials was 1977 and 2005; respectively (Galdames and Guihen, 2020). However, the term Millennials is mostly applied to describe a part of society born approximately between the early 1980s and early 2000s (Laurie et al. 2019).

1.4 Contribution

This dissertation contributes to the literature by conducting a comprehensive analysis to advance the current understanding of the potential market of ridesourcing. The dissertation investigates the factors that influence the public's mode choices between conventional modes and ridesourcing services, focusing on attitudinal factors.

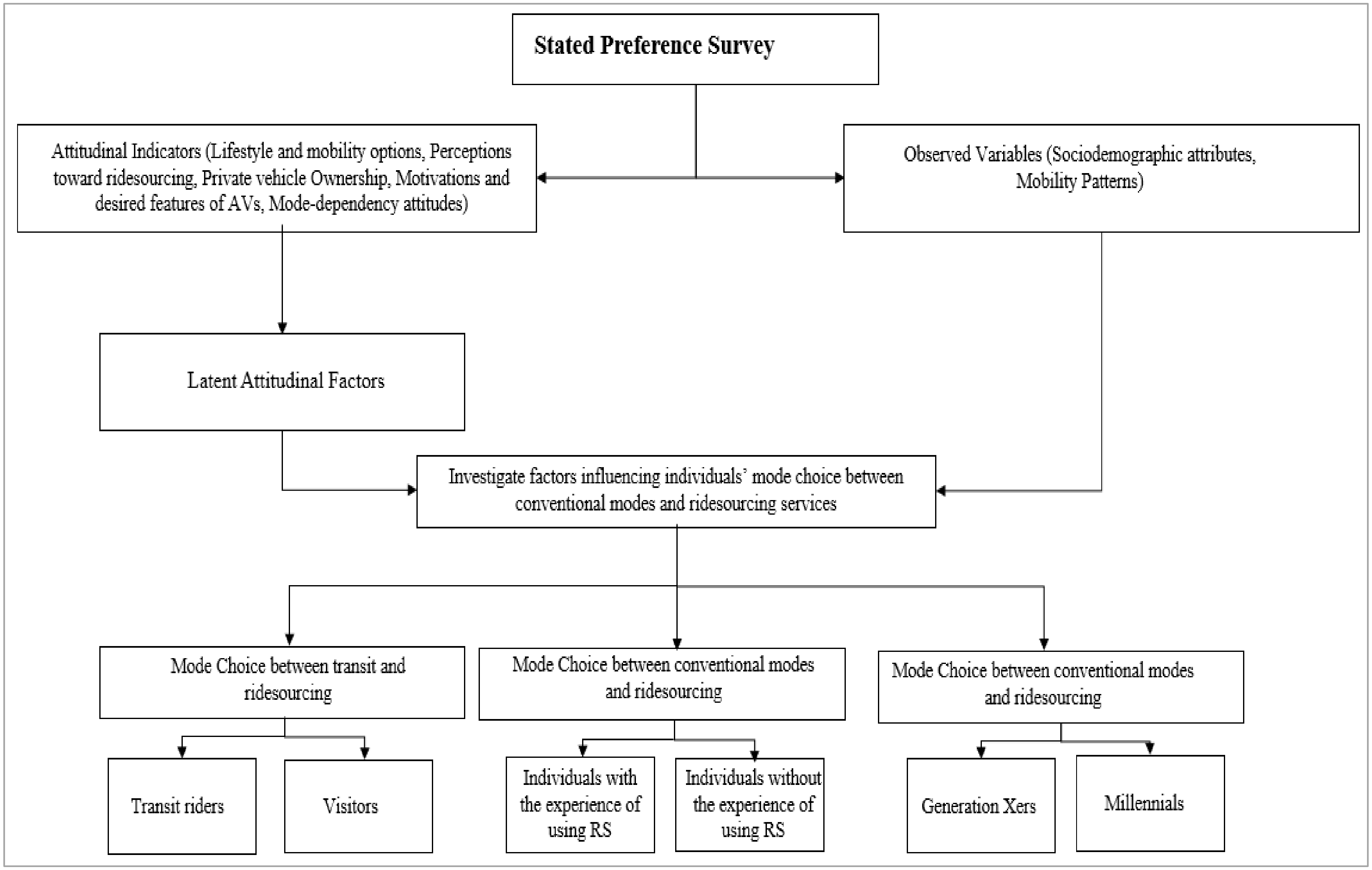


Figure 1-1 Research framework

1.5 Organization

This dissertation includes eight chapters. Chapter two provided a comprehensive review of the studies on the adoption of ridesourcing services. Chapter three provided detailed information on the data used for this dissertation. Chapter four explained the quantitative modeling methodologies applied in this dissertation. The results of modeling analysis for each research topic were presented in the following chapters. In this regard, Chapter five presented the results of mode choice analysis for transit riders and visitors, Chapter six explained the findings on the role of experience in the propensity toward ridesourcing services, and Chapter seven discussed generational effects on the adoption of ridesourcing services. Chapter eight summarized the findings, contributions, and limitations of the study.

CHAPTER 2

LITERATURE REVIEW

The literature review is divided into five sections. In the first section, literature on the characteristics of ridesourcing users, mode choice behavior with ridesourcing, and the impacts of ridesourcing on public transit are reviewed. The second section reviews the literature on the choice between shared and exclusive ridesourcing services. The third section focuses on known significant attitudes toward ridesourcing currently documented in the literature. The fourth section reviews studies that investigated how experience with a specific travel mode might influence people's mode choice behavior. The last section reviews the methodologies that have been applied to analyze choice behavior involved in using ridesourcing services.

2.1 Mode Choice Behavior in Light of Ridesourcing

2.1.1 *Characteristics of Ridesourcing Users*

Alemi et al. (2018) investigated factors affecting the adoption of ridesourcing services among Millennials (people born between 1981 and 1997) and Generation Xers (people born between 1965 and 1980) in California. They used the California Millennials Dataset, which was conducted in 2015 and consisted of 1975 respondents. The findings indicated that older Millennials with high education levels were especially likely to use ridesourcing services. Greater land-use mix and regional accessibility by vehicle were related to a larger likelihood of utilizing ridesourcing services. Individuals with a higher frequency of long-distance business and airplane trips were also more interested in adopting these services. Moreover, regular users of applications related to transportation (e.g., Google Maps, applications for finding the transit schedule) and those with experience of using taxi and carsharing services showed a higher propensity toward ridesourcing services. Circella et al. (2018) expanded the previous study by taking into account the variations (due to distinct individual and household characteristics and lifestyle) in the impact of ridesourcing on different market segments. They used a latent-class adoption model to better address individuals' heterogeneity and taste variations, and they found three latent classes. The highest adoption rate (47%) was detected among the class consisting of well-educated, financially independent Millennials who can be defined as multimodal travelers living in walkable and transit-accessible neighborhoods. The second-highest adoption rate (27%) was observed among suburban residents with pro-environmental preferences living in less transit-accessible areas but trying to be multimodal travelers. The lowest adoption rate (5%) was related to the rich suburban residents with positive attitudes towards car ownership and high vehicle miles traveled (VMT).

Alemi et al. (2019) evaluated the frequency of on-demand services, such as Uber and Lyft, among Millennials and Generation Xers in California using the aforementioned California Millennials Dataset. Five major categories were considered as explanatory variables: SED characteristics, built environment attributes, technology embracing and social media use, travel-related choices, and attitudinal factors. The findings indicated that land use mix and activity density reduce and increase the frequency of on-demand services, respectively. Moreover, those who frequently use smartphone applications for assistance on routing and destination choices, individuals living in zero-vehicle households, and people with higher frequency of long-distance vacation airplane trips showed a positive tendency to adopt on-demand services. Dias et al. (2017) estimated the impact of socioeconomic and demographic variables on the frequency of using ridesourcing services. They used survey data derived from the 2014–2015 Puget Sound Regional Travel Study with 2789 respondents. They found that riders of these services tend to be young, well-educated, higher-income, and working individuals residing in higher-density areas. The presence of children in the households decreased ridesourcing and carsharing usage among low and middle-income households, possibly due to budget constraints and more complex activity-travel patterns. Households with one or more vehicles who live in a high-density location were more likely to adopt ridesourcing services than those living in low-density zones.

Sikder (2019) explored the socioeconomic and demographic characteristics as well as land use factors that influence the frequency of using ridesourcing services. They used the National Household Travel Survey (NHTS) performed by the U.S. Department of Transportation (USDOT) administration from March 2016 to May 2017, with 129,696 surveyed households. The NHTS data is a randomized, voluntary, large-scale national travel survey. The results showed that young people, full-time employed individuals with flexible schedules, and individuals with inadequate vehicles per household were more likely to use ridesourcing services. Moreover, African American individuals, low-income individuals, and households with children and/or older adults are less likely to adopt ridesourcing services. It was also found that ridesourcing has complementary effects on public transit, especially in the Metropolitan Statistical Areas (MSA) with rail services.

Deka and Fei (2019) examined the characteristics of ridesourcing users and neighborhoods using the aforementioned NHTS dataset. Because of the limited information about the neighborhood characteristics in the NHTS dataset, they added additional data from the 2016 American Community Survey and National Transit Map Data (which includes the exact locations of transit stops and stations). The findings indicated that young persons and individuals with higher education and income had a higher frequency of ridesourcing usage. In contrast, drivers and people with more cars in the households had a lower frequency of ridesourcing adoption.

Clewlow and Mishra (2017) investigated the factors that impact ridesourcing adoption and the potential impact of ridesourcing on travel choices. They conducted a survey in seven major U.S. cities from 2014 to 2016. Accordingly, the results showed that 24% of ridesourcing users in metropolitan areas used it weekly or daily. Parking issues and driving avoidance were noted as the top reasons for shifting to ridesourcing services. Young individuals (18-29 years old), college-educated, high-income groups, black individuals, and those living in urban neighborhoods reflected higher levels of ridesourcing adoption.

Rayle et al. (2016) investigated the characteristics of ridesourcing users, their reasons for using ridesourcing, and the potential impacts of ridesourcing on public transit using a survey conducted in San Francisco during May and June 2014 by intercepting ridesourcing's customers in critical locations expected to have a high prevalence of such users. The final data consisted of 380 completed questionnaires. The results indicated that ridesourcing users tend to be younger and well-educated individuals looking for lower wait times and fast origin-to-destination services. They also want to avoid the disutility associated with driving, such as parking or having to drink and drive.

Zhen (2015) compared the differences between users of traditional transportation services and ridesourcing services. An online survey, including 89 respondents, was conducted in the Pittsburgh region to measure users' attitudes and travel habits toward using ridesourcing services. The results specified that ridesourcing users are generally younger people and those who use ridesourcing for social trips.

Asgari and Jin (2020) investigated potential changes in individuals' mode choice behavior due to ridesourcing services. They used an online SP survey containing 878 respondents. Their objective was to analyze the role of habitual behavior correlated with traditional modes and private mobility costs (parking expense and time) in mode choice behavior. The findings indicated that habits play a crucial role in inhibiting travelers from shifting to ridesourcing services; however, private mobility costs might encourage users to break these habits. In terms of SED and trips characteristics, high-income people, full-time individuals, and social and school trips had a positive impact on the adoption of exclusive ridesourcing services. Moreover, middle-income individuals, college students, and young (18–24 years old) and middle-aged people (50 and 54 years old) showed a positive propensity toward shard ridesourcing services. Finally, lower education levels and retired employment status had negative associations with the adoption of ridesourcing services.

Aninanya et al. (2020) examined the use of ridesourcing services among young people in Ghana. They employed a stratified random sampling survey conducted on the Kwame Nkrumah University. The survey gathered information from 400 respondents. The results showed that young people favor ridesourcing services due to their cost advantages over conventional taxis. However, these people use ridesourcing occasionally, primarily for social trips and during weekends

Acheampong et al. (2020) explored the factors that have an impact on ridesourcing adoption in Ghana. They applied a multi-variable structural equation model on a survey dataset with 1,188 respondents. Results showed that younger people, and users with higher education and income, are more likely to use ridesourcing services. Ridesourcing is more likely to be adopted for commuting trips and trips with shorter travel times.

To summarize, the literature showed that full-time users (Sikder 2019, Asgari and Jin 2020), young individuals (Acheampong et al. 2020, Asgari and Jin 2020, Zhen 2015, Rayle et al. 2016, Clewlow and Mishra 2017, Gehrke et al. 2018, Deka and Fei 2019, Sikder 2019, Dias et al. 2017), users with high income (Acheampong et al. 2020, Asgari and Jin 2020, Clewlow and Mishra 2017, Deka and Fei 2019, Dias et al. 2017), and individuals with higher education (Acheampong et al. 2020, Asgari and Jin 2020, Rayle et al. 2016, Clewlow and Mishra 2017, Circella et al. 2018, Deka and Fei 2019, Dias et al. 2017, Alemi et al. 2018) are more likely to use ridesourcing services. Moreover, users living in households with zero vehicles (Gehrke et al. 2018, Alemi et al. 2019) or inadequate vehicles (Sikder 2019) and frequent users of smartphone apps (Alemi et al. 2018, Alemi et al. 2019) showed a positive inclination toward using ridesourcing services.

In terms of land-use characteristics, higher regional accessibility by car (Alemi et al. 2018), working or living in high-density locations (Dias et al. 2017, Circella et al. 2018), and higher land use mix (Alemi et al. 2018, Alemi et al. 2019) are associated with higher use of ridesourcing services.

In view of trip characteristics, disutility associated with private vehicles (e.g., parking cost, attending parties where alcohol is served) (Asgari and Jin 2020, Rayle et al. 2016, Clewlow and Mishra 2017), commuting trips (Acheampong et al. 2020), trips with shorter travel time (Acheampong et al. 2020), and social trips (Aninanya et al. 2020, Asgari and Jin 2020, Zhen 2015) increased the probability of using ridesourcing. Table 2-1 summarizes the studies that investigated the potential users of ridesourcing services.

Table 2-1 Summary of literature on ridesourcing users

Study	Study data	Objective(s)	Findings	
			Positive impact on ridesourcing adoption	Negative impact on ridesourcing adoption
Alemi et al. (2018)	California Millennials Online Survey (2015)	Investigate the ridesourcing adoption among Millennials and Generation X	• Highly educated; older Millennials • Greater land-use mix, • Greater regional accessibility by car, • A higher number of long-distance business trips, • A higher number of airplane trips, • Frequent users of smartphone transportation-related apps, • Previous Experience of using the taxi and carsharing	
Dias et al. (2017)	Puget Sound Regional Travel Study (2014-2015)	Estimate the impact of SED variables on the frequency and adoption of ridesourcing	• Young users • Well-educated individuals • Working individuals residing in higher-density areas • Higher-income people • Households with one or more vehicles and living in a high-density location	• Presence of children among low and middle-income
Sikder (2019)	National Household Travel Survey (2016-2017)	Explore SED and land-use factors that influence the frequency and use of ridesourcing	• Young individuals • Full-time individuals with flexible schedules, • Individuals with inadequate vehicles per household	• African American users • Low-income individuals, • The presence of children • Older people
Deka and Fei (2019)	National Household Travel Survey (2016-2017)	Explore the characteristics of ridesourcing users and neighborhoods	• Young persons • Individuals with higher education • Higher-income level	• Drivers • People with more cars in their households
Alemi et al. (2019)	Online Survey, California (2015)	Evaluate the frequency of on-demand services among members of Generation X	• Higher land use mix • Zero-vehicle households • Frequent use of smartphone applications for path and destination finding • Higher frequency of long-distance vacation plane-trips	• A higher density of activity
Gehrke et al. (2018)	Boston Metropolitan Area Planning Council	Understand the ridesourcing industry and its users	• Users younger than 35 years old • Users who do not own a car or • Households with one vehicle	

Study	Study data	Objective(s)	Findings	
			Positive impact on ridesourcing adoption	**Negative impact on ridesourcing adoption**
	Survey (2017)		• Households earning less than $38,000 per year	
Clewlow and Mishra (2017)	An online survey in seven major U.S. cities (2014-2016)	Investigate the factors that impact ridesourcing adoption	• Parking issues • Driving avoidance • Young individuals • College-educated • High-income • Black individuals • Living in urban neighborhoods	
Rayle et al. (2016)	Intercept Survey, San Francisco, USA (2014)	Investigate the characteristics of ridesourcing users and their reasons to use ridesourcing	• Young and well-educated individuals who look for lower wait time and fast origin-to-destination service. • Parking issues • Having to drink and drive.	
Zhen (2015)	An online survey, Pittsburgh, USA (2015)	Compare the differences of users of traditional transportation services and ridesourcing	• Young users • Male individuals • Social trips	
Asgari and Jin (2020)	An online survey, USA (2017)	Investigate potential changes in mode choice behavior in the era of ridesourcing with a focus on habits	• Private mobility expenses • High income • Full employment individuals, • Social and school trips, • Middle-income individuals • Students • Young graduates • Users between 50 and 54 years old	• Habits • Lower education • Retirees
Aninanya et al. (2020)	Stratified random sampling survey, Ghana	Use of ridesourcing services among young people	• Social trips • Weekends	
Acheampong et al. (2020)	Survey dataset with 1188 respondents	Explore the factors with significant impacts on the ridesourcing adoption	• Younger people • Users with higher education • Higher-income people • Female users • Commuting trips • Trips with shorter travel time	

2.1.2 *Impact of Ridesourcing on Public Transit*

In terms of the connection between ridesourcing and transit, the literature presented conflicting findings. Zhang and Zhang (2018) examined the relationships between the frequency and adoption of ridesourcing and the frequency of public transit in the U.S. They utilized individual-level travel frequency data from the aforementioned NHTS dataset. The marginal effect results showed that a unit increase in public transit usage was significantly related to a 1.2% increase in the monthly frequency of ridesourcing use. Moreover, the positive relationship between ridesourcing and public transit use was more noticeable for individuals living in high population density areas or households with fewer vehicles.

Murphy (2016) examined the correlation between public transportation and shared modes, including bike-sharing, carsharing, and ridesourcing services. The research was performed in seven cities: Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, and Washington, DC. The study elicited data from numerous sources. One source for this study was comprehensive interviews with more than 75 officials and representatives from the public and private sectors. They also conducted a survey gathering information from 4,500 shared-mobility and transit agency workers. Finally, they studied and analyzed transit and ridesourcing supply and demand in the study areas. The findings showed that ridesourcing services are most regularly utilized for social visits (between 10 pm and 4 am) and when transit runs less frequently or is inaccessible. Shared modes replace automobile trips more than public transit trips. Additionally, the more people use shared modes, the more likely they become interested in using public transit, own fewer vehicles, and spend less money on transportation expenses. Rayle et al. (2016) investigated the impact of ridesourcing services on public transit. They showed that ridesourcing both completes and competes with public transit. Respondents said that they often preferred ridesourcing due to travel time savings. The findings also showed that ridesourcing competes with transit when it operates inadequately, such as links to transit stations, trips to or from low-density neighborhoods, and late-night-time trips.

Hall et al. (2018) estimated the impact of Uber on public transit ridership using a difference-in-differences method that considers the discrepancy across the U.S. This difference could be related to both Uber penetration as well as the time Uber entered the city. They gathered information on transit ridership, Uber entry and exit, and various controls (e.g., average price, number of vehicles for service in a month, population) between 2004 and 2015. They collected the data for 196 MSA, which Uber exists. The observation unit is a transit agency, and the average MSA contains 2.21 transit agencies. The results indicated that ridesourcing has a replacement impact in areas with low transit ridership before its entrance. When the transit level of service is poor, ridesourcing's ability to offer additional flexibility in trip scheduling will reduce transit ridership. Moreover, they found that Uber has a complementary impact on the average transit agency in terms of increasing transit ridership. This average impact had significant variations. It was shown that Uber increases transit ridership more in bigger cities and for smaller transit agencies.

Babar and Burtch (2017) examined the impact of ridesourcing services on the deployment of public transit in the United States, focusing on detecting heterogeneity in the effects. They used a panel dataset that merges the entry time of ridesourcing in various areas of the U.S. with data on public transit ridership. The results implied that ridesourcing had caused a significant decrease in the ridership of city buses but increased the usage of subways and commuter rails. These impacts vary depending on the population, frequency of violent crimes, environmental conditions, and average trip distance.

Lavieri et al. (2018) analyzed the demand for ridesourcing using trip-level information from RideAustin, a ridesourcing company in Austin, Texas, between August 2016 and January 2017. They combined this information with other public data, Traffic Analysis Zone (TAZ)-level demographic information. Their focus was on trips from Central Austin to the north of the city, consisting of 458 TAZs. They developed two models. The first model is a spatially lagged multivariate count model, describing the number of trips created in a particular zone. The second model is the fractional split model, which identifies the attributes of the destination zone. They noticed a possible replacement impact between ridesourcing and transit during weekdays. Moreover, the results indicate that people with different income levels may use ridesourcing for various activity purposes. High-income individuals are more likely to adopt ridesourcing for leisure trips, while low-income people are inclined to use it for running errands.

Chavis and Gayah (2017) examined the choices between traditional fixed-route transit systems, shared flexible-route systems (i.e., paratransit), and door-to-door, on-demand systems (e.g., taxis or ridesourcing). They used a stated preference survey with 177 respondents, the survey was conducted in Baltimore, Maryland. They concluded that some individuals always selected the same mode, possibly due to familiarity or personal preference. Moreover, significant factors that affect the choice of the type of flexible transit include financial expenses and anticipated in-vehicle and waiting time. Table 2-2 summarizes the literature that assessed the potential impacts of ridesourcing on public transit in terms of the study area, the study objective, and significant findings.

Table 2-2 Ridesourcing impact on public transit

Study	Study area	Objective(s)	Findings
Zhang and Zhang	National Household Travel Survey (2016-	Examine the relationships between the	• A unit increase in public transit usage was significantly related to a 1.2% increase in ridesourcing use

Study	Study area	Objective(s)	Findings
(2018)	2017)	frequency and adoption of ridesourcing and public transit	• Ridesourcing complements public transit for: ○ Individuals living in areas with a high population density ○ Households with fewer vehicles
Rayle et al. (2014)	San Francisco, USA (2014)	Investigate the impacts of ridesourcing on public transit	• Ridesourcing competes with transit for some trips but often serves as a complementary mode. • Ridesourcing services are often used for trips that would have taken much more time if made by public transit
Murphy (2016)	Seven major cities in the U.S.	Examine the connection between public transit and shared modes.	• Ridesourcing is most often utilized for: ○ When public transit runs occasionally or is unavailable. ○ Social visits between 10 pm and 4 am • The more individuals use shared modes, the more likely: ○ Use transit, ○ Buy cars ○ Pay less money for trips.
Rayle et al. (2016)	San Francisco, USA (2014)	Investigate the connection between public transit and ridesourcing services	• Ridesourcing competes with mass transit when mass transit does not perform well, such as: ○ Links to transit ○ Low-density regions ○ Late-night trips
Hall et al. (2018)	196 Metropolitan Statistical Areas in the USA (2004-2015)	Estimate the impact of Uber on public transit ridership	• Uber increases public transit ridership for: ○ Transit in larger cities ○ Smaller transit agencies. • Uber decreases public transit ridership for: ○ Cities with low transit ridership ○ When transit supply is not sufficient
Babar and Burtch (2017)	United States (2012-2018)	Examine the impact of ridesourcing services on the utilization of public transit	• Ridesourcing increases public transit ridership for subways and commuter rails. • Ridesourcing decreases public transit ridership for city buses. • These average effects are also subject to a great deal of contextual heterogeneity depending on various factors.
Lavieri et al. (2018)	Austin, Texas (2016-2017)	Analyze the demand for ridesourcing using trip-level information	• Ridesourcing competes with public transit for weekday trips.

Study	Study area	Objective(s)	Findings
			• People with various income levels might use ridesourcing for different activity objectives.
Chavis and Gayah (2017)	Baltimore, Maryland (2015)	Examine the choice between traditional fixed-route transit systems, shared flexible-route systems, and door-to-door and on-demand transit systems	• Some individuals always select the same mode, perhaps because of familiarity or personal preference. • Significant factors that affect the choice of the type of flexible transit are: o Anticipated in-vehicle and waiting time o Financial expenses

2.2 Exclusive-Ride versus Shared-Ride Services

A few studies examined the factors that impact individuals' mode choices between shared-ride and exclusive-ride services. Considering the role of age, Gehrke et al. (2021) used the dataset previously mentioned for the study by Gehrke et al. (2018). They investigated the choice between shared-ride and exclusive-ride services. They showed that young individuals (18 to 24 years old), lower education level, lower household income, and zero vehicle household increased the likelihood of choosing shared rides over exclusive rides. Also, they found that shared rides were more desired in the inner core neighborhoods.

Spurlock et al. (2019) conducted a survey in San Francisco Bay Area and gathered information on 1,045 respondents. The results showed that people younger than 39 years old had a positive tendency to use shared rides over exclusive services. Using the data from a 2016 online survey with 997 respondents, Sarriera et al. (2017) showed that individuals younger than 35 years old or those living in households with zero vehicles increased the probability of choosing shared rides over exclusive rides.

Chen et al. (2018a) explored the choice between shared and exclusive services by using two sources of datasets. First, they derived data from a ridesourcing platform, DiDi

Chuxing, with 668,177 observations. Second, an online behavior survey, with 744 respondents, was conducted through the DiDi survey. The results indicated that younger people (31-40 years old) and a lower number of household vehicles had a positive impact on the preference of shared rides over exclusive rides. Brown (2020) investigated the choice between shared and exclusive rides using data from 1.9 million shared-ride trips and 4.4 million exclusive-ride trips in Los Angeles. He showed that young people (15-34 years old) and zero household vehicles or limited access to cars increased the probability of using shared rides over exclusive rides.

Lee et al. (2018b) conducted an online survey among ridesourcing users in Hong Kong and gathered information from 295 respondents. They found that higher time variability of shared rides was the main reason that discouraged people from using these services over exclusive rides. They also showed that people were more inclined to adopt shared rides for short trips due to lower time variability. Young et al. (2020) utilized data on 12 million ridesourcing trips in Toronto to examine the matching rate of shared rides. The results suggested that reducing the detour time of shared rides might increase the probability of choosing shared rides over exclusive rides. They also found that higher demand for shared services in downtown areas could be related to the higher matching rates in these areas.

In summary, the literature showed that younger people (Gehrke et al. 2021, Sarriera et al. 2017, Chen et al. 2018, Spurlock et al. 2019, Brown 2020), lower education-level (Gehrke et al. 2021, Spurlock et al. 2019), and zero household vehicles or limited access to private vehicles (Gehrke et al. 2021, Sarriera et al. 2017, Chen et al. 2018, Brown 2020), have a positive association with the use of shared rides over exclusive rides.

In view of trip patterns, higher time variability has a negative impact on the use of shared rides (Lee et al. 2018b). On the other hand, short-distance trips (Lee et al. 2018b) and trips to/from inner core neighborhoods (Gehrke et al. 2021, Young et al. 2020) increase the probability of using shared rides over exclusive rides due to a higher matching rate and lower detour time

2.3 The Impact of Attitudinal Factors on Ridesourcing Adoption

As mentioned before, while literature showed that attitudes have substantial impacts on mode choice behavior, only a few studies have considered the role of these factors in the choices between ridesourcing services and conventional modes. Loa and Khan (2021) applied factor analysis to investigate the association between the attitudinal indicators and latent factors. In view of the measures considered for attitudinal factors, the respondents were asked to respond to two types of five-point Likert scale questions, including the level of importance and level of agreement about ridesourcing (e.g., safety, travel cost, convenience, parking cost). The results indicated that being concerned about the reliability, comfort, and security of ridesourcing services is negatively associated with the use of ridesourcing services.

Lavieri and Bhat (2019) developed a Generalized Heterogeneous Data Model (GHDM) to simultaneously extract attitudinal factors and investigate their impacts on the ridesourcing frequency and adoption. They used Likert scale indicators on individuals' privacy concerns, technology use, and lifestyle preferences to define the attitudinal factors. Their results indicated that tech-savviness and variety-seeking attitudes are positively associated with the use of ridesourcing services.

Circella et al. (2018) and Alemi et al. (2018) applied a principal axis factor analysis with an oblique rotation to reduce the dimension of attitudinal statements. They used five-point Likert scale attitudinal statements to measure users' attitudes and inclinations toward travel preferences, environmental concerns, technology savviness, and car ownership. The results indicated that users with pro-environmental, technology-embracing, and variety-seeking attitudes are more inclined to adopt ridesourcing services.

Asgari and Jin (2020) used a heuristic combined index to account for habitual behavior. The heuristic combined index combined two factors to determine habitual behavior. First, the respondents were asked about the frequency of using modes. Second, they were asked to consider various situations (e.g., bad weather, tight money, running late) and select their preferred mode under these circumstances. In this way, the habits linked with each mode can be estimated. The findings indicated that habits significantly impact mode choice behavior, discouraging the users of conventional modes from switching to ridesourcing services. Alemi et al. (2019) applied a factor analysis method to derive latent constructs. They considered Likert-scale statements focusing on perceptions of shared mobility, environmental concerns, lifestyle, and technology use as the measures for extracting attitudinal factors. The results showed that individuals with higher inclinations to own and use a private vehicle and those with concerns about the safety of ridesourcing are less likely to be regular users of ridesourcing services.

Acheampong et al. (2020) considered respondents' attitudes toward perceived benefits, ease of use, ridesourcing innovations attributes, and perceived safety concerns as the measures for attitudinal factors. To find attitudinal factors, they applied a Structural Equation Model (SEM), which uses a Confirmatory Factor Analysis (CFA) to estimate latent variables. Then, SEM regresses the observed and latent variables on the outcome variable to assess their impacts. The results showed that tech-savviness perceived instrumental and environmental benefits of ridesourcing services had positive impacts on ridesourcing use.

Simmons (2018) applied a qualitative interpretive case study approach to investigate ridesourcing adoption. The study used affordance theory to explain ridesourcing service as a disruptive digital technology. The results indicated that technology-savvy users are more likely to use ridesourcing services. Table 2-3 reviews the studies that investigated the impact of attitudes on the propensity toward the adoption of ridesourcing services.

In summary, studies that considered the impact of attitudes and lifestyle on the use of ridesourcing services showed that environmental concerns (Acheampong et al. 2020, Circella et al. 2018, Alemi et al. 2018), technology-based lifestyle (Lavieri and Bhat 2019, Acheampong et al. 2020, Circella et al. 2018, Alemi et al. 2018), and variety-seeking attitudes (Lavieri and Bhat 2019, Circella et al. 2018, Alemi et al. 2018) encouraged the adoption of ridesourcing. Moreover, perceived ease or convenience of use and perceived hedonic benefits also had a positive impact on the ridesourcing use (Acheampong et al. 2020). On the other hand, safety or data privacy concerns (Loa and Khan 2021, Lavieri and Bhat 2019, Alemi et al. 2019) and the inclination to own and use private cars (Alemi et al. 2019) decreased the probability of using ridesourcing

Table 2-3 The impact of attitudes on ridesourcing adoption

Study	Attitudinal measures	Findings	
		Positive impact on ridesourcing adoption	Negative impact on ridesourcing adoption
Loa and Khan (2021)	• Likert Scale Questions on level of importance and level of agreement about: o Safety o Travel Cost o Convenience		• Concerns about the reliability, comfort, and security of

Study	Attitudinal measures	Findings	
		Positive impact on ridesourcing adoption	Negative impact on ridesourcing adoption
	○ Parking Cost		ridesourcing services
Lavieri and Bhat (2019)	• Likert Scale Indicators On: ○ Privacy ○ Technology Use ○ Lifestyle	• Tech-Savviness • Variety Seeking	• Privacy-Sensitivity
Circella et al. (2018) and Alemi et al. (2018)	• Five-Point Likert Scale Attitudinal Statements On: ○ Environmental Concerns ○ Lifestyle ○ Technology Use ○ Car Ownership	• Pro-Environmental • Technology-Embracing • Variety Seeking	
Asgari and Jin (2020)	• Questions On: ○ Frequency of Using Modes ○ Mode Choice Under Various Situations		• Habits associated with each mode
Alemi et al. (2019)	• Likert Scale Statements on: ○ Perceptions of Shared Mobility ○ Environmental Concerns ○ Lifestyle ○ Technology Use		• Stronger inclinations to use and own a private vehicle • Concerns about the security of ridesourcing
Acheampong et al. (2020)	• Five-Point Likert Scale Attitudinal Statements On: ○ Perceptions of Ridesourcing ○ Environmental Concerns ○ Car-ownership ○ Lifestyle ○ Technology Use	• Tech-savvy users, • Perceived instrumental/hedonic benefits • Perceived environmental benefits of using ridesourcing services	
Simmons (2018)	• Attitudinal Statements On: ○ Technology Use	• Technology-savvy	

2.4 Impact of Experience on the Mode Choice Behavior

This sub-section reviews the studies focused on the role of users' experience in the mode choice toward public transit, electric vehicles (EVs), and cycling. The primary purpose of reviewing these studies is to understand how providing an opportunity to use a specific travel mode could impact the individuals' attitudes and opinions and affect their willingness to the future adoption of that mode.

Fujii and Kitamura (2003) explored the impact of a temporary change (offering a free bus ticket for one month) on individuals' inclination to ride transit. They targeted 43 students at Kyoto University, Japan, who used cars as their primary mode. Twenty-three students were randomly assigned to the experimental group, and the remaining 20 students were in the control group. Comparing the attitudes before, immediately after, and one month after the experiment showed that respondents' perception of public transit became more positive over time. Interestingly, respondents were less inclined to use automobiles as their primary travel mode at the end of the trial.

Thøgersen and Møller (2008) conducted a similar study. They analyzed the changes in auto drivers' mode choice after offering them a one-month free bus ticket. A field experiment was performed in 2002 in the Greater Copenhagen area with 1,071 respondents. The experiment had three phases, including before, on-month after, and four months after the experiment. The findings showed that the free trial helped break the user's habitual behavior of private vehicle use. The inclination to use transit increased significantly even after the one-month trial period. However, it was also stated that if the level of service for transit did not improve in the long-term, the respondents might switch back to their previous travel mode.

Fujii et al. (2001) investigated how individuals' tendency to use transit changes due to an obligatory situation (an 8-day freeway closure). They used data from a survey conducted in 1998 in Osaka, Japan, and collected information on 335 private vehicle drivers. The survey revealed that those who had never used transit for commute had higher perceived commute times using transit than the actual travel time. The study concluded that the experience of using transit had a positive correlation with the respondents' tendency and attitudes to use transit as their primary commute mode.

Brown et al. (2003) employed a transactional method (reducing available parking spaces) to encourage switching from private vehicles to a light rail system. The experiment was conducted at the University of Utah, and two waves of surveys were collected. The first wave (before reducing parking spaces) gathered information from 90 respondents, and the second wave (during the parking shortage) collected data on 67 respondents. The study showed that students were not interested in giving up their private cars before the reduction in the number of parking spaces; however, after they used the light rail system, they had more positive attitudes toward the rail system. They were attracted to use rail mainly due to the pleasant experience and productive activities they had during the trip as well as the system's high quality of service. The survey indicated a significant change in the respondents' perceived advantages of private vehicles and the light rail system.

Other studies explored the role of experience in the adoption of electric vehicles (EVs).

Rauh et al. (2015) studied the impact of experience with EVs on reducing people's anxiety about the associated driving ranges. Two groups of respondents, including 12 experienced and 12 inexperienced users of EVs, were recruited in Germany. The results indicated that experienced drivers had a considerably lower level of stress compared to inexperienced drivers. The findings also suggested that experience with EVs substantially impacted the individuals' willingness to adopt these vehicles. Franke et al. (2012) conducted a similar study in Berlin, Germany. Forty drivers with diverse socioeconomic demographic characteristics and mobility-related attitudes rode an EV for six months. The trial was conducted in three distinct periods: before receiving an EV, three months after driving an EV, and when the users returned the EV. The results suggested that the experience of using electronic vehicles brought significant improvements in the participants' perceptions of these vehicles. Accordingly, participants were comfortable using EVs and believe these vehicles fulfill their mobility needs.

Bunce et al. (2014) explored how experience with recharging batteries of EVs affected people's tendency to adopt these vehicles. They used survey data from the UK Ultra Low Carbon Vehicle trial, which collected information on 135 drivers before and three months after adopting EVs. The results showed that respondents were more likely to find the recharging procedure convenient after the trial. The respondents' attitudes became more positive over time as they gained knowledge and experience. Several other studies presented similar results (Burgess et al. 2013, Nilsson 2011)

A few studies focused on the cycling experience on the individuals' preferences toward bicycles' adoption. Namgung and Jun (2019) studied the attitudes affecting bicycle use among individuals with different experience levels. They used the 2015 Campus Transportation Survey conducted at the Ohio State University. This survey collected information on 1,189 respondents' commute mode, attitudes toward bicycles, and cycling experience levels. The results showed that individuals' attitudes differed significantly based on their experience levels. It was found that experienced bicyclists had more positive attitudes toward cycling than those with lower experience levels. Moreover, experienced users were more aware of cycling benefits, and they were less likely to perceive cycling barriers. Other studies also presented similar findings (Heinen et al., 2011; Dill and Voros, 2007). Table 2-4 summarized the literature that studied the impact of experience on mode choice behavior in terms of their targeted mode and data collection methods.

Table 2-4 The impact of experience on mode choice behavior

Study	Targeted mode	Data collection method
Fujii and Kitamura (2003)	Public transit	Choice experiment with three phases (Before, immediately after, and one month after the one-month free bus ticket)
Thøgersen and Møller (2008)	Public transit	Field experiment with three phases (Before, one month, and four months the one-month free bus ticket)
Fujii et al. (2001)	Public transit	A survey with two phases (Before and during a freeway closure)
Brown et al. (2003)	Light rail system	Transactional method (Reducing available parking spaces for students) with two phases (Before and during parking shortage)
Rauh et al. (2015)	Electric vehicles	Field experiment with two sets of respondents (Experienced and inexperienced EV drivers)
Franke et al. (2012)	Electric vehicles	Field trial with three waves (Before, three months, and six months after receiving EVs)
Bunce et al. (2014)	Electric vehicles	Field trial with two phases (Before and three months after using EVs)
Burgess et al. (2013)	Electric vehicles	Field trial with two phases (Before and three months after using EVs)
Nilsson (2011)	Electric vehicles	Interview with EV drivers
Namgung and Jun (2019)	Bicycles	In-person survey
Heinen et al. (2011)	Bicycles	Online survey
Dill and Voros (2007)	Bicycles	Phone survey

In summary, the literature showed that the experience of using a specific mode could significantly influence people's perceptions and attitudes. Although numerous studies have investigated the role of experience in the use of transit, bicycle, and EVs, no study has examined its impact on the propensity to use ridesourcing services. Moreover, these studies mainly gathered information based on providing a free trial or field experiment. No study has employed an SP-based survey to understand the role of experience in the individuals' choice preferences toward ridesourcing services.

2.5 Modeling Methodology

2.5.1 *Ridesourcing Adoption*

Various approaches have been applied to investigate the adoption of ridesourcing services. Several studies used logit models, including the binary logit model (Alemi et al. 2018, Circella et al. 2018), the multinomial logit model (Chavis and Gayah 2017), and the nested logit model (Chavis and Gayah 2017, Asgari and Jin 2020). Logit models have been widely used for mode choice modeling. The binary logit model provides two choice alternatives for the individuals, whereas, in the multinomial logit model, people have multiple-choice alternatives (Khan 2007).

The multinomial logit model is a popular method to investigate the relationship between mode choice behavior and explanatory variables (Lee et al. 2018a). This model has a simple mathematical formula that accounts for the unobserved utilities in choice-making (McFadden 1973, Ben-Akiva et al. 1985, Koppelman et al. 2000). The underlying assumption of the multinomial logit model states that the random utility components of various alternatives are independent and identically (IIA) distributed. This assumption means that the unobserved utilities of other options are not co-related. Also, there might be similarities between some mode alternatives, which might result in a correlation between the similar modes not accounted for by the multinomial logit models (Sekhar, 2014). The nested logit model solves this shortcoming by grouping the similar alternatives in the same subsets, thus accommodating some degrees of correlation between these alternatives (Day, 2008). While nested logit models have some advantages over multinomial logit models, some literature stated that placing similar choices into subsets might not be a proper procedure to represent the relationship among alternatives because there also might be dependencies across subsets (Sekhar, 2014, Saini 2020).

Some papers applied more complex methods to investigate ridesourcing adoption to avoid the shortcomings of logit models. These models include SEM (Acheampong et al. 2020) and latent-class choice models (Circella et al. 2018). Acheampong et al. (2020) applied the SEM method to simultaneously derive latent variables and regress latent and observed variables on the outcome variables. With SEM, the latent factors are determined by Confirmatory Factor Analysis (CFA). Then, the impacts of identified latent factors and observed factors on the dependent variable are estimated using multiple regression analysis. SEM is a flexible method with a sophisticated underlying theory and greater statistical power than conventional multiple regression analyses (Donaldson 2015, Beran and Violato 2010, Nachtigall et al. 2003). On the other hand, for SEM, inadequate study planning, inaccurate and invalid data, lack of theoretical supervision, and over-interpretation of causal relationships can result in incorrect and false conclusions (Beran and Violato 2010, Nachtigall et al. 2003). The latent-class choice model is another method to account for the individuals' heterogeneity and taste variations. The latent-class choice models address both unobserved and observed heterogeneity by segmenting users into distinct groups that are not recognizable from the data. Latent-class choice models cluster individuals with similar characteristics concurrently and estimate how different features affect the outcome variable.

2.5.2 *Ridesourcing Frequency*

To explore the impact of explanatory variables on a dependent variable of counts, like trip frequency, zero-inflated negative binomial models have been used frequently (Lewsey and Thomson 2004, Xu et al. 2015, Böcker et al. 2017). Some authors applied this method to investigate ridesourcing frequency (Deka and Fei 2019, Zhang and Zhang 2018). Zero-inflated negative binomial models can address the probability of excess zero counts for the predicted variable (Allison, 2012). Therefore, they are considered appropriate when a significant number of the dependent variables are zero (which is expected in ridesourcing frequency as most people do not use ridesourcing). Due to the discrete and ordered nature of ridesourcing frequency, some studies applied models that consider this ordered nature, including the ordered logit model (Sikder 2019), bivariate ordered probit model (Dias et al. 2017), ordered probit models with sample selection (Alemi et al. 2019), and zero-inflated ordered probit with correlated error terms (Alemi et al. 2019).

Logit and probit models have similar mathematical formulations; however, their underlying assumption about error distribution is different (Sekhar, 2014). For logit models, the error term is assumed to follow a standard logistics distribution, whereas, for probit models, the error term follows a normal distribution. Although the theoretical base of probit models is more robust and reliable than logit models, logit models have shown superior goodness of fit compared to probit models (Dow and Endersby, 2004).

Dias et al. (2017) used bivariate ordered probit modeling for joint modeling of two ordinal dependent variables (e.g., ridesourcing and carsharing frequency) while considering the possible common latent factors (e.g., attitudes). This method simultaneously models two ordered probit models while considering the possible error covariance between them. The model is different from traditional mode choice models. It is a person-level model that predicts the adoption and frequency of outcome variables and accounts for unobserved attitudes that may impact the outcome variable. On the other hand, the simultaneous estimation of ridesourcing adoption and frequency could result in some issues when a part of individuals has not adopted ridesourcing services (yet). Removing the data associated with the individuals with zero ridesourcing frequency would inflate the coefficients when common factors exist between the dependent variables (Alemi et al., 2019). The ordered probit model with sample selection solves this issue by using a two-sage decision process to model the frequency variable. The first decision involves the adoption of the ridesourcing and the second decision the frequency of usage.

For individuals who recorded zero frequency of using ridesourcing during the survey period, there are two distinct meanings for the dependent variable with a value of zero. The first represents users who will never use ridesourcing services (structural zeros). In contrast, the second refers to those who had used ridesourcing before and/or those who may adopt it in the future (random zeros). The ordered probit model with sample selection does not have such capability to distinguish these two groups of users from each other. In these situations, the zero-inflated ordered probit model with correlated error terms is an appropriate method to address this issue as it can differentiate between two sources of zero-frequency responses.

2.6 Summary

In summary, numerous transportation studies examined the adoption and frequency of ridesourcing services in the last few years. While most existing studies used household travel surveys, such as the 2017 NHTS data or other revealed preference (RP) surveys, only a few studies employed SP surveys. With SP surveys, the propensity toward ridesourcing services could be examined under different circumstances, such as reduced ridesourcing fares. Income has been identified as one of the most influential factors in mobility choices. The current fare of ridesourcing services may present considerable barriers to frequent service adoption for many people. Moreover, future AV technologies may reduce the cost of ridesourcing services by removing the fee associated with human drivers (Compostella et al., 2020; Walker Johnson, 2016; Stocker and Shaheen, 2018;

Spieser et al., 2014; Karamanis wt al., 2018). Given the above discussion, there is a gap in the literature on understanding the adoption of ridesourcing services when travel cost is not the primary concern.

Furthermore, although previous studies demonstrated that psychological constructs considerably affect mode choice behavior, the focus of these studies was mainly on traditional travel modes. Considering ridesourcing services, the impact of individuals' SED characteristics and mobility profiles have been well-documented; however, literature paid less attention to the role of attitudinal factors in the decision-making process and mode choice behavior. This lack of knowledge makes it difficult for transportation planning and policymakers to clearly predict the ridesourcing market.

Another primary focus of the literature regarding ridesourcing behavior was investigating the impact of ridesourcing services on public transit ridership. Mixed results have been found in the literature, and the interaction between ridesourcing and transit is probably still evolving. These studies mainly focused on the general pattern in the choices between ridesourcing and transit without distinguishing various market segments. Auto users (when they do not have access to their car) and transit riders could be attracted to use ridesourcing services by very distinct motivations. Analyzing the adoption of ridesourcing services based on user markets can help transportation planning agencies better understand the users of these services and provide customized solutions coordinating public transit with ridesourcing services based on specific user needs.

The role of travelers' experience should also be considered in mode choice models to help achieve a more accurate estimation of ridesourcing adoption. The literature showed that providing an opportunity to use a specific travel mode can significantly impact individuals' attitudes and opinions. Several studies have investigated the role of experience in using traditional modes, such as transit, bicycle, and EVs. However, there is a lack of knowledge on the possible correlation between the experience of using ridesourcing in the past and becoming a frequent user of these services in the future. Taking into account the role of experience may provide valuable insights into the attitudes and perceptions that may have prevented or encouraged the adoption of ridesourcing services.

As for the role of generational effects in ridesourcing adoption, literature suggested that younger individuals are more likely to use ridesourcing services than older cohorts, especially Generation Xers. This different behavior toward the ridesourcing market may be related to their distinct attitudes and perceptions. However, there is currently insufficient understanding of the root causes of these differences and how they affect individuals' mode choice behavior. Considering the role of age in mode choices can provide a more in-depth understanding of the distinct behavior of Generation Xers and Millennials toward shared mobility services, leading to the development of strategies and policies addressing the needs and concerns of individuals based on their characteristics and attitudes.

CHAPTER 3

STATED PREFERENCE SURVEY

The data employed for this dissertation was retrieved from an online travel behavior survey conducted in March and April of 2017. The survey was designed and implemented by Florida International University's Travel Behavior and System Modeling Lab and covered the entire state of Florida and ten other major metropolitan areas in the U.S. The metropolitan areas were chosen based on the 2010 Census data considering their population sizes and geographical locations. The geographical extent of the survey is presented in Figure 3-1.

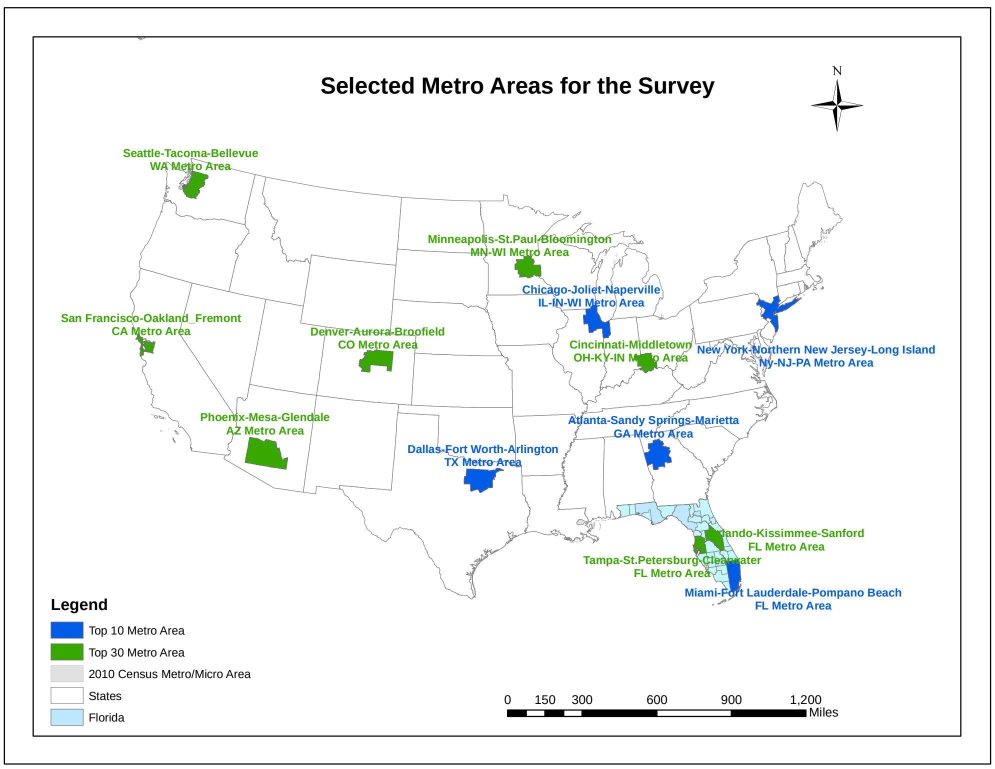


Figure 3-1 Selected metro areas for survey sampling

3.1 Survey Design

The survey was implemented through a survey firm, which maintained a panel of respondents, covering a broad range of nationwide population classes. A sample monitoring mechanism was employed to assign a quota to every cohort for various demographic characteristics, including gender, age, household income, ethnicity, and education. The survey targeted 2010 Census representative samples. Details of the survey design were discussed in (Asgari et al. 2018, Jin et al. 2020, Rahimi et al. 2020).

Table 3-1 presents descriptive statistics for the dataset used for this dissertation. It also shows the statistics from Census 2010 as a reference. The data consists of 1,087 respondents. As presented in Table 3-1, Millennials (25-39 years old) have the highest percentage (35.2%) among all other age groups. Moreover, the sample had higher proportions of males, people who described their racial status as White, those with bachelor's degrees, and lower household income groups than the census data.

3.2 Scenario Design

The primary objective of the survey is to investigate how people perceive the trade-offs between emerging mobility options (AVs and shared mobility services) and traditional modes (private vehicles and public transit). Driving private cars can have the advantages of better mobility, accessibility, reliability, and flexibility. On the other hand, ridesourcing and autonomous vehicles may offer multitasking opportunities and relieve people from chauffeuring engagements.

Table 3-1 Descriptive statistics

Attribute			Survey Data	Census 2010
			Share	Share
Age	Generation Z (16-24 years old)	16-17	1.3%	17.6%
		18-24	12.3%	-
	Millennials (25-39 years old)	25-29	13.2%	8.5%
		30-34	12.0%	8.1%
		35-39	10.0%	8.2%
	Generation X (40-54 years old)	40-44	5.5%	8.4%
		45-49	7.4%	9.2%
		50-54	6.8%	9.0%
	More than 55 years old	55-59	8.7%	7.9%
		60-64	7.9%	6.8%
		65-69	7.4%	5.0%
		70-74	4.2%	3.7%
		75 and older	3.4%	7.5%
Gender	Male		54.8%	49.2%
	Female		45.2%	50.8%
Race	White		73.4%	63.7%
	Hispanic		13.7%	16.3%
	Asian		1.7%	4.9%
	Native American/American Indian		.5%	0.7%
	Black/ African American		10.4%	12.2%
	Other		.3%	2.4%
Education	Less than 9th grade		.6%	5.2%
	9th to 12th grade, no diploma		3.7%	8.3%
	High school graduate		27.0%	28%
	Some college, no degree		29.0%	23.7%
	Associate degree		7.1%	7.7%
	Bachelor’s degree		27.2%	17.3%
	Graduate or professional degree (Master’s/Ph.D. or equivalent)		5.4%	9.9%
HH income	0-$25K		19.6%	23.1%
	$25K-$50K		32.4%	23.5%
	$50K-$75K		23.4%	17.8%
	$75K-$100K		14.8%	12.1%
	$100K-$125K		3.3%	13.1%
	$125K-$150K		2.9%	-
	$150K-$175K		1.4%	5.1%
	$175K-$200K		.9%	-
	More than $200K		1.4%	5.3%
Employment status	Full-time		43.3%	-
	Part-time		13.2%	-
	Unemployed		13.5%	-
	Student		5.5%	-
	Retired		20.0%	-
	Others		4.4%	-

To better understand the trade-offs between transportation options under various circumstances, four different scenarios were designed for the survey:

1. Scenario 1 (Private Vehicle Drivers): Designed for those with access to private cars for their daily activities. These travelers were asked to choose between private vehicles and ridesourcing services. Modal attributes involved in the scenario's decision-making include travel time, travel cost, and multitasking level.
2. Scenario 2 (Private Vehicle Passengers): Designed for those who rely on rides with others (as drivers of privately owned vehicles) for their daily activities. These respondents were asked to select between private vehicles (as passengers) and ridesourcing services. Modal features involved in decision-making consist of travel time, travel cost, and availability of a driver with a car.
3. Scenario 3 (Transit riders): Designed for those who rely on public transit for their daily activities. These respondents were asked to select between public transit and ridesourcing. Modal features of the scenario include travel time, travel cost, and multitasking level.
4. Scenario 4 (Visitors): Designed for respondents who were assigned to the first and second scenarios. These respondents were asked to consider a situation when they do not have access to their cars or drivers and choose between transit and ridesourcing. Modal attributes for the choice are travel time, travel cost, and multitasking level. Figure 3-2 presents a sample of the SP scenario for the survey.

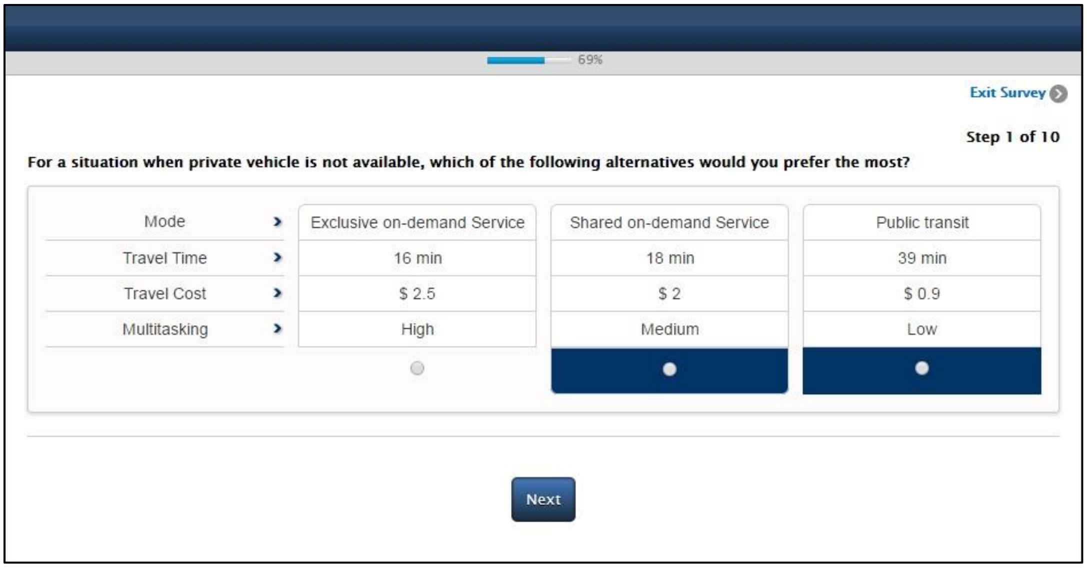


Figure 3-2 A sample of SP scenarios

The SP survey began by asking the respondents to think of a typical daily trip. Based on their regular travel mode, respondents were allocated to one of the first three scenarios. Those designated to scenarios 1 and 2 were also assigned to scenario 4 (visitors) and asked to think about an occasional situation they do not have access to their private vehicle. The primary purpose of scenarios was to investigate how people's behavior may vary between those with full access to personal cars and those with no regular or daily access.

Each mode was associated with three attributes: travel time, travel cost, and level of multitasking (scenarios 1, 3, and 4) or driver availability (scenario 2). For each mode and attribute, the respondents were presented with their definitions before taking them to the SP scenarios. Travel time refers to the door-to-door travel time, including parking times for private vehicles, walking to/from transit stations, and waiting time for transit and ridesourcing services. Travel cost was defined as travel fare for public transit or ridesourcing and average driving cost (per mile) for private vehicles. Three levels were considered for travel cost and time, varying from -30% to 30% of the base value.

The values of travel time and costs presented in the scenarios were determined by trip distance. Average travel time was derived from Google Map estimates. Six distance segments, varying from 5 miles to 30 miles by 5-mile increments, were considered. The base values for travel time were calculated as below:

- Private Vehicle=Trip Time+ 5 minutes (for parking+ access/egress)
- Public Transit= Trip Time +10 minutes (for waiting+ access/egress)
- Exclusive Ridesourcing= Trip Time +2 minutes (for waiting time)
- Shared Ridesourcing= Trip Time +8 minutes (for waiting time)

The base values of travel cost were determined based on a comprehensive review of recent mobility studies in the United States (Corwin et al. 2015, American Public Transportation Association (APTA), 2016). By considering an average of 15,000 miles per car per year, the average travel cost per mile for a private car is estimated to be about $0.57.

The travel cost and time reported by the 2016 APTA were considered for transit, with an average fare of $0.25 per mile. For ridesourcing services, the current average costs were reduced to one-third of their current values to relax the cost constraint involved in ridesourcing adoption. The artificial reduction in ridesourcing cost is also made to simulate future conditions when the introduction of AV technologies reduces ridesourcing cost by eliminating the role of human drivers (Walker and Johnson 2016). The base travel cost for exclusive and shared rides was $0.5 and $0.4 per mile, respectively. The base values for travel cost were calculated as shown below:

- Private Vehicle =$0.5(Trip Distance) +$0.8 (For Parking)
- Public Transit=$0.25(Trip Distance)
- Exclusive Ridesourcing=$0.5(Trip Distance)

- Shared Ridesourcing= \$0.4(Trip Distance)

Driver availability for the passenger mode had three values randomly assigned to each scenario: low, medium, and high. This attribute measures the level of scheduling convenience for those who depend on others for travel activities. Higher driver availability means there is always a drive available to drive the respondents at their desired time. The level of multitasking was defined as how easy it is for the respondents to perform other activities during the trip. The level of multitasking was a fixed attribute (low for transit, medium for shared ridesourcing service, and high for exclusive service). It was included as an additional feature to differentiate transit service from ridesourcing. A low level of multitasking was considered for public transit as this mode may offer a more constrained space because of occasional crowdedness and the likelihood of having to stand during the trip. Crowdedness has been found to decrease individuals' willingness to multitask, especially for the use of smart devices (Van der Waerden et al., 2009). On the other hand, people were more likely to multitask during ridesourcing services, probably because of more space, privacy, and comfort than public transit (Krueger et al., 2019).

3.3 Attitudinal Factors

In addition to the scenarios, the survey included four sets of questions that focused on different aspects of attitudes:

- General mobility preferences,
- Perceived benefits and concerns of shared mobility,
- Motivations for and against private vehicle ownership, and
- Motivations to drive or ride in an AV and the most desired AV features.

These questions were designed to capture respondents' views on mobility options and to measure the respondents' attitudes and opinions toward different mobility options, including driving, shared services, and AV technologies. For each question, respondents can pick multiple choices that describe their preferences and motivations. The following figures summarize respondents' answers to these questions. Figure 3-3 presents a summary of general mobility preferences by the respondents. A high percentage of users agreed that it is much more convenient to travel by themselves. The majority of respondents were interested in learning about new technologies and regularly use smartphone applications. On the other hand, users were less likely to believe that shared mobility increases the quality of their lives. Interestingly, multitasking was not a critical issue for most users.

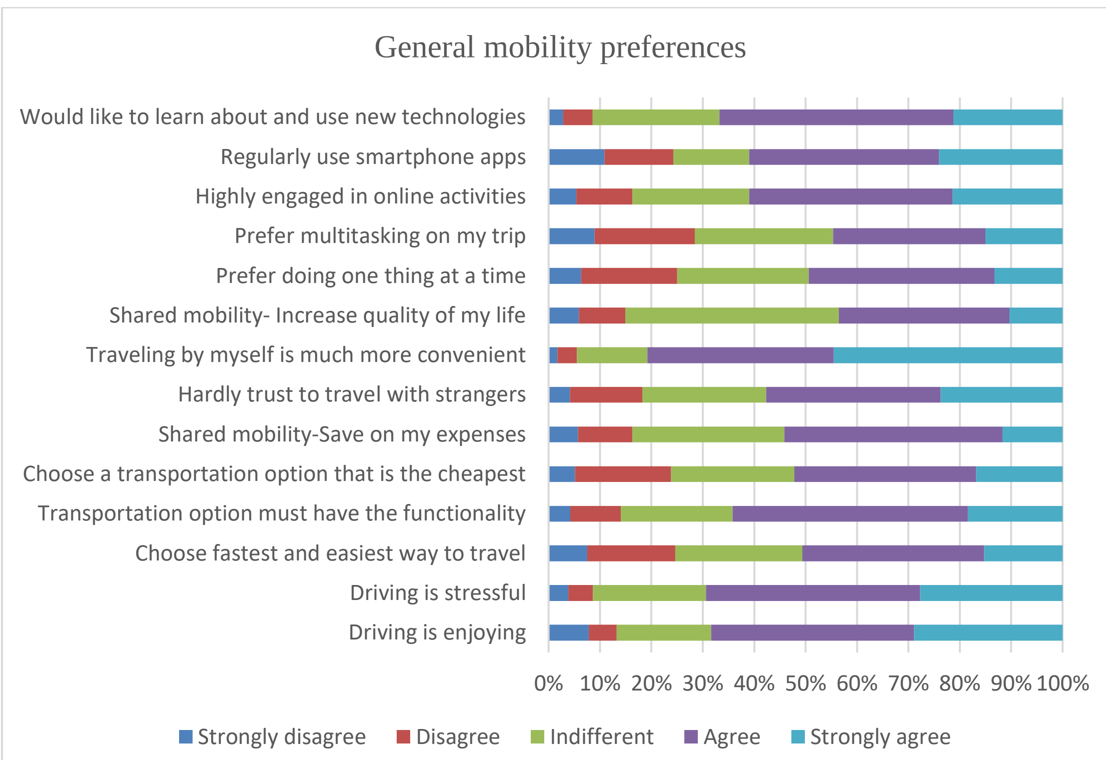


Figure 3-3 General mobility preferences

Figure 3-4 presents a summary of the perceived benefits and concerns of shared mobility. As it illustrates, less driving stress and cost-effectiveness were more likely to be valued as a priority. Interestingly, higher travel time and data privacy were selected as the top two concerns for most travelers, but complicated service request procedures and unreasonable fares were not the primary concerns of the respondents.

When it comes to reasons for private vehicle ownership or against it, the results are presented in Figure 3-5. The horizontal axis indicates the frequency of selection. Each respondent could select multiple reasons. It shows that the cheaper option than other modes and reliability were the top reasons for owning a vehicle. Affordability and lack of parking space were the top reasons for not owning a car.

Figure 3-6 presents the motivations to drive or ride in an AV and the most desired features for AV. In terms of motivations, less driving stress and improved safety are the top motivations to drive or ride an AV. Furthermore, avoiding collision and improving fuel efficiency are selected as the top desired features.

3.4 Summary

An online travel behavior survey consisting of SP-based scenarios was used for this study. Various scenarios were designed to better recognize the mode choice behavior under different circumstances. These scenarios represent private vehicle drivers, private vehicle passengers, transit riders, and visitors. The survey also contained comprehensive data on SED characteristics, mobility patterns, online shopping behavior, and attitudes. Regarding attitudes, distinct sets of statements focusing on general mobility preferences, perceived benefits and concerns of shared mobility, motivations for and against private vehicle ownership, motivations to drive or ride in an Autonomous Vehicle (AV), and the most desired AV features were presented to the respondents. The comprehensive information provides a solid basis for the detailed analysis of mode choice behavior in the era of ridesourcing.

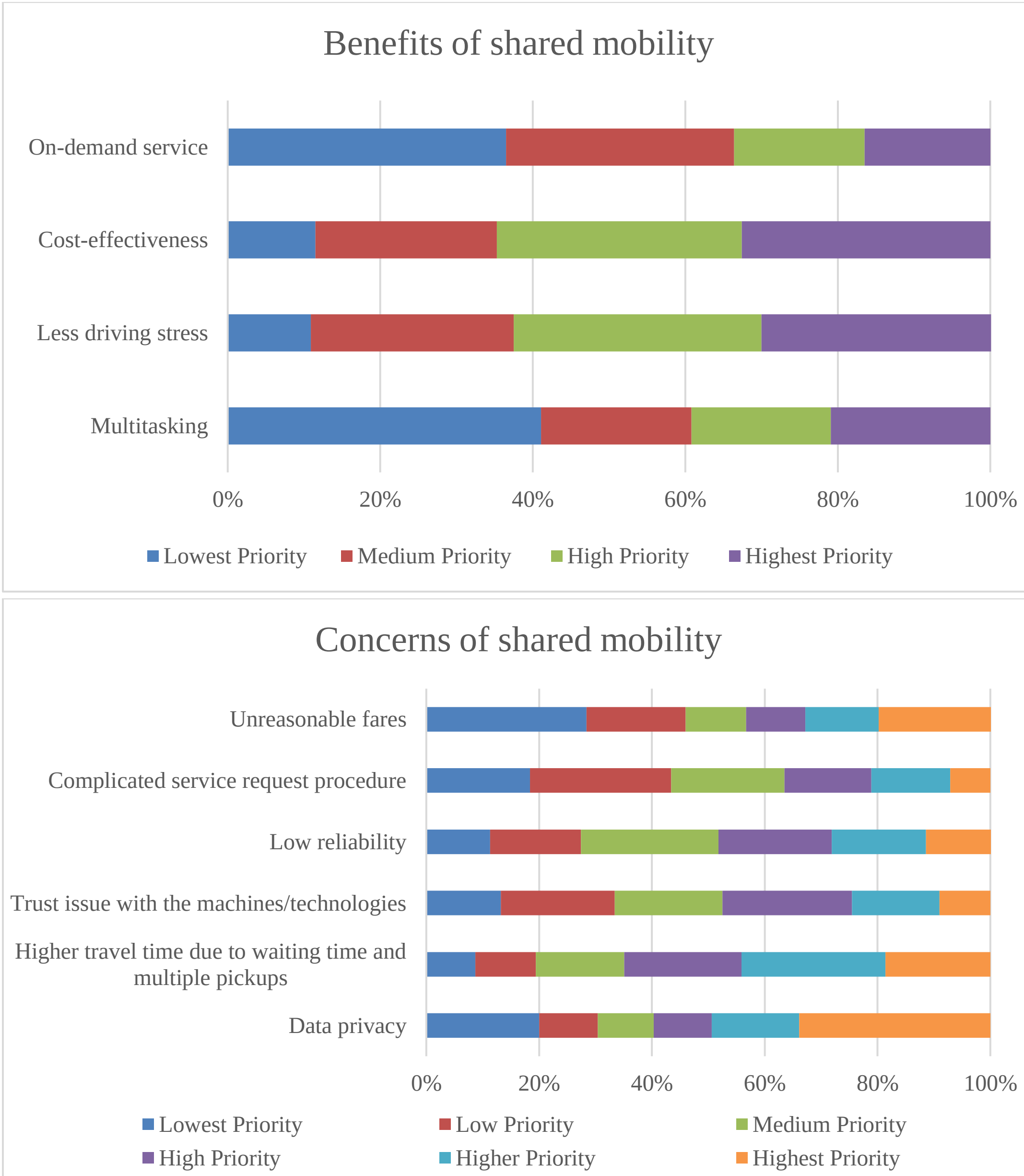


Figure 3-4 Perceived benefits and concerns of shared mobility

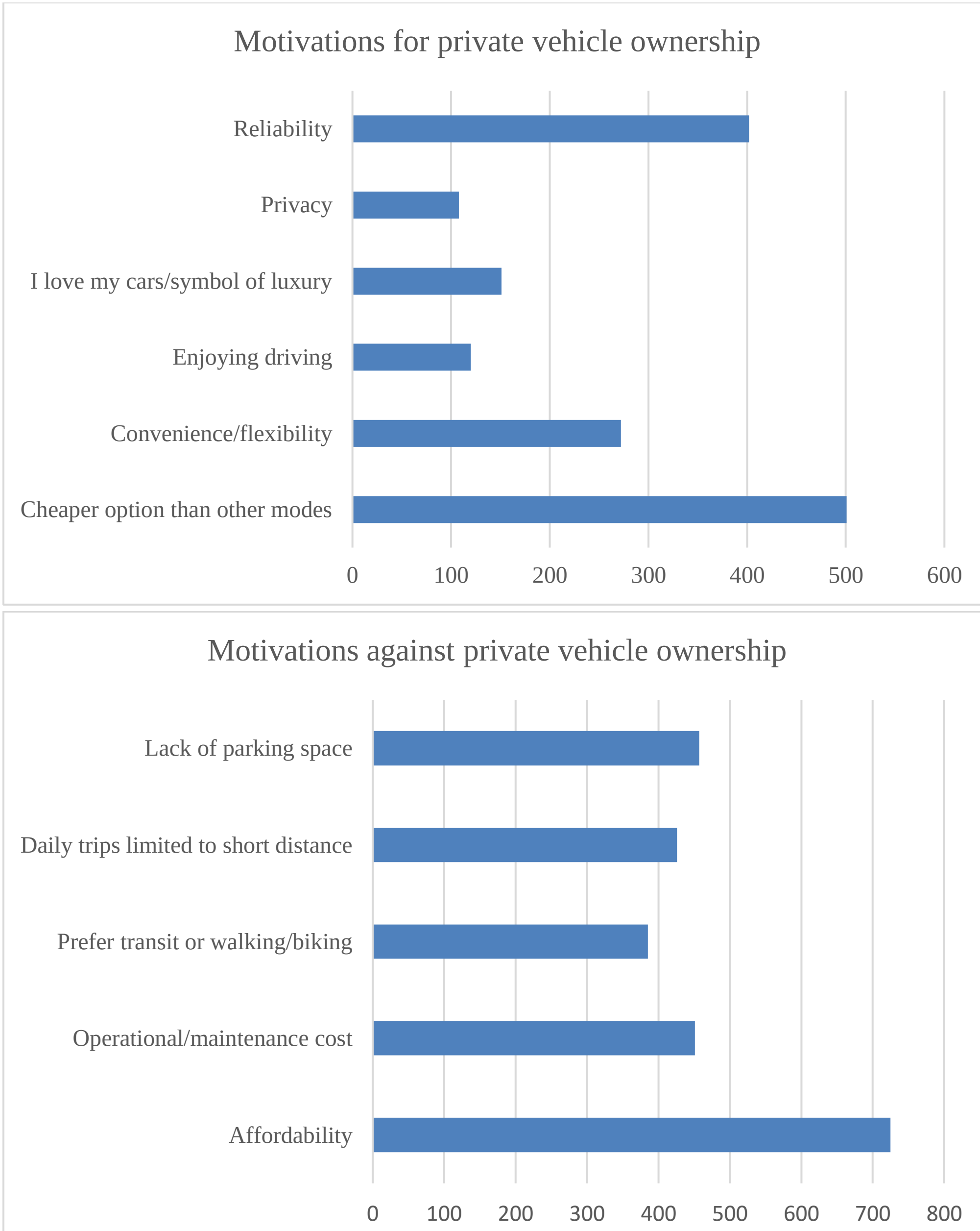


Figure 3-5 Motivations for and against private vehicle ownership

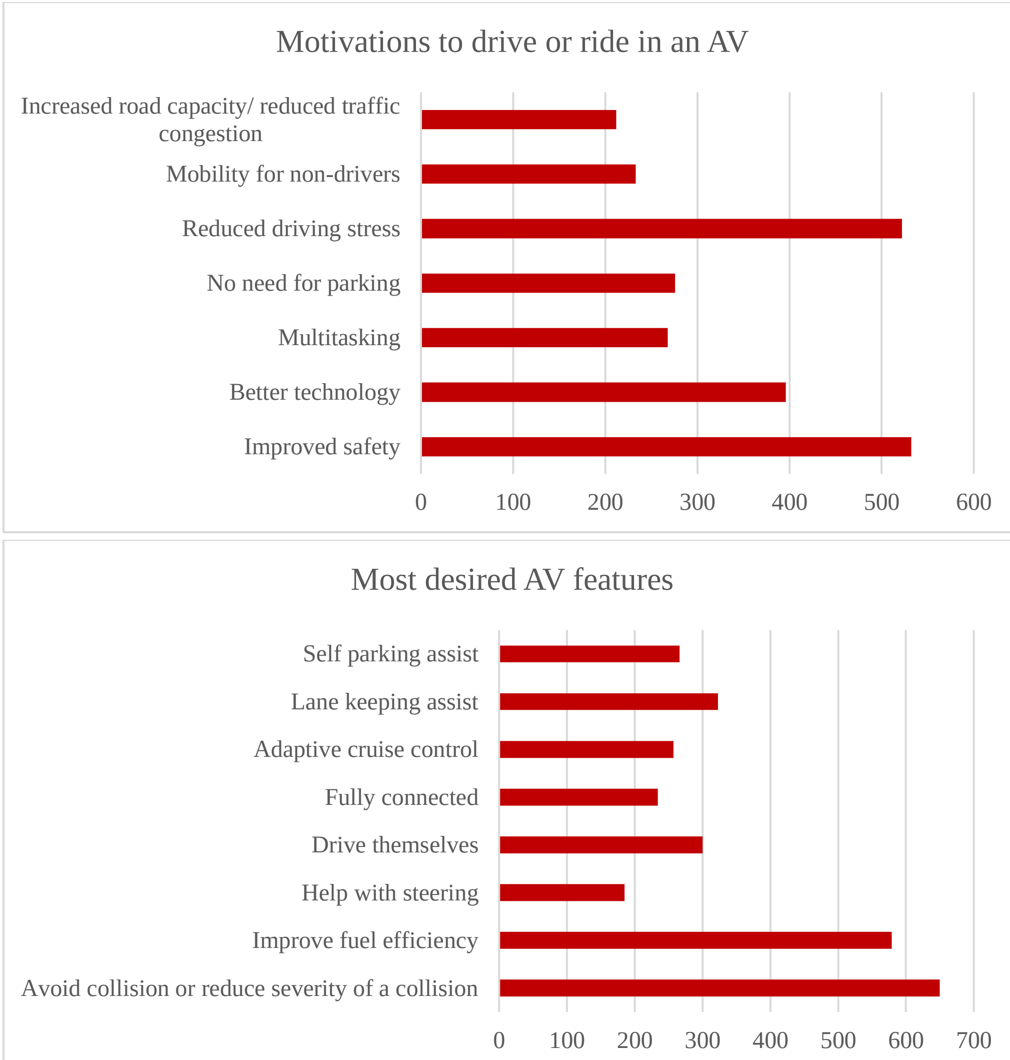


Figure 3-6 Motivations for and desired features of AV

CHAPTER 4

MODEL STRUCTURE

In this chapter, model structures developed for the analysis of ridesourcing behavior are elaborated. For each research topic, the applied methodology is described in the corresponding sections.

4.1 Error Component Multinomial Logit Model

For the SP survey, each respondent was presented with seven to eight different SP scenarios. They were asked to choose between their conventional modes and two ridesourcing services (exclusive and shared rides). Because several scenarios were presented to each respondent, the survey data have a panel structure. Panel data refers to multi-dimensional data with repeated cross-section observations over time. In this regard, the error component model was used for this dissertation, which is among the most widely used methods to deal with the potential heterogeneity in panel data (Hensher et al., 2005). This variability has two possible elements: cross-group variations measuring individuals' heterogeneity and within-group variability reflecting intra-person heterogeneity among the scenarios.

An error component logit model is applied since it is a more robust method to explain heterogeneity than basic mix logit models (Hensher et al., 2007). This method permits a higher flexibility level in specifying the observed and unobserved cross-group and within-group variations (Train 2009). Moreover, it allows for a fuller relaxation of the assumption on the independent and identically distributed (IID) error term (Hensher et al., 2007; Hensher et al., 2005). It also provides a more accurate behavioral description and deeper understanding of the impact of dependent variables on the outcome (Scarpa et al., 2005; Hensher et al., 2007).

Assume the utility that individual i perceives from alternative j is U_{ij}. This utility is assumed to be stochastic and could be expressed as the combination of two different terms: a deterministic portion, which is a linear form of explanatory variables, such as socioeconomic and demographic characteristics and choice-related attributes; and the stochastic portion (error term) ε_{ij}. The utility function can thus be shown as:

$$U_{ij} = \alpha_j + \beta x_{ij} + \varepsilon_{ij} \tag{4-1}$$

where β is the vector of coefficients that need to be estimated. x_{ij} is the vector of explanatory variables, α_j is the alternative-specific constant measuring the mean impact of alternatives' unobserved utility, and ε_{ij} is the random error. There are various assumptions about ε_{ij}. One typical assumption involving the random error term is that it is independently and identically distributed (IID), which produces the multinomial logit model (MNL) (McFadden et al. 1973, Parsa et al. 2019). MNL models assume that individuals choose the alternative that maximizes their utility. To allow for the possibility of underlying heterogeneity in individuals' mode choice between alternatives, additional error components can be added to the utility of each option, resulting in the basic assumption of mixed logit models. The error component, μ_{ij}, is assumed to follow a normal distribution, $N(0, \sigma^2)$. The utility function of alternative j for individual i of a mixed logit model can be represented as below:

$$U_{ij} = \alpha_j + \beta x_{ij} + \mu_{ij} z_{ij} + \varepsilon_{ij} \tag{4-2}$$

where z_{ij} is the vector of observed information for individual i and alternative j for mixed logit models. z_{ij} is a subset of explanatory variables that have random distributions among individuals. As mentioned before, respondents were represented with three choices in every scenario: conventional modes (private vehicles and public transit), exclusive on-demand services, and shared on-demand services. In this dissertation, only heterogeneity of travel time and travel costs among different individuals are accounted for. Thus, the utility function becomes:

$$U_{ijt} = \alpha_j + (\beta x_{ij}) + (\overline{\beta_{TT}} + \sigma_{TT}\mu_{i,TT})TT_{jt} + (\overline{\beta_{TC}} + \sigma_{TC}\mu_{i,TC})TC_{jt} + \varepsilon_{ijt} \quad (4\text{-}3)$$

where

U_{ijt} = utility of individual *i* selecting alternative *j* in scenario *t*,

α_j = alternative-specific constant (ASC),

β = vector of fixed coefficients,

x_{ij} = observed variables (fixed) for individual *i* choosing alternative *j*,

$\overline{\beta_{TT}}, \overline{\beta_{TC}}$ = mean of travel time and cost,

σ_{TT}, σ_{TC} = standard deviations of travel time and cost,

TT_{jt} = travel time of alternative *j* in scenario *t*,

TC_{jt} = travel cost of alternative *j* in scenario *t*,

$\mu_{i,TT}$ = standard normal random effect for travel time ~ N (0,1),

$\mu_{i,TC}$ = standard normal random effect for travel cost ~ N (0,1), and

ε_{ijt} = IID error term.

4.2 Error Component Nested Logit Model

There might be some degrees of interdependency and similarity between the single- and shared-on-demand services. Thus, it seems logical to define a nesting structure for decisions involving exclusive and shared ridesourcing services to capture the potential correlations among these two options. One nest in the decision structure can be specified for exclusive and shared on-demand services, effectively converting the error component

MNL structure to NL. The utility function of an error component nested logit model can be expressed as follows:

$$U_{ijt} = \alpha_j + (\beta x_{ij}) + (\overline{\beta_{TT}} + \sigma_{TT}\mu_{i,TT})TT_{jt} + (\overline{\beta_{TC}} + \sigma_{TC}\mu_{i,TC})TC_{jt} + \tau_r \delta_n \theta_{kn} + \varepsilon_{ijt} \quad (4\text{-}4)$$

where

θ_{kn} = standard normal random effect ~ N (0,1),

τ_r = if mode *r* goes to the nest, it is equal to 1; otherwise, it is 0, and

δ_n = the covariance factor for the nest.

Similar to the error component multinomial logit model, it was assumed that travel time and costs have random distributions among individuals. Other variables are defined in the previous section.

4.3 Factor Analysis

As discussed previously, the survey included sets of attitudinal questions that potentially measure different aspects of individuals' mobility attitudes. This large number of attitude-related variables makes it challenging to incorporate them into behavior models, particularly when the variables are correlated. To address this issue, factor analysis, which converts a set of observed correlated variables into uncorrelated groups of variables, called factors, was conducted to extract latent attitude factors based on individuals' responses to the survey questions (Mahdinia et al. 2018). With factor analysis, rotations can be applied to the solution, which allows for finding a solution with a more coherent explication to each of the identified factors. The feasibility of rotation in factor analysis makes it an excellent tool for treating multivariate questionnaire studies involving psychological constructs such as attitudes. Suppose there are *P* variables to be fitted to a model with *M* factors, the equation of factor analysis can be defined as below (Jennrich, 2007)

$$X = \mu + LF + \epsilon \tag{4-5}$$

where X is the vector of observed responses, μ is the vector of means, L is the matrix of loadings, F is the vector of factors, and ϵ the vector of residuals. F and ϵ are assumed to be independent, and F's are also independent of each other. The mean of F and ϵ are 0, $COV(F) = I$, the identity matrix, and $COV(\epsilon) = \Psi$, a diagonal matrix.

The factor analysis was conducted separately on each set of questions to extract latent factors. The eigenvalue, a measure describing the proportion of the variance of the observed variables explained by a factor, was used as the criterion to select the number of factors.

4.4 Summary

For this dissertation, two error component-based structures were developed to investigate the choice between conventional and ridesourcing modes. Error component models are among the most extensively applied models for panel data. The models include error component multinomial and nested logit models. The difference between multinomial and nested logit structures is that for the latter one a nest is defined for single and shared ridesourcing services. Furthermore, factor analysis was conducted on the attitudinal statements to extract a group of uncorrelated latent attitudinal factors.

CHAPTER 5

RIDESOURCING ADOPTION FOR TRANSIT RIDERS AND VISITORS

5.1 Introduction

With recent advances in information and communication technologies, as well as the rise of sharing economy, ridesourcing, also referred to as transportation network company (TNC), has flourished during the past decade. Using app-based platforms and smart matching algorithms, ridesourcing connects passengers with drivers of private vehicles in real-time. These services provide on-demand and “door to door” transportation services. Ridesourcing, as a new transportation option, is attractive from many perspectives. It provides travelers with fast, flexible, and convenient mobility. This demand is unmet by existing taxi or transit services. On the other hand, people are motivated to work as ridesourcing drivers by the promise of revenue through exploiting their under-used cars.

Given the rapid growth of the ridesourcing market, many studies have looked at the user and travel characteristics of ridesourcing and examined its impacts on the transit market. Literature reported both replacement and complement impacts of ridesourcing on transit ridership (Mahmoudifard et al. 2017, Rahimi et al. 2019, Rayle et al. 2014, Babar and Burtch 2017, Zhang et al. 2015, Yan et al. 2019). Ridesourcing might become attractive to transit users for its accessibility, convenience, and broader spatial and temporal coverage (Rahimi et al. 2020). On the other hand, travelers might prefer to adopt ridesourcing as the first/last-mile connection to transit. Though the impact of ridesourcing depends on the area’s density, individuals’ private vehicle usage, and the public transit level-of-service, ridesourcing usually reduces ridership for local transit. On the other hand, it usually serves as a connector to subway and commuter rail services (Babar et al. 2017, Zhang et al. 2015, Rayle et al. 2016, Lavieri et al. 2018, Murphy et al. 2016). Interestingly, several studies found that frequent ridesourcing users also used various transit services forms (Clewlow and Mishra 2017, Smith 2016). Ridesourcing users share similar characteristics with transit riders; they are younger, live in denser areas, and have lower vehicle ownership. (Zhang et al. 2015, Rayle et al. 2016, Lavieri et al. 2018, Clewlow and Mishra 2017, Circella et al. 2018).

With a focus on understanding the potential market of ridesourcing, this chapter puts effort into examining the factors that influence travelers' mode choice between transit and ridesourcing. This study extends existing research in two major aspects. First, besides the transit users that could be attracted to ridesourcing services as discussed above, another potential market of ridesourcing services is also studied; visitors or those who temporarily have no access to a private vehicle. These people could be highly auto-dependent, but in situations without access to a personal car, such as visiting other places or traveling to or from the airports, they may find ridesourcing more attractive than transit or conventional taxi services. Second, it is of particular interest to explore how these two groups (transit users and visitors) might have different attitudes and preferences toward mobility options and how their attitudes may affect their mode choice toward ridesourcing options. While the literature has indicated that psychological constructs, such as attitudes, perceptions, and desires have considerable impacts on individuals' mode choice behavior (Hagman 2003, Jensen 1999, Verplanken et al. 2008, Johansson et al. 2006, Paulssen et al. 2014, Domarchi et al. 2008, Verplanken et al. 1994), only a few papers have investigated the impacts of attitudes on travelers' mode choice in the context of ridesourcing (Dias et al. 2017, Shabanpour et al. 2018, Bansal et al. 2019, Alemi et al. 2018, Alemi et al. 2019).

Given the above motivations, this study investigated the differences between the mode choice of transit riders and visitors, focusing on attitudinal factors. A previous study illustrated that visitors and transit users exhibited very different patterns in their mode choices (Asgari et al. 2018). This prompted the author to explore the latent attitudes that might have influenced their choice decisions.

5.2 Descriptive Analysis

This section compares the observed patterns in transit riders' and visitors' socioeconomic and demographic characteristics, trip attributes, and attitudinal factors.

5.2.1 *Definition of Transit Riders and Visitors*

Transit users were identified as those who reported using transit for a regular or most frequent trip in the RP section. They were asked to think of this RP trip as a reference for the SP scenarios. Visitors were those who used private vehicles (driver or passenger) for a regular trip. They were then given the instructions to think of when their private vehicles were unavailable, such as a trip from/to the airport or when visiting a place, filling out the RP trip information. Then visitors would continue to the SP scenarios with this non-regular or occasional RP trip in mind. As can be seen, the two scenario types represent two user groups, as well as regular versus occasional situations.

The dataset consists of 136 transit users with 1,088 scenarios and 951 visitors with 7,608 scenarios. Table 5-1 presents descriptive statistics for transit users and visitors. Transit users had a higher frequency of young and male individuals than visitors. They were also more ethnically diverse and had lower education levels.

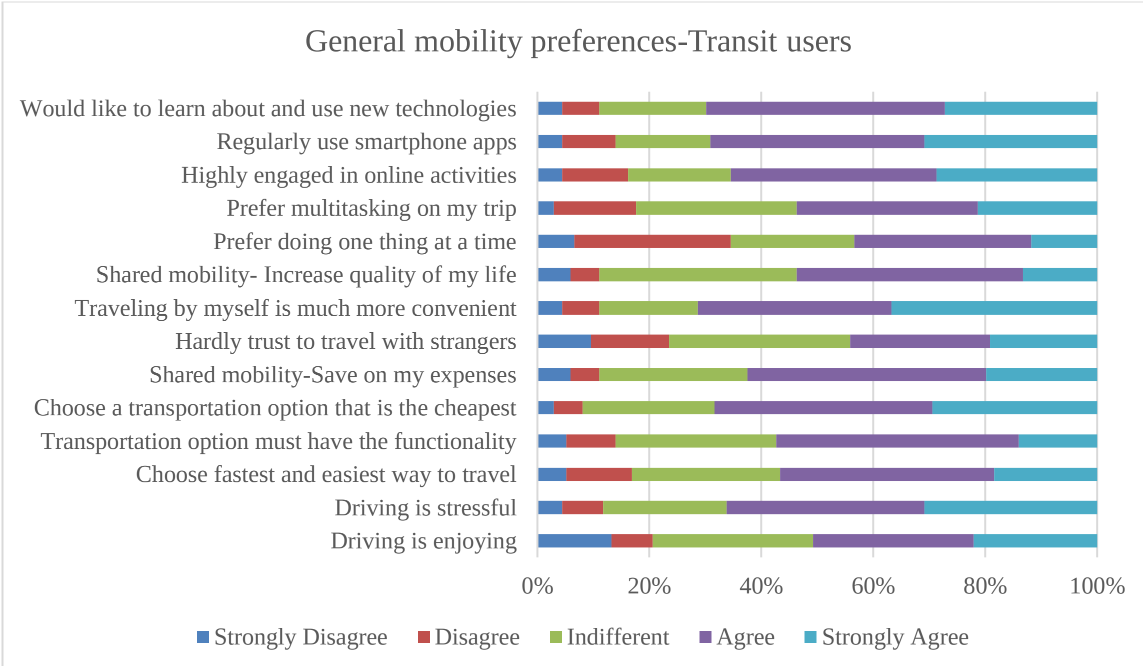
Table 5-1 Descriptive statistics

Attribute			Transit users	Visitors	Census 2010
			(136)	(951)	
			Share	Share	Share
Age	Generation Z (16-24 years old)	16-17	2.9%	1.2%	17.6%
		18-24	26.5%	11.3%	-
	Millennials (25-39 years old)	25-29	19.1%	12.7%	8.5%
		30-34	16.9%	11.6%	8.1%
		35-39	5.9%	10.4%	8.2%
	Generation X (40-54 years old)	40-44	8.8%	5.2%	8.4%
		45-49	4.4%	7.6%	9.2%
		50-54	3.7%	6.9%	9.0%
	More than 55 years old	55-59	6.6%	8.9%	7.9%
		60-64	1.5%	8.4%	6.8%
		65-69	1.5%	7.9%	5.0%
		70-74	1.5%	4.4%	3.7%
		75 and older	0.7%	3.6%	7.5%
Gender	Male		59.6%	54.2%	49.2%
	Female		40.4%	45.8%	50.8%
Ethnicity	White		56.6%	75.8%	63.7%
	Hispanic		19.9%	12.8%	16.3%
	Asian		0.0%	2.0%	4.9%
	Native American/American Indian		0.7%	0.4%	0.7%
	Black/ African American		22.1%	8.7%	12.2%
	Other		0.7%	0.2%	2.4%
Education	Less than 9th grade		0.7%	0.5%	5.2%
	9th to 12th grade, no diploma		8.1%	3.0%	8.3%
	High school graduate		36.8%	25.7%	28%
	Some college, no degree		28.7%	29.0%	23.7%
	Associate degree		5.9%	7.3%	7.7%
	Bachelor's degree		16.9%	28.7%	17.3%
	Graduate or professional degree (Master's/PhD or equivalent)		2.9%	5.8%	9.9%
HH income	0-$25K		30.1%	18.1%	23.1%
	$25K-$50K		32.4%	32.4%	23.5%
	$50K-$75K		19.9%	23.9%	17.8%
	$75K-$100K		9.6%	15.6%	12.1%
	$100K-$125K		2.9%	3.4%	13.1%
	$125K-$150K		2.9%	2.8%	-
	$150K-$175K		0.7%	1.5%	5.1%
	$175K-$200K		0.0%	1.1%	-
	More than $200K		1.5%	1.4%	5.3%
Employment status	Full-time		41.7%	43.5%	-
	Part-time		12.9%	13.4%	-
	Unemployed		20.1%	12.6%	-
	Student		12.2%	4.5%	-
	Retired		7.2%	21.7%	-
	Others		5.8%	4.3%	-

5.2.1 *Attitudes and Personal Preferences*

Figure 5-1 presents a summary of general mobility preferences for transit users and visitors, respectively. Transit riders and visitors showed similar patterns, except that a higher percentage of visitors do not trust to travel with strangers. Transit users were more likely to choose the cheapest travel mode and believe that shared mobility can help them save on expenses. This could indicate that cost is one primary concern of transit users. Also, they were less likely to enjoy driving, while they were more inclined to have multitasking opportunities during their trips.

Regarding the perceived benefits and concerns of shared mobility services, Figure 5-2 presents the summary for transit users and visitors, respectively. As it shows, multitasking is less likely to be valued as a priority for visitors than transit users. Regarding concerns of shared mobility, transit users generally were more concerned about these services than visitors. Interestingly, both transit users and visitors ranked higher travel time and data privacy as the top two concerns about shared mobility. Moreover, transit users were more likely to exhibit trust issues with technologies.



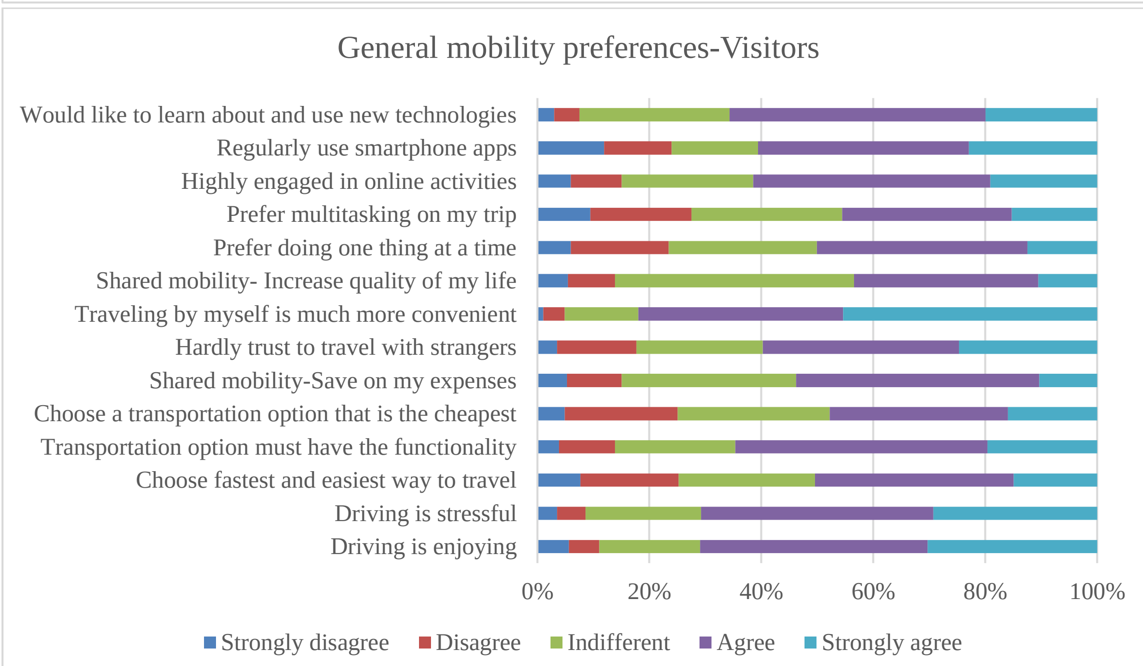


Figure 5-1 General mobility preferences for transit riders and visitors.

Figure 5-2 Perceived benefits and concerns of shared mobility for transit riders and visitors

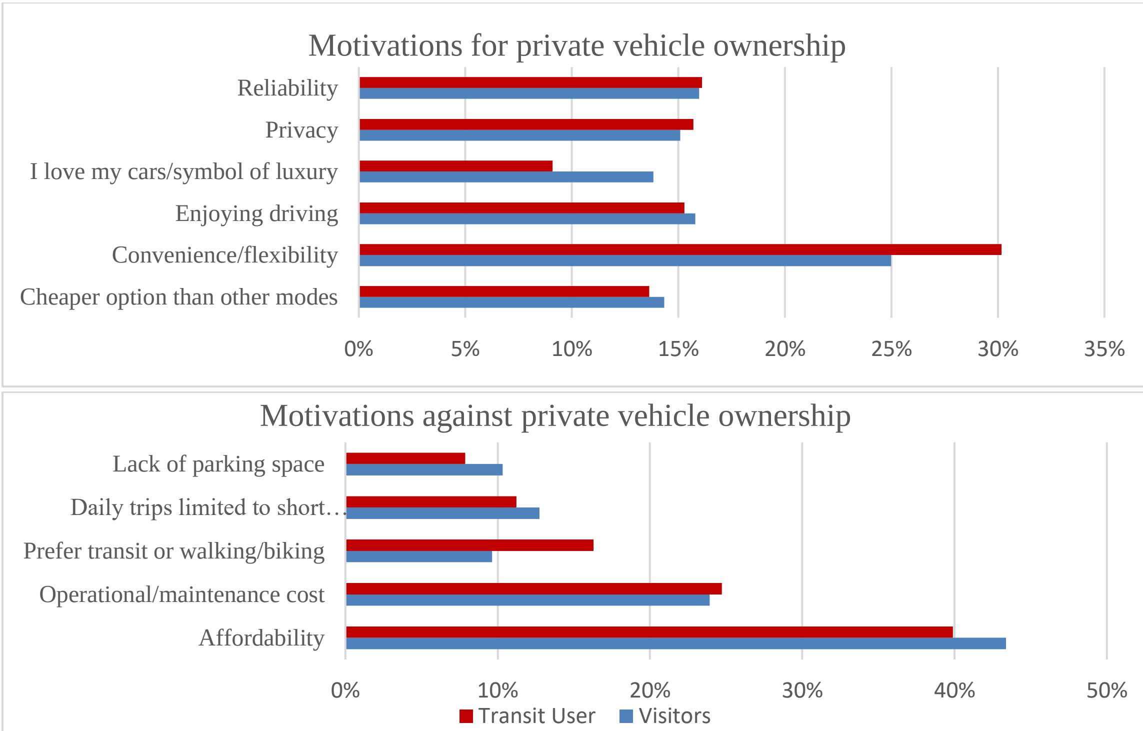


Figure 5-3 Motivations for and against private vehicle ownership for transit riders and visitors

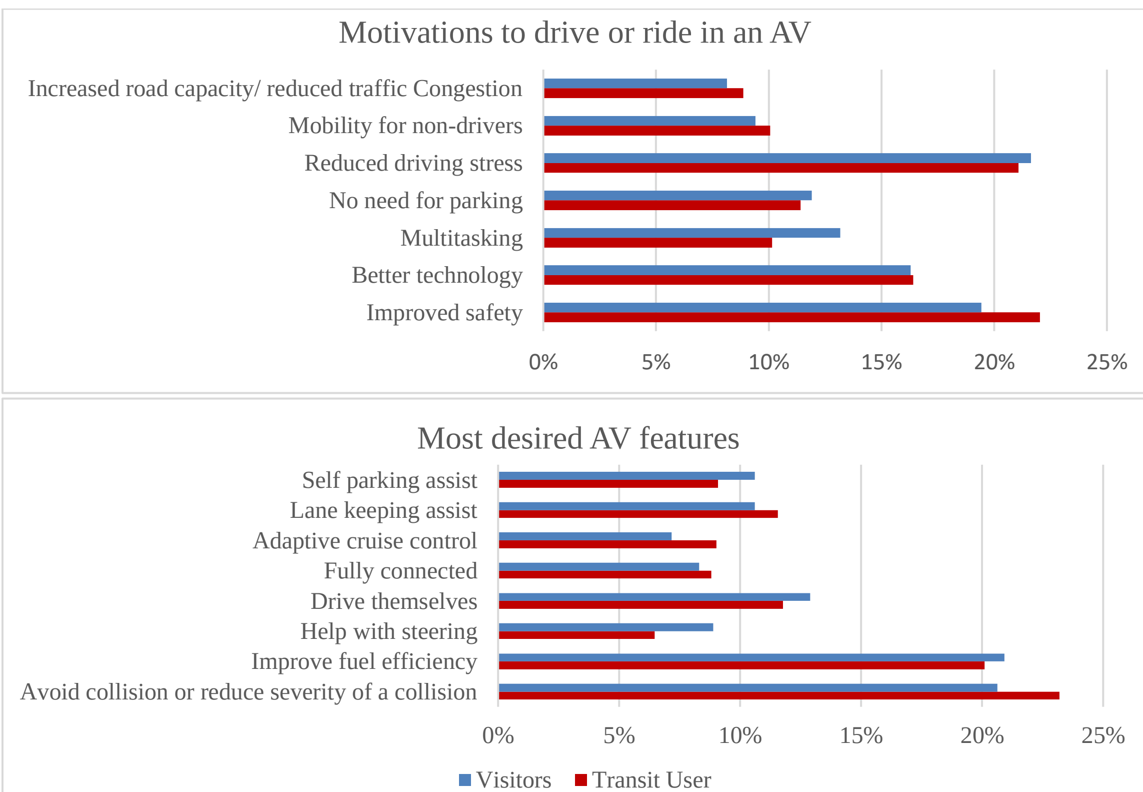


Figure 5-4 Motivations for and desired features of AV for transit riders and visitors

When it comes to motivations for and against private vehicle ownership, the results are presented in Figure 5-3. The horizontal axis indicates the percentage of selection. Each respondent could select multiple reasons. It shows that convenience/flexibility was the top reason chosen by both transit riders and visitors. A higher percentage of visitors choose driving joy as the reason for owning a private vehicle, indicating their higher attachment to driving, which might be a barrier to adopting ridesourcing. On the other side, ownership cost and operation/maintenance cost were the top reasons for not owning a vehicle for both transit and visitors. It should be noted that a higher percentage of transit users preferred alternative modes as a reason against vehicle ownership compared with visitors.

Figure 5-4 summarizes the motivations to drive or ride in an AV and the most desired features for AV. Again, each respondent can select multiple options. Regarding motivations, transit users and visitors showed similar patterns—less driving stress and improved safety were the top motivations for both groups. However, transit users were more likely to be motivated by reducing traffic congestion and mobility for non-drivers compared to visitors.

5.3 Results

This section is divided into two distinct sub-sections. First, the results of the factor analysis are presented. Then, the error component multinomial logit results will be discussed for transit riders and visitors.

5.3.1 *Factor Analysis Results*

Table 5-2 presents the derived factors and their corresponding factor loadings. Each derived latent factor was labeled based on the variables that were associated with it. Highlighted cells show the indicators related to each identified factor; green cells represent a positive association with the factor, while blue cells reflect a negative association.

Table 5-2 Derived attitudinal factors

General mobility preferences	Factors					
	1	2	3		4	
Highly engaged in online activities	0.805	0.143	0.041		0.081	
Regularly use smartphone apps	0.773	0.203	-0.002		-0.012	
Would like to learn about and use new technologies	0.750	0.206	0.069		0.089	
Prefer multitasking on my trip	0.504	0.370	0.001		-0.298	
Choose a transportation option that is the cheapest	0.048	0.644	0.072		0.062	
Choose fastest and easiest way to travel	0.255	0.640	-0.120		0.140	
Shared mobility-Save on my expenses	0.265	0.634	-0.223		0.038	
Shared mobility- Increase quality of my life	0.334	0.590	-0.168		0.096	
Driving is stressful	0.024	0.570	0.319		-0.321	
Transportation option must have the functionality	0.208	0.490	0.302		0.167	
Hardly trust to travel with strangers	-0.026	-0.067	0.818		0.093	
Traveling by myself is much more convenient	0.080	0.002	0.779		0.113	
Prefer doing one thing at a time	-0.248	0.256	0.193		0.716	
Driving is enjoying	0.267	0.021	0.095		0.641	
Perceived benefits and concerns of shared mobility	1	2	3	4	5	6
Concerns-Trust issue with machines/ technologies	0.759	-0.018	0.048	-0.032	0.114	-0.333
Concerns-Unreasonable fares	-0.702	-0.001	0.267	0.108	0.006	-0.204
Concerns-Complicated service request procedure	-0.571	0.194	-0.174	-0.200	0.034	-0.450
Benefits-On-demand service	-0.074	0.919	-0.148	0.099	-0.300	-0.007
Benefits-Multitasking	0.093	-0.702	-0.560	-0.074	-0.401	0.019
Benefits-Cost-effectiveness	-0.073	-0.046	0.950	-0.012	-0.161	-0.047
Concerns-Low reliability	0.044	0.034	-0.027	0.935	-0.052	-0.010
Concerns-Data privacy	0.513	-0.179	-0.077	-0.582	-0.114	0.081
Benefits-Less driving stress	0.045	-0.129	-0.128	-0.009	0.974	0.032
Concerns-Higher travel time due to waiting time and multiple pickups	-0.001	0.020	-0.081	-0.081	0.043	0.933
Motivations for and against private vehicle ownership	1	2	3		4	
Own a vehicle – Privacy	0.765	-0.106	-0.004		0.020	
Own a vehicle – Reliability	0.763	-0.226	0.014		0.037	
Own a vehicle – Enjoying driving	0.671	0.269	-0.015		-0.030	
Own a vehicle - I love my cars/symbol of luxury	0.567	0.350	0.140		-0.287	
Own a vehicle - Convenience/flexibility	0.501	-0.298	-0.265		0.425	
Don’t own a vehicle - Prefer transit or walking/biking	-0.092	0.660	-0.060		0.058	

Don’t own a vehicle - Daily trips limited to short distance	0.019	0.511	0.016	0.131
Don’t own a vehicle - Lack of parking space	0.089	0.410	-0.352	-0.244
Don’t own a vehicle -Affordability	-0.135	-0.095	0.686	0.223
Own a car-Cheaper option than other modes	0.205	0.043	0.667	-0.233
Don’t own a vehicle-Operational/maintenance cost	-0.017	0.310	0.101	0.791
Motivations for and desired features of AV	1	2	3	4
Desired features- Lane keeping assist	.709	.095	.032	-.077
Desired features- Avoid collision	.671	-.178	.003	.066
Motivation-Improved safety	.639	-.059	-.056	.196
Desired features- Self parking assist	.555	-.033	.196	-.107
Desired features- Adaptive cruise control	.534	.334	-.190	.043
Motivation-Increased road capacity/ reduced traffic congestion	.502	-.012	.216	.124
Motivation- Reduced driving stress	.426	.111	.308	.310
Desired features- Fully connected	.005	.669	.081	-.138
Desired features- Help with steering	-.049	.599	.034	-.068
Motivation-Multitasking	.006	.473	.164	.227
Desired features- Drive themselves	-.038	.149	.675	.106
Motivation- Mobility for non-drivers	.190	-.057	.644	.038
Motivation- No need for parking	.040	.220	.467	-.355
Desired features- Improve fuel efficiency	.112	-.073	.095	.777
Motivation- Better technology	.058	.524	-.089	.529

Table 5-3 presents a short description for each factor, the percentage of variance explained by each factor, the total variance explained for each category, and the associated eigenvalues. An eigenvalue larger than one was used as the criterion to specify the number of factors. T-tests showed significant differences between the two groups for all 18 factors.

Table 5-3 Statistical results of the factor analysis

Category	Factor	Description	% of var.	Cumulative % of var.	Eigen value
General mobility preferences	F1- Pro-technology	Represents an individual's engagement with online activities, the use of smartphone apps, eagerness to learn about and use new technologies, and their interest in multitasking.	26.62	26.62	3.73
	F2- Service quality	Refers to the consideration of service quality (ranging from travel time, cost, functionality, to convenience) in mobility decisions.	12.96	39.28	1.75
	F3- Travel with strangers	Indicates an individual's concerns about traveling with strangers.	8.98	48.199	1.26
	F4- Joy of driving	Positively associated with the joy of driving and individuals' reluctance to multitask.	7.37	55.569	1.03
Perceived benefits and concerns of shared mobility	F5- Trust and data privacy concerns	Positively associated with an individual's concern on data privacy and trust with technologies, and negatively related to cost and service request procedure concerns.	22.64	22.644	2.26
	F6- Pro-on-demand service	Reflects people's positive beliefs in on-demand services and unwillingness to multitasking during the trips.	12.96	35.605	1.30
	F7- Cost-effectiveness	Refers to the beliefs in the cost-effectiveness of ridesourcing. It is negatively associated with willingness in multitasking.	12.68	48.281	1.27
	F8- Reliability concerns	Represents an individual's concerns on system reliability of ridesourcing and is negatively associated with data privacy concerns.	12.32	60.598	1.23
	F9- Driving stress relief	Refers to the belief in reducing driving stress by using ridesourcing.	11.21	71.804	1.12
	F10- Travel time concerns	Indicates an individual's positive concerns on travel time due to multiple pickups and waiting time, and negative concerns on technology (trust and procedure)	10.78	82.583	1.08
Private vehicle ownership	F11- Pro-private vehicle	Refers to the positive preference for a private vehicle due to privacy, reliability, the joy of driving, flexibility, and attachment to cars.	20.64	20.641	2.27
	F12- Pro-alternative modes	Indicates the preference for transit, walking, or biking. Interestingly, the lack of parking space significantly contributed to this factor.	12.17	32.807	1.34
	F13- Travel cost concerns	Indicates the consideration of cost as a dominant factor for ownership decisions.	10.22	43.028	1.124
	F14- Ownership cost	Represents the concern on ownership and maintenance costs which may act	9.72	52.753	1.070

Category	Factor	Description	% of var.	Cumulative % of var.	Eigen value
	concerns	as a barrier toward vehicle ownership.			
AV features	F15- Driving assistance & safety	Indicates the desire for driving assistance features, such as lane-keeping, self-parking, adaptive cruise control, as well as safety features of AVs, like collision avoidance.	17.97	17.970	2.696
	F16- Automation	Represents the preferences for better technology and full connectivity.	10.86	28.835	1.630
	F17- Mobility for non-drivers	Refers to the desire for auto-driving feature, especially for those how cannot drive.	8.28	37.121	1.243
	F18- Efficiency & technology	Positively associated with the desire for higher efficiency and better technology.	7.09	44.211	1.064

5.3.2 *Model Results*

Separate error component multinomial logit models were applied for the transit riders and visitors. For each user group, a full model with all explanatory variables was considered. Then the model was optimized by removing insignificant variables (at the 90% level of significance) while preserving the model's goodness of fit improvement. Table 5-4 presents the results of the error component models for transit riders and visitors.

As shown in Table 5-4, for transit riders, travel time showed a significant mean and standard deviation (i.e., they are significantly different from zero at the 90% level of significance). This confirms the presence of taste variations among transit users. Interestingly, heterogeneity in travel cost was not detected among transit users. For visitors, both travel time and travel cost had mean and standard deviations significantly different from zero. The final model embraces several socioeconomic and demographic characteristics as well as attitudinal factors (that offer a more profound vision of the role of attitudes in the propensity to use ridesourcing services).

Table 5-4 Model results for transit riders and visitors

Users	Transit riders	Visitors
Variable	**Coefficient**	**Coefficient**
Constant		
Exclusive rides	-1.06 ***	1.83***
Shared rides	-0.872***	1.23***
Private vehicle/public transit (base)	-	-
Attitudinal factors		
General Mobility Preferences		
Pro-technology (Specific to exclusive rides)	0.735***	0.437***
Pro-technology (Specific to shared rides)	0.307*	0.369***
Service quality (Specific to exclusive rides)	-	0.227***
Service quality (Specific to shared rides)	-	0.463***
Travel with strangers (Specific to exclusive rides)	-	-0.384***
Travel with strangers (Specific to shared rides)	-	-0.565***
Joy of driving (Specific to exclusive rides)	-	-0.316***
Joy of driving (Specific to shared rides)	-	-0.278***
Perceived benefits and concerns of shared mobility		
Cost-effectiveness (Specific to exclusive rides)	-	-0.104**
Pro-on-demand service (Specific to exclusive rides)	0.55***	0.195***
Pro-on-demand service (Specific to shared rides)	0.409***	0.409***
Travel time concerns (Specific to exclusive rides)	0.468***	-
Travel time concerns (Specific to shared rides)	0.366***	-
Driving stress relief (Specific to exclusive rides)	-	0.088**
Motivations for and against private vehicle ownership		
Pro-private vehicle (Specific to exclusive rides)	-0.477 **	0.147**
Pro-private vehicle (Specific to shared rides)	-0.332*	-
Pro-alternative mode (Specific to exclusive rides)	-0.379***	-0.087*
Ownership cost concerns (Specific to shared rides)	0.359***	
Motivations for and desired features of AV		
Driving assistance & safety (Specific to exclusive rides)	-	0.229**
Driving assistance & safety (Specific to shared rides)	-	0.244**
Automation (Specific to shared rides)	0.257*	-
Mobility for non-drivers (Specific to exclusive rides)	0.275**	-
Efficiency & technology (Specific to shared rides)	0.343***	-
Socioeconomic and demographic attributes		
Gender (Base: Male)		
Female (Specific to exclusive rides)	0.657**	-
Female (Specific to shared rides)	0.611**	-
Ethnicity (Base: White)		
Native American (Specific to exclusive rides)	-	1.04**
Native American (Specific to shared rides)	-	0.925**
Employment (Base: Part-time)		
Full Time (Specific to exclusive rides)	0.544***	-
Student (Specific to exclusive rides)	-	1.45***
Student (Specific to shared rides)	-	1.05***
Education (Base: Some college, no degree)		
Less than 9th grade (Specific to exclusive rides)	-2.15***	-
Less than 9th grade (Specific to shared rides)	10.2***	-
High school graduate (Specific to shared rides)	0.59**	-
Bachelor (Specific to exclusive rides)	1.1**	-
Bachelor (Specific to shared rides)	1.56***	-
HH Income (Base $50K-$75K)		

Users	Transit riders	Visitors
$0K-$25K (Specific to exclusive rides)	-	-0.462***
$25K-$50K (Specific to exclusive rides)	-1.00***	-
$25K-$50K (Specific to shared rides)	-0.689*	0.373***
$75K-$100K (Specific to exclusive rides)	1.52***	-0.318**
$75K-$100K (Specific to shared rides)	1.94***	-
$100K-$125K (Specific to exclusive rides)	1.72*	-
$125K-$150K (Specific to exclusive rides)	3.22***	0.562**
More than $200K (Specific to shared rides)	-1.96*	-0.625*
Random parameters		
Travel time		
Mean	-0.97***	-1.02***
Standard deviation	1.01***	1.06***
Travel cost		
Mean	-1.29*	-0.77*
Standard deviation	1.1	2.02**
Number of observations	Respondents =136, Observations=1,088	Respondents=951, Observations=7,608

*** Significant at 1% Level, ** Significant at 5% Level, * Significant at 10%

5.3.2.1 Transit Riders

In view of attitudes, pro-technology users showed a positive impact on using ridesourcing options, especially for exclusive rides. This positive association was expected since those with a technology-driven lifestyle are more likely to adopt the technology-related services (Acheampong et al. 2020, Simmons 2018, Dias et al. 2017, Alemi et al. 2018). Regarding the perception of ridesourcing, as expected, individuals who believed in the on-demand aspect of ridesourcing were likely to choose these services over transit. Interestingly, those who are concerned about higher travel time had a positive tendency toward ridesourcing services. The positive association could be due to the unreliability of transit (which could result in high waiting times) in certain areas, such as areas with poor transit service or low and medium-density land-use patterns and first/last-mile connections to transit stations. Interestingly, people with this attitude showed a higher inclination toward exclusive rides than shared rides.

In view of attitudinal factors related to private vehicle ownership, results showed that transit riders who enjoyed the utility of private vehicles preferred to use transit rather than ridesourcing services. A potential reason could be that their use of private vehicles was associated with congestion, delay, or other factors. In this case, ridesourcing could not provide better services than transit. Similarly, those who preferred alternative modes or had short travel distances were also likely to choose transit over ridesourcing. This positive association could be related to lifestyle preferences, environmental concerns, and cost considerations.

When it comes to views toward AVs, positive associations were observed between the tendency to use shared rides and the interest in full automation and technology and efficiency. Moreover, individuals seeking efficiency and technology were interested in using shared-ride services, presumably because shared travel modes are technology-based options that are efficient in travel time and cost. Moreover, those who cared about mobility for non-drivers were inclined to use exclusive services. This may suggest a potential market of ridesourcing services among those who cannot drive (e.g., older people, individuals with disabilities, children) or do not enjoy driving but prefer a private travel experience.

In relation to socioeconomic and demographic variables, female users showed a positive tendency to use ridesourcing services, but they were more inclined to use exclusive rides than shared rides, which could be related to a higher level of safety concerns. Full-time workers had a positive impact on exclusive rides, which may indicate the impact of work-schedule restrictions associated with full-time employees and that they may prefer exclusive services for lower travel times and probably higher reliability. Also, this positive correlation can indicate an affluent lifestyle or relative wealth (which is different from income), in which full-time workers are more willing to use exclusive rides. Full-time employment might be a proxy for latent attitudinal factors that affect willingness to pay for ridesourcing services and results in cost preference heterogeneity. Such a positive correlation between full-time employers and ridesourcing is also supported in the literature (Dias et al., 2017; Asgari and Jin, 2020; Sikder et al., 2019).

Interestingly, users with a lower level of education (less than 9th grade) had a negative tendency to use exclusive rides than transit but a very high positive tendency to use shared rides. Results also showed that users with high school degrees are more interested in using shared rides than transit. Those holding a bachelor's degree showed a positive tendency toward both exclusive and shared rides. It seems that people with higher education are more aware of such services, and they can leverage such services through technology. Similar findings have been documented in the literature (Rayle et al. 2016, Murphy 2016, Clewlow and Mishra 2017, Dias et al. 2017).

The pattern associated with income also sounds sensible. Low-income individuals ($25K-$50K) were less likely to use ridesourcing, particularly exclusive rides. The negative association could be related to cost concerns, not having access to credit cards, unfamiliarity with technology, and limited smartphone access. Very high-income groups ($200K and above) were less likely to use shared services. Those in-between generally showed a higher tendency to use exclusive rides compared with transit.

5.3.2.2 Visitors

Regarding attitudinal factors, similar to transit riders, technology-savvy individuals were more likely to choose ridesourcing services over public transit. Service quality showed a positive impact on using ridesourcing services, especially for shared-ride services. This positive tendency could imply that visitors would use ridesourcing services when they believe that the service provides better utility. As expected, those concerned about traveling with strangers were less likely to choose ridesourcing, especially shared services. This issue may be considered a critical predicament that discourages ridesourcing services adoption (Ma et al. 2019, Alemi et al. 2019). Interestingly, people who enjoyed driving also showed a negative tendency toward ridesourcing.

In relation to perceptions, individuals concerned about the cost-effectiveness of their trips were less likely to use exclusive ride, probably because of cost considerations. On the other hand, as expected, users who are fans of on-demand services showed a positive tendency to choose both exclusive-ride and shared-ride over transit. Individuals who cared about driving stress had a trivial positive propensity toward exclusive ride.

In view of private vehicle ownership, there was a positive impact on the use of exclusive rides for those who value the utility of private vehicles and a negative association between the preference of alternative modes and the tendency of ridesourcing adoption, which could be anticipated. Considering AV features, those who desire driving assistance and safety were more likely to use ridesourcing than transit services.

In view of socioeconomic and demographic characteristics, Native Americans were associated with a higher tendency to use ridesourcing services, especially exclusive rides. Students showed a positive tendency to use on-demand services for both exclusive- and shared-ride services. This might be related to the fact that students usually are more open and eager to experience new technologies. Mixed results were observed in the impact of income level. In general, low-income individuals were less likely to use exclusive rides, and high-income individuals were less likely to use shared rides.

5.4 Discussions

With a focus on the role of attitudes, this section discusses the factors that may contribute to a shift from transit to ridesourcing.

5.4.1 *Transit Riders*

In view of regular transit riders, exclusive rides would be attractive to those engaged with technology, time-sensitive individuals, and those who appreciate the mobility for non-drivers, especially when they were full-time employed with household income higher than $100k annually. A shift to shared rides would be highly likely for those who believed in the efficiency and automation aspects of the AVs but could not afford a private vehicle (i.e., they probably could not afford regular exclusive rides either). Those who believed they could benefit from the on-demand aspect of these services favored both ridesourcing options, with a slightly higher inclination toward exclusive rides.

Considering users with a negative tendency toward ridesourcing options, those who enjoyed the utilities of a private vehicle tended to continue with transit. They probably chose transit for their regular trips because of potentially unobserved utilities that they received from transit. For instance, they could be living in a neighborhood with highly accessible transit services, or it might just be a short trip that supported their decision to use transit. In parallel with these groups, there were also extremely high-income people (more than $200k) as well as those who preferred alternative modes. These individuals were also less likely to shift from transit to ridesourcing but in different ways. High-income people were reluctant to use shared rides. On the other hand, alternative mode users were not inclined to use exclusive rides.

5.4.2 *Visitors*

For visitors, those who appreciated stress relief, or the utilities of a private car were more likely to choose exclusive rides. Technology-savvy individuals favored both ridesourcing options with a slightly higher propensity toward exclusive rides. Individuals with a high service quality factor (i.e., those who evaluate different choices based on time, cost, and other characteristics) along with those who cared about the on-demand aspect of the services also favored both ridesourcing options. However, they were more likely to choose shared rides because they provide the best combination of time, cost, and convenience, compared with transit and exclusive rides.

In view of users with a negative propensity toward ridesourcing, individuals who preferred alternative modes or were concerned about cost-effectiveness were less likely to take the exclusive ride, which sounds reasonable. Those who enjoyed driving, or had issues with traveling with strangers, were very unlikely to switch to ridesourcing.

5.4.3 *Discussion*

In comparison, some attitudinal factors showed similar effects for both groups. For instance, technology savviness and the perceived benefit of on-demand service showed positive impacts on the usage of ridesourcing services (both shared and exclusive rides) for transit riders and visitors. On the other hand, the preference for alternative modes (including short trips and lack of parking) discouraged the use of exclusive rides for both groups.

Besides these common factors, it seems that the mode choice was driven by intrinsically different motivations for the two groups. For transit users, attitudes toward time and cost had significant impacts, possibly because of the regular nature of the trip. Specifically, those concerned about the higher travel time of ridesourcing (because of waiting time and multiple pickups) showed a higher tendency toward taking exclusive services than shared services. Those who were concerned about vehicle cost preferred shared rides, probably because of cost considerations. Moreover, for transit users, those who enjoyed the utility of a private vehicle were less likely to switch to ridesourcing from transit. Other determinant factors for transit users were the desire and motivation for automation, technology, and mobility for non-drivers, which encouraged the use of ridesourcing.

For visitors, the dominant factors that discouraged the use of ridesourcing were the issues with traveling with strangers and the joy of driving. Furthermore, it seems that the decision to use ridesourcing was affected by how much the individual believed in the utility he/she may gain from the service. Particularly, those who desire driving assistance and safety and stress relief were more likely to choose ridesourcing services, the same as those with a high service quality factor. Visitors who appreciated the utility of private vehicles showed a higher tendency to take the exclusive ride, probably because it provides similar utilities to private vehicles.

5.5 Policy Implications

This study provides valuable visions into the contributing factors to the choice between public transportation and ridesourcing services. The results present a more apparent knowledge of the market for ridesourcing and underscore the fundamental attitudes that significantly influence choice behavior. The findings of this paper can help officials to understand transit's potential market in the era of ridesourcing. Individuals with specific characteristics, such as those who live in a neighborhood with highly accessible transit services, low-income individuals, or those with trust issues, probably are willing to continue with transit, unless ridesourcing services become much more attractive in terms of convenience, reliability, and overall quality of service. Transit agencies, therefore, could focus on strategies and policies that improve the quality of transit services to remain competitive. Reducing the headway between buses in highly accessible transit areas (e.g., downtown areas) and offering free-ride or reward programs could be effective plans to persuade these people to continue with public transit.

On the other hand, ridesourcing service providers may attract users through policies or programs that target specific users. Technology-savvy individuals, those who care about their travel time, fans of on-demand services, and users with high-income levels are the potential ridesourcing users. Moreover, reducing ridesourcing fares and strategies addressing traveling with strangers' issues (e.g., security camera installation) may considerably increase ridership of ridesourcing services.

CHAPTER 6

ROLE OF EXPERIENCE IN ADOPTION OF RIDESOURCING

6.1 Introduction

Experience can be described as feelings, assessments, and thoughts that happen during or after an event (Goode et al., 2010). These thoughts and feelings are profoundly interrelated and might be stored as knowledge and information that can be retrieved for evaluations and decision-making in the future (Staats and Gino 2018, Goode et al. 2010, Comblain et al. 2005). Experiences, especially if they are personal, can substantially influence individuals' beliefs and attitudes and bring fundamental behavioral changes. Therefore, people with distinct sets and degrees of experience might perceive objects and ideas in very different ways (Bartle and Harvey 2017, Ribeiro, R. 2014).

Experience has been extensively used in the marketing literature as a decisive factor to describe customers' behavior toward products and services (Rather and Hollebeek 2021, Chen et al. 2018b. Leong et al. 2018, Liébana-Cabanillas et al. 2016). Users with a pleasant experience usually show a higher level of trust and loyalty toward a product or service (Pappas et al., 2014; Füller et al., 2017; Füller et al., 2011). In addition, customers with more experience using a product usually have more positive attitudes and perceptions toward that product (Liébana-Cabanillas et al., 2016; Dill and McNeil, 2013).

With regard to travel behavior, numerous studies provided evidence of how users' experience can impact their attitudes and perceptions toward transportation modes (Namgung and Jun 2019, Franke et al. 2012, Rauh et al. 2015, Bunce et al. 2014, Brown et al. 2003, Dill and McNeil 2013). The findings of these studies indicated that users' experience with a specific mode would substantially affect their intention to the future adoption of that travel mode. Also, it was shown that experienced people were more confident and comfortable using a mode than inexperienced ones or those who have not it at all (Rauh et al. 2015, Namgung and Jun 2019, Franke et al. 2012, Dill and McNeil 2013, Bunce et al. 2014). Although several studies analyzed the impact of experience on travelers' mode choice behavior, the focus of these studies was mainly on traditional travel modes. To the best of the author's knowledge, no study explored the correlation between the experience of using ridesourcing and the future adoption of these services.

Ridesourcing services are the most widely used type of shared mobility services, with tremendous growth in the past few years (Malik et al., 2021; Sikder, 2019). However, according to a Pew Research Center study, by 2018, only 36% of adults had used these services in the United States (Jiang, 2019). The relatively low penetration rate of these services in the U.S. market could be due to several reasons, such as automobile-oriented lifestyle, habitual preferences, and dispersed city structures (Alemi et al. 2019, Jiang, J. 2019, Fung 2016, Asgari and Jin 2020). In addition, the literature showed that individuals' concerns about ridesourcing services, including data privacy, trust issues with strangers, and higher travel time and cost, were considered other critical barriers to adopting these services (Ma et al., 2019; Alemi et al., 2019). These concerns might be related to the lack of experience as most Americans have not used these services at all, and they could be alleviated as the public starts to use these services and become more acquainted with them.

Given the above discussion, this study investigates the role of experience in the mode choice of using ridesourcing services. This study analyzes mode choice behavior between two distinct groups- those who have had the experience of using ridesourcing services and those who have never used them. The main interest was understanding the differences between the two groups regarding their attitudes and perceptions toward ridesourcing services and how these attitudes may influence their mode choice behavior. To understand the mode choice behavior, respondents were asked to choose between traditional modes and ridesourcing services through designed scenarios. Error component nested logit models were applied separately for the two groups, and the results were compared with a focus on the impacts of attitudinal factors.

The following section describes the data used for this study. The next section discusses the model results and policy implications.

6.2 Descriptive Analysis

As discussed earlier, this study focuses on the role of experience in travelers' mobility attitudes and mode choice. For this purpose, the respondents were classified into two groups: those with experience of ridesourcing services (referred to as users in a broad term) and those with no experience of ridesourcing services (referred to as non-users). The survey data include 494 travelers with experience with 6,815 SP scenarios and 593 travelers with no experience with 8,538 SP scenarios. The descriptive statistics for the two groups are presented in Table 6-1. As shown, about 70% of those with experience were younger than 40 years old (Generation Z and Millennials), while this share for those with no experience was less than 33%. This confirms findings of previous studies that younger people were more likely to use on-demand services (Acheampong et al. 2020, Asgari and Jin 2020, Zhen 2015, Rayle et al. 2016, Clewlow and Mishra 2017, Gehrke et al. 2018, Deka and Fei 2019, Sikder 2019, Dias et al. 2017). In addition, individuals with experience were more ethnically diverse and generally had higher education levels than those who had not adopted ridesourcing services.

Table 6-1 Descriptive statistics

			Users with no experience	Users with experience	Census 2010
			Share	**Share**	**Share**
Age	Generation Z (18-24)	16-17	1.0%	1.7%	17.6%
		18-24	7.9%	17.9%	-
	Millennials (25-39)	25-29	9.5%	17.8%	8.5%
		30-34	6.3%	19.0%	8.1%
		35-39	7.9%	12.8%	8.2%
	Generation X (40-54)	40-44	6.6%	3.9%	8.4%
		45-49	6.5%	8.4%	9.2%
		50-54	8.3%	4.7%	9.0%
	More than 55 years old	55-59	11.8%	5.0%	7.9%
		60-64	11.7%	3.2%	6.8%
		65-69	10.6%	3.4%	5.0%
		70-74	6.4%	1.4%	3.7%
		75 and older	5.5%	0.7%	7.5%
Ethnicity	White		81.8%	63.4%	63.7%
	Hispanic		8.1%	20.4%	16.3%
	Asian		1.5%	2.0%	4.9%
	Native American/American Indian		0.2%	0.8%	0.7%
	Black/ African American		8.3%	13.0%	12.2%
	Other		0.2%	0.4%	2.4%
Education	Less than 9th grade		0.5%	0.6%	5.2%
	9th to 12th grade, no diploma		4.0%	3.2%	8.3%
	High school graduate		32.7%	20.2%	28%
	Some college, no degree		32.2%	25.1%	23.7%
	Associate degree		6.6%	7.7%	7.7%
	Bachelor's degree		21.1%	34.6%	17.3%
	Graduate or professional degree		2.9%	8.5%	9.9%
HH income	0-$25K		24.3%	14.0%	23.1%
	$25K -$50K		35.2%	28.9%	23.5%
	$50K-$75K		22.1%	24.9%	17.8%
	$75K-$100K		11.5%	18.8%	12.1%
	$100K-$125K		1.5%	5.5%	13.1%
	$125K-$150K		2.7%	3.0%	-
	$150K-$175K		1.3%	1.4%	5.1%
	$175K-$200K		0.2%	1.8%	-
	$200K and above		1.2%	1.6%	5.3%
Employment status	Full-time		29.8%	59.5%	-
	Part-time		12.5%	14.2%	-
	Unemployed		17.5%	8.7%	-
	Student		3.5%	7.9%	-
	Retired		31.5%	6.1%	-
	Other		5.1%	3.6%	-
Online Shopping Frequency	Never		7.4%	1.4%	-
	Less than once a month		25.0%	10.9%	-
	Once a month		21.2%	13.4%	-
	Once per two weeks		18.5%	16.4%	-
	Once a week		14.5%	22.3%	-
	More than once a week		13.3%	35.6%	-

In view of household income, those with ridesourcing experience had less share in the low-income (less than $50K) groups (43%) compared to those who never used ridesourcing before (60%). This suggests that under-privileged individuals might not have adopted ridesourcing services because of the high cost of these services. Moreover, the under-privileged groups may not have credit cards or smartphones, which could be another reason they have not used ridesourcing services yet.

The share of unemployed and retired respondents was significantly higher for non-users, which could also be linked to their age and income patterns. Also, a higher percentage of those with experience had a driver's license. Interestingly, the majority (58%) of users did online shopping at least once a week, compared to 28% of non-users

6.2.1 *Attitudes and Personal Preferences*

Figure 6-1 shows the pattern in general mobility preferences for users and non-users. It can be observed that non-users were more likely to enjoy driving than users, which might help explain why they have not used ridesourcing services yet. On the other hand, users were more likely to choose the fastest and easiest travel mode and care about travel mode functionality. This implies that users are less likely to be attached to driving private vehicles and more likely to focus on the utility of the mode options in terms of travel time, convenience, and functionality.

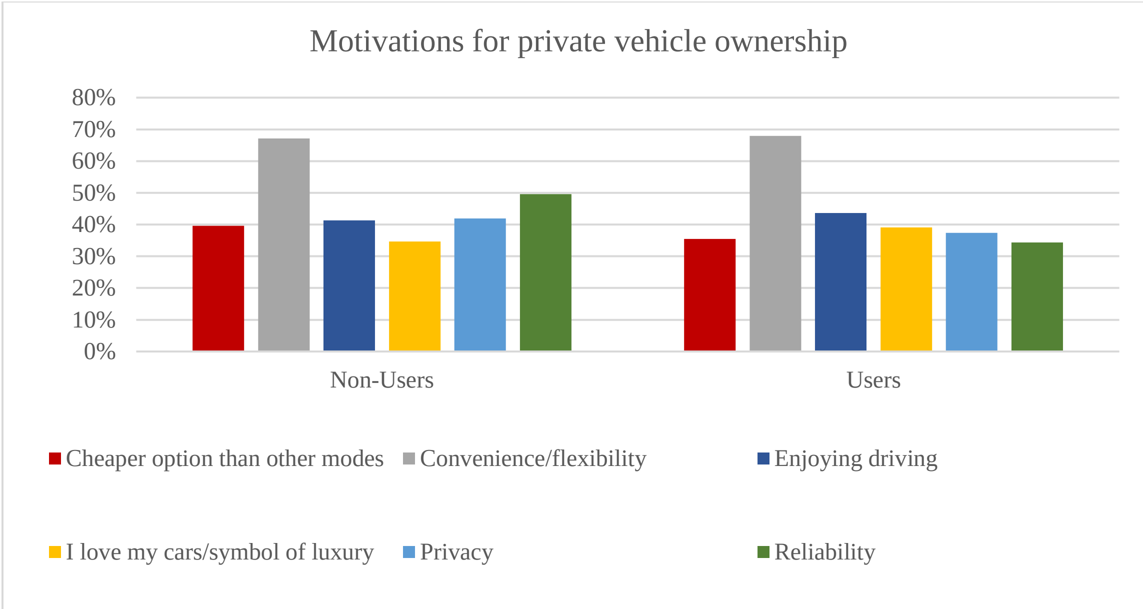
Figure 6-1 also shows that a higher percentage of users preferred the cheapest travel option and believed that shared mobility reduced their expenses, indicating that travel costs could motivate users to adopt ridesourcing services. On the other hand, non-users were less likely to believe that shared mobility could improve quality of life, which could be connected to the lack of experience in using these services. Furthermore, as expected, a higher proportion of non-users had trust issues with traveling strangers, and they were more comfortable traveling alone, which is consistent with the findings of literature that trust issues may be a critical factor preventing people from adopting on-demand services (Alemi et al. 2019). Users were also more likely to be engaged in online activities, use smartphones regularly, and be interested in learning and using new technologies.

When it comes to the perceived benefits and concerns of shared mobility, Figure 6-2 shows that users were more likely to consider less driving stress, multitasking, and on-demand service as the top benefits of ridesourcing. On the other hand, non-users were more likely to consider cost-effectiveness as the top benefit. Data privacy was the top concern for non-users, while higher travel time due to multiple pickups was the top concern for those with ridesourcing experiences. The general ranking patterns were similar between users and non-users, with slightly higher shares of non-users with more concerns about unreasonable fares, complicated service request procedures, and trust issues with machine/technology.

In terms of motivations for and against private vehicle ownership, the general patterns were similar between users and non-users, except that non-users were more likely to emphasize the reliability associated with private vehicles compared to their counterparts, as shown in Figure 6-3. When asked about reasons for not owning/leasing a private vehicle or not planning to do so in the near future, Figure 6-3 shows that a much higher share of users stated operational and maintenance cost as the reason. They were also more likely to prefer walking and alternative modes, having short trips, and live/work in areas with parking issues. This could be associated with their age and lifestyle preferences. The users were generally younger and might be less attached to private vehicles and more open to alternative modes.

Figure 6-1 General mobility preferences for users and non-users

Figure 6-2 Perceived benefits and concerns of shared mobility for users and non-users



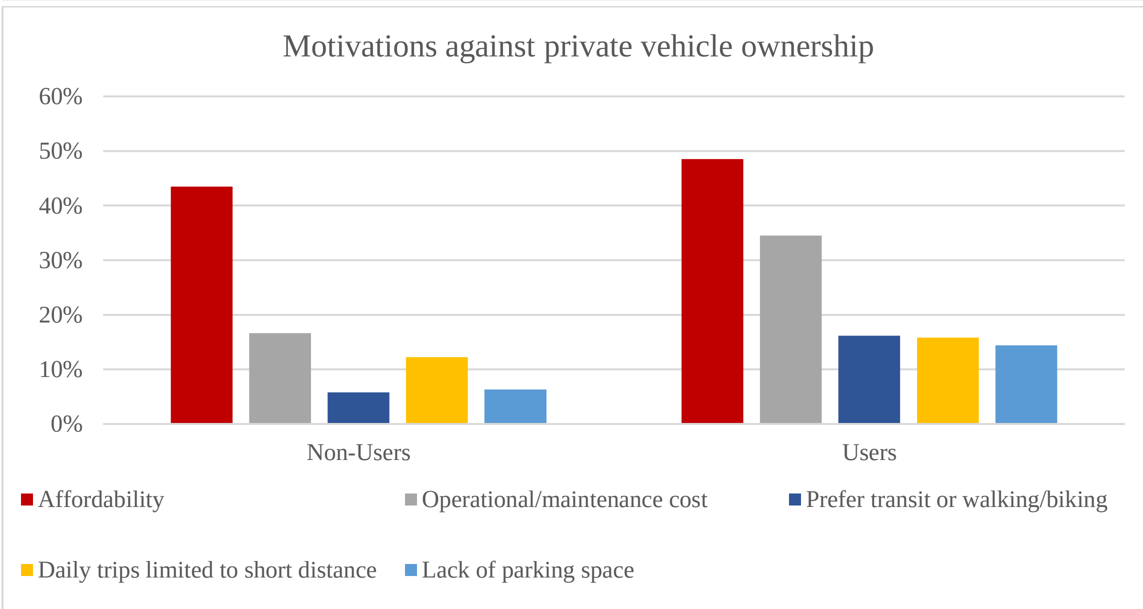


Figure 6-3 Motivations for and against private vehicle ownership for users and non-users

In summary, those who have ridesourcing experience and those without experiences exhibited different mobility preferences, perceptions toward shared mobility, and underlying logic regarding vehicle ownership. These findings provide further insights for understanding users' needs and preferences and the potential market for ridesourcing.

6.3 Results

The results are presented in two different parts. First, the results of factor analysis are discussed. Then, the results of the error component nested logit will be presented for users and non-users.

6.3.1 *Factor Analysis Results*

The same dataset was used for this study and the previous study (role of attitudes in transit and visitors' mode choice of ridesourcing); therefore, the factor analysis results are identical. To avoid duplication, the results of factor analysis on attitudinal factors are not presented in this section. However, it should be noted that this study did not consider attitudinal statements related to the motivations for riding AVs and the most desired AV features. Besides the attitudinal factors, variables related to respondents' mode choice for daily activities as well as occasional situations were also considered for factor analysis. The categories that were considered are as follows:

- Regular travel mode: respondents were asked to report their primary travel mode for regular trips.
- Mode usage: respondents were asked to select all transportation modes they have used in the past three months for commute, shopping, and social trips.
- Mode preference: respondents were asked to select one dominant travel mode for how they would typically travel under different situations, including:
    - Running late
    - Be somewhere at a specific time (e.g., airport)
    - Unavailability of a reliable vehicle
    - New to the area
    - High parking costs or limited parking

The factor analysis results for mode dependency are presented in Table 6-2. T-tests results indicated significant differences between the two groups.

Table 6-2 Derived mode-dependency factors

	Factors						
	1	2	3	4	5	6	7
Regular travel mode-PT	-0.220	0.022	0.027	0.137	0.747	-0.059	-0.127
Regular travel mode-PV driver	0.818	0.042	0.012	-0.161	-0.046	-0.143	-0.225
Regular travel mode-PV passenger	-0.711	-0.068	-0.038	0.063	-0.281	-0.033	0.472
Regular travel mode-Ridesourcing	-0.128	0.026	0.020	0.135	-0.174	0.621	-0.257
Commute mode- PT	-0.071	0.001	0.016	0.334	0.563	0.323	0.123
Commute mode- PV driver	0.647	0.072	-0.122	-0.006	-0.204	-0.022	0.185
Commute mode- PV passenger	-0.096	0.055	0.205	0.039	0.069	0.038	0.711
Commute mode- Ridesourcing	0.034	0.214	-0.013	-0.098	0.142	0.618	0.221
Shopping trip mode- PT	-0.189	0.070	-0.055	0.056	0.629	0.110	0.090
Shopping trip mode- PV driver	0.736	0.026	-0.198	-0.064	-0.155	-0.112	0.103
Shopping trip mode- PV passenger	-0.028	0.029	0.407	0.060	-0.044	-0.009	0.546
Shopping trip mode- Ridesourcing	-0.035	0.196	-0.019	-0.099	0.172	0.661	0.208
Social trip mode- PT	-0.049	0.046	-0.048	0.214	0.329	0.241	0.222
Social trip mode- PV driver	0.727	-0.073	-0.155	-0.097	-0.112	-0.047	0.094
Social trip mode- Ridesourcing	0.077	0.572	-0.076	-0.058	0.088	0.352	0.243
Do not have a reliable PV access-PT	-0.059	-0.045	-0.040	0.675	0.337	0.060	0.059
Do not have a reliable PV access-RS	0.031	0.737	-0.034	-0.067	-0.098	0.098	0.008
Have parking issues- PT	-0.008	-0.018	-0.017	0.706	0.087	-0.063	0.029
Have parking issues- PV driver	0.206	-0.381	-0.583	-0.413	-0.041	-0.045	-0.044
Have parking issues- PV passenger	-0.086	-0.221	0.706	-0.156	-0.092	0.037	0.092
Have parking issues- Ridesourcing	0.054	0.822	0.001	-0.068	0.004	-0.012	0.024
New to area- Public transit	-0.140	-0.032	-0.074	0.680	0.024	0.047	-0.023
New to area- PV driver	0.317	-0.329	-0.593	-0.344	-0.116	-0.050	-0.075
New to area- PV passenger	-0.100	-0.151	0.775	-0.104	0.026	-0.039	0.098
New to area- Ridesourcing	-0.001	0.754	-0.057	-0.011	0.122	0.094	0.056
Need to be on-time- PT	-0.140	-0.025	-0.020	0.177	0.041	0.005	-0.044
Need to be on-time- PV driver	0.467	-0.271	-0.440	-0.160	-0.043	-0.093	0.038
Need to be on-time- PV passenger	-0.275	-0.042	0.607	-0.124	-0.007	-0.109	0.186
Need to be on-time- Ridesourcing	-0.054	0.601	-0.009	0.134	-0.022	0.193	-0.153
Running late- PT	-0.116	-0.059	-0.064	0.173	0.312	-0.061	-0.057
Running late- PV driver	0.713	-0.017	-0.250	-0.099	-0.105	-0.175	-0.061
Running late- PV passenger	-0.476	-0.050	0.397	-0.096	-0.126	-0.041	0.299
Running late- Ridesourcing	-0.165	0.186	-0.022	0.154	0.060	0.515	-0.177
Have driver license	0.605	0.010	-0.143	0.020	-0.241	0.096	-0.123

Each derived latent factor was labeled based on the associated indicators. The results are shown in Table 6-3. A brief description of each factor is provided for each factor. The statistical results are also presented, including the percentage of variance explained, the cumulative percentage of variance explained, and the Eigenvalue.

Table 6-3 Statistical results for mode-dependency factors

Category	Factor Name	Description	% of var.	Cumulative % of var.	Eigen value
Mode-dependency	Regular private vehicle drivers	Uses private vehicles as a driver regularly, for all purposes, and under different conditions. This factor is negatively associated with being a passenger. This indicates high usage and dependency on private vehicles.	13.046	13.046	4.436
	Occasional ridesourcing users	Uses ridesourcing for social trips or under specific conditions. Indicates occasional use of ridesourcing services.	8.931	21.977	3.037
	Occasional private vehicle passengers	Prefers to be the passenger (drove by other people or carpool) under certain situations but not regularly.	8.557	30.534	2.909
	Occasional transit riders	Prefers to use transit under certain situations (such as with no vehicle access, having parking issues, or being new to an area), but on a regular basis.	6.416	36.951	2.181
	Regular transit riders	Uses transit regularly for commute and shopping activities.	5.863	42.813	1.993
	Regular ridesourcing users	Uses ridesourcing regularly for commute and shopping activities.	5.732	48.546	1.949
	Regular private vehicle passengers	Ride with others regularly for commute and shopping activities.	4.797	53.343	1.631

6.3.2 *Model Results*

Separate error component nested logit models were developed for those with and without ridesourcing experience. The results are presented in Table 6-4. The alternative choices include one conventional mode (either driver, passenger, or transit depending on their regular trip mode) and two ridesourcing modes (exclusive ride and shared ride). The contributing factors included attitudinal variables, sociodemographic attributes, and alternative attributes (travel time, travel cost, driver availability for the passengers, and level of multitasking for the other modes).

Table 6-4 Model results for travelers with and without ridesourcing experience

Users	**Users with ridesourcing experience**	**Users without ridesourcing experience**
Variable	**Coefficient**	**Coefficient**
Constant		
Exclusive rides	0.139***	1.17***
Shared rides	-0.004	0.945***

Users	Users with ridesourcing experience	Users without ridesourcing experience
Private vehicle/public transit (Base)	-	-
Alternative-specific variables		
High availability (Specific to private vehicle passenger)	0.65***	0.711***
Nest coefficient		
Ridesourcing nest coefficient	0.346***	0.701***
Attitudinal factors		
General mobility preferences		
Pro-technology (Specific to exclusive rides)	0.24***	0.0985***
Service quality (Specific to shared rides)	-	0.332***
Travel with strangers (Specific to shared rides)	-	-0.323***
Joy of driving (Specific to exclusive rides)	-	-0.101***
Perceived benefits and concerns of shared mobility		
Trust and data privacy concerns (Specific to exclusive rides)	0.145***	-
Trust and data privacy concerns (Specific to shared rides)	0.483***	-
Cost-effectiveness (Specific to exclusive rides)	-0.107**	-
Cost-effectiveness (Specific to shared rides)	0.123**	-
Pro-on-demand service (Specific to exclusive rides)	-	0.268***
Travel time concerns (Specific to exclusive rides)	-	-0.107**
Private vehicle ownership		
Pro-private vehicle (Specific to exclusive rides)	-	-0.231***
Pro-alternative mode (Specific to shared rides)	0.14***	-
Mode-dependency		
Regular PV drivers (Specific to exclusive rides)	0.218***	-
Regular PV drivers (Specific to shared rides)	-0.21***	-
Regular PV passengers (Specific to exclusive rides)	-	0.134***
Irregular RS users (Specific to exclusive rides)	0.176***	-
Irregular RS users (Specific to shared rides)	0.277***	-
Regular RS users (Specific to shared rides)	0.148***	
Irregular transit riders (Specific to exclusive rides)	-	-0.115***
Irregular transit riders (Specific to exclusive rides)	0.179***	-0.101***
Regular transit riders (Specific to exclusive rides)	-	-0.182***
Regular transit riders (Specific to shared rides)	0.959***	-
Socioeconomic and demographic attributes		
Age (More than 55 years old)		
Generation Z (Specific to exclusive rides)	-	0.626***
Generation Z (Specific to shared rides)	-	0.499***
Millennials (Specific to shared rides)	0.475***	0.437***
Generation X (Specific to exclusive rides)	-0.378***	-
Generation X (Specific to shared rides)	-	-0.285***
HH Income (Base $25K-$50K)		
$50K-$75K (Specific to shared rides)	-	-0.295***
$150K-$175K (Specific to shared rides)	-	-1.08***
$175K-$200K (Specific to exclusive rides)	1.01***	-
More than $200K (Specific to exclusive rides)	-	0.804***
Employment (Base: Full-time)		
Unemployed (Specific to shared rides)	-0.367**	-
Part-time (Specific to exclusive rides)	-	-0.364***
Retired (Specific to shared rides)	-	-0.21***
Ethnicity (Base: White)		

Users	Users with ridesourcing experience	Users without ridesourcing experience
Black (Specific to exclusive rides)	-	0.477***
Education (Base: Some college, no degree)		
High school graduate (Specific to exclusive rides)	-0.484***	-
Associate degree (Specific to exclusive rides)	-	-0.566***
Bachelor (Specific to exclusive rides)	-	-0.52***
Online shopping frequency (Base: Once a week)		
Less than once a month (Specific to exclusive rides)		-0.188***
Less than once a month (Specific to shared rides)		-0.274***
Once a month (Specific to exclusive rides)	-0.544***	
More than once a week (Specific to exclusive rides)		0.325***
More than once a week (Specific to shared rides)	0.249**	
Random parameters		
Travel time		
Mean	-2.1***	-2.41***
Standard deviation	1.5***	1.65***
Travel cost		
Mean	-1.45***	-1.32***
Standard deviation	2.5***	2.21***
Number of observations	Respondents =494, Observations=6,815	Respondents=593 Observations=8,538

***** Significant at 1% Level, ** Significant at 5% Level, * Significant at 10%**

For both groups, travel time and travel cost had significant mean and standard deviations, suggesting the existence of heterogeneity. High driver availability (i.e., there is always a driver available to drive the respondent), an alternative-specific attribute only for the passenger mode, showed a positive impact in both models. Furthermore, for both groups, the significant positive value of the nest coefficient indicated a positive correlation between shared and exclusive ride services.

6.3.2.1 General Mobility Preferences

Looking into general mobility preferences, the only attitude that showed similar impacts for those with and without ridesourcing experiences is pro-technology, which increased the probability of choosing exclusive rides. This positive impact is consistent with the literature's findings (Acheampong et al. 2020, Simmons 2018, Dias et al. 2017, Alemi et al. 2018). Moreover, the results show that non-users who focus on the service quality of travel modes (such as travel time, travel cost, convenience) and have positive views toward shared mobility were more likely to use shared rides over traditional modes. On the other hand, as expected, non-users with trust issues traveling with strangers and those who enjoy driving were less likely to use ridesourcing modes, consistent with the literature (Ma et al. 2019, Alemi et al. 2019). Interestingly, these attitudes did not affect the mode choice behavior of those who already have ridesourcing experience.

6.3.2.2 Perceived Benefits and Concerns of Shared Mobility

Regarding perceptions of ridesourcing services, different attitudes were at play for individuals with and without ridesourcing experience. For those who have used ridesourcing services, trust and privacy concerns had a positive impact on the use of exclusive and shared ride services. This contradicts the finding of Lavieri and Bhat (2019), which identified privacy concerns as one of the main barriers discouraging people from using ridesourcing services. One potential reason might be their experience with ridesourcing services, which could alleviate users' concerns about data privacy and trust issues with the technology. People with ridesourcing experience may become more inclined to choose these services over traditional modes as they already have experience with these services. The literature showed that the experience of using a mode played a significant role in reducing individuals' concerns about that mode (Rauh et al., 2015; Franke et al., 2012; Bunce et al., 2014).

Moreover, for users with ridesourcing experience, cost-effectiveness had a positive impact on the use of shared rides, but it had a negative impact on the use of exclusive rides. This shows that shared-ride services have established their market among those who appreciate the cost-effectiveness of travel modes. In contrast, exclusive-ride services (even at the reduced fare level) might still not be perceived as a cost-effective option. For those who have not used ridesourcing services, pro-on-demand service showed a positive impact on the use of exclusive rides. This indicates that on-demand service is an attractive feature for non-users, and this might be a potential growth area for ridesourcing services. Interestingly, travel time concerns decreased the probability of choosing exclusive rides over traditional modes for non-users. Perhaps this concern can be addressed when non-users have actual experience with ridesourcing services and get better ideas on the waiting time of the services. As it shows, this concern did not show any impact for those who have used the services before.

6.3.2.1 Private Vehicle Ownership

When it comes to reasons for and against car ownership, the results highlighted the different underlying factors affecting the mode choice decisions for those with and without the experience. Particularly, non-users who were pro-private vehicles were less likely to choose exclusive rides. While users who were pro-alternative modes (those who prefer transit, walking, or biking over private cars or those with short-distance daily trips) preferred shared rides over traditional modes.

6.3.2.2 Mode Dependency

Noteworthy patterns were observed for the mode-dependency factors. For users, regular private vehicle drivers, defined as licensed drivers who frequently use private vehicles for various trip purposes and under different circumstances, showed a positive inclination toward exclusive rides and a negative propensity toward shared ride services.

It can be inferred that users with ridesourcing experiences find ridesourcing a suitable alternative to their regular mode (i.e., driving). However, they were less likely to choose shared rides probably because they prefer the utility of exclusive rides, such as convenience, flexibility, and privacy, similar to those provided by a private vehicle. For those who have not experienced ridesourcing services, regular passengers showed a positive tendency toward exclusive rides, indicating a potential market for ridesourcing services.

Model results also showed that transit riders and ridesourcing users, whether regularly or occasionally, were more likely to choose ridesourcing services (especially shared rides) over their regular modes when they already had experience with ridesourcing services. Parking expenses and time, transit access/egress times, unfamiliarity with the area, and lower cost with shared rides could be the main motivations to choose ridesourcing services. This also indicates a potential growth area for ridesourcing services when they provide competitive prices (the SP scenarios adopted reduced costs than the current fares in the market). On the other hand, transit riders (both regular and occasional users) were less likely to adopt exclusive ridesourcing if they have not used them before.

6.3.2.3 Socioeconomic and Demographic Attributes

In view of age, similar impacts were observed between the two groups. Millennials showed a positive tendency toward shared rides, while Generation Xers were less likely to use ridesourcing services, whether they had experience with ridesourcing or not. Interestingly, Generation Zers (18-24 years old) showed a positive inclination to use ridesourcing services even if they have not used them before. This might indicate that this generation is more open to using new services and products. Previous studies also showed that younger people are more inclined to use shared rides due to lifestyle preferences, environmental concerns, and lower travel costs (Acheampong et al. 2020, Asgari and Jin 2020, Zhen 2015, Rayle et al. 2016, Clewlow and Mishra 2017, Gehrke et al. 2018, Deka and Fei 2019, Sikder 2019, Dias et al. 2017).

Looking at the impacts of household income on mode choice behavior, as expected, for both users and non-users, people with high-income levels ($175K and above) were more likely to choose exclusive rides, which is consistent with the findings of previous studies (Acheampong et al. 2020, Asgari and Jin 2020, Clewlow and Mishra 2017, Deka and Fei 2019, Dias et al. 2017). For those who had not used ridesourcing services, medium-income individuals ($50K-$75K) and high-income ($150K-$175K) individuals were less likely to choose shared rides over traditional modes. The former group might not have used ridesourcing services due to cost considerations, which discourages them from using these services unless they become more affordable. On the other hand, the latter group might not be interested in using the shared rides since they do not see them as suitable substitutes for their current mode, especially private vehicles. The lack of experience probably plays a role in this reluctance, as for the other group (individuals with experience), a comparable income level ($175K-$200K) had a positive impact on the adoption of ridesourcing services.

In terms of employment status, unemployed individuals were less likely to choose shared rides for users. Similarly, for non-users, part-time workers and retired individuals were less likely to choose ridesourcing services over conventional modes. As expected, users with a lower education level (high school graduate) showed a negative propensity toward exclusive rides. However, among those without ridesourcing experience, people with relatively high education levels (associate and bachelor's degree) were less likely to choose ridesourcing services. This finding contradicts the findings of previous studies suggesting that high education-level encourage the use of ridesourcing modes (Lavieri et al. 2018, Clewlow and Mishra 2017, Smith 2016, Dias et al. 2017). The lack of experience may have contributed to this negative association. Looking at online shopping frequency as an indirect indicator for technology use/acceptance, the results are similar between the two groups. Generally, people with less frequent online shopping behavior (once a month or less) also showed a negative tendency to adopt ridesourcing services. On the other hand, higher online shopping frequency was associated with a positive inclination toward ridesourcing services.

6.4 Discussion

Generally, model results showed distinct underlying factors contributing to the mode choice decisions for people with and without ridesourcing experience. Although pro-technology individuals increased the probability of choosing exclusive rides for both groups, other factors only affected only one of the groups. For non-users, service quality encouraged the adoption of shared rides, indicating that shared rides are a viable option in terms of travel time, travel cost, convenience, and functionality for those who care about the level of service of their modes. On the other hand, travel with strangers acted as an inhibitor for non-users to adopt shared rides. Similarly, travel time concerns had negative effects on the choice of exclusive rides for non-users. Potentially, these concerns could be addressed once they have experienced the services since these factors did not influence the choice of those who had ridesourcing experiences.

In addition, the joy of driving and the preferences for private vehicles due to its convenience, flexibility, privacy, and reliability had negative impacts on the choice of ridesourcing services for those without ridesourcing experiences, even though both groups had similar attitudes toward these two aspects (ash shown in Figure 6-1 and Figure 6-3). Car-dependent people usually overestimate private vehicles' utility and can be highly uninterested in using other modes. This reluctance could be why this group has not used ridesourcing so far. This finding is confirmed by concerns of non-users about the higher travel time of exclusive services. Although these services could eliminate parking time and cost, those who have not used them may not be aware of these features and be more concerned about waiting time. Interestingly, non-users were generally less likely to appreciate the on-demand service feature of shared mobility than users (as shown in Figure 6-2). However, non-users who were fans of on-demand service were more likely to use exclusive rides than conventional mode, which might underline another potential market for ridesourcing services. For those who already had experience with ridesourcing, cost-effectiveness and pro-alternative modes showed positive impacts on the choice of using shared rides. This confirmed the benefits of ridesourcing service and its attractiveness among people who care about the cost-effectiveness of transportation modes and those who prefer modes other than private vehicles.

Interestingly, data privacy concerns and trust issues with technologies did not affect the choice for non-users, even though they were more likely to show these concerns than users (as shown in Figure 6-2). On the other hand, users who had trust and privacy concerns (or less concerned about unreasonable fares and complicated service request procedures) were more likely to choose ridesourcing modes, implying that having experienced the services could alleviate their privacy concerns.

Mode dependency also exhibited significant impacts on the choice of mode for both groups. In general, transit users and ridesourcing users were the potential market for ridesourcing services (especially shared rides) when they already had the experience. In contrast, transit users who had not used ridesourcing services before were hard to be convinced to switch from their regular mode. Exposing this group to ridesourcing services or providing more competitive prices might change their opinions and choice behavior.

Regular private vehicle drivers who had used ridesourcing services showed a positive inclination to use exclusive rides rather than driving. This finding implies that ridesourcing services (when provided at affordable fare levels) could potentially impact private vehicle usage in the longer term, especially among younger generations, as they are generally less attached to private vehicles. Regular passengers also showed a positive tendency toward exclusive rides, indicating a new potential market for ridesourcing services. For this group, being dependent on others for their daily activities might not be convenient or time-efficient, so they probably would be attracted to regular use of ridesourcing services if they find them as travel options with desirable utility.

6.5 Policy Implications

Trust issues with traveling with strangers did not play significant roles in the mode choice decisions for those with ridesourcing experience. In contrast, for people without ridesourcing experience, trust issues with strangers discouraged the adoption of shared rides. The strict hiring process for drivers (checking the criminal background, mental health, and driving skills), installing security cameras in ridesourcing vehicles, mandatory educational programs focusing on driving abilities and communication skills, and supportive customer service could be recommended to address these concerns. Informing the public about these applied strategies could encourage more people to adopt ridesourcing services.

Moreover, although concerns about higher travel time of ridesourcing (due to waiting time and multiple pickups) did not affect the mode choice behavior of users, it significantly reduced the probability of using these services for non-users. Publicity campaigns could focus on promoting the convenience of ridesourcing trips (such as the ability to book in advance, on-demand aspect of these services, providing door-to-door trips, and multitasking) and its benefits in reducing travel time (e.g., car parking time, transit access/ egress and waiting time) to persuade individuals with this attitude to switch from their current mode to ridesourcing services.

Interestingly, non-users who care about the service quality of their travel mode were more likely to choose shared rides over traditional modes. Ridesourcing companies could also benefit from marketing strategies in this matter. These campaigns could emphasize the ridesourcing advantages in avoiding driving in challenging conditions (e.g., traffic jams, peak-hour, driving under the influence (DUI)), reducing travel expenses (parking, toll, and fuel expenses), and providing multitasking opportunities. Moreover, the joy of driving and the preferences for private vehicles acted as a barrier to adopting ridesourcing modes only for those who had never used ridesourcing services. This attachment and auto-dependency could be addressed through promotion strategies and free-trial programs. Highly car-dependent individuals usually might be very hesitant to use other modes. Until ridesourcing companies develop policies and plan to encourage highly-car-dependent individuals to experience their services, these users may not change their perceptions toward these services. These policies could include offering free rides and deep discounts, reducing fares, and providing reward programs.

The connections observed between mode dependency and choice of mode also provide valuable information that could help better design services and develop promotion strategies. Particularly, transit users who had used ridesourcing services showed high potential to switch to ridesourcing modes, given that the services are provided at competitive price levels. This finding could help both transit officials and ridesourcing companies to better identify their potential market and focus on addressing their needs. The integration of public transit and ridesourcing can be a powerful strategy helping both public agencies and ridesourcing companies.

CHAPTER 7

GENERATIONAL EFFECTS ON ADOPTION OF RIDESOURCING

7.1 Introduction

A generation is a peer group identified by its demographic characteristics as well as its historic life events within a given period (Borges et al. 2006). While each generation member has unique features, a generational cohort is likely to possess shared values and behaviors due to similar significant events, social influences, and technological experiences (Borges et al. 2006, Fernandez, 2009). These generational characteristics may affect the attitudes, lifestyles, and priorities of the cohort (Rogler 2002).

As the largest adult group in the United States (Fry 2016, Rainer and Rainer, 2011), Millennials are defined as those born between 1981 and 2000. Millennials have distinct characteristics, values, and attitudes that set them apart from the preceding generations, particularly Generation Xers, another large cohort composed of people born between 1965 and 1980 (Fishman 2016, Borges et al. 2006, Alemi et al. 2019). Compared to Generation Xers, Millennials are more confident and idealistic, more socially active, better educated, and more racially diverse (Reisenwitz and Iyer 2009, Howe and Strauss 2000).

Millennials also show different attitudes and behaviors toward travel modes compared to Generation Xers (Blumenberg et al. 2016, Kuhnimhof et al. 2012). They have higher preferences for walking and transit than the previous generations (Blumenberg et al. 2016, Kuhnimhof et al. 2012). They generally are less likely to make substantial investments in private vehicles (Thompson and Weissmann 2012). This generation has a lower driver's license and car ownership rate and makes fewer trips with lower vehicle miles traveled (Polzin et al. 2014, Sivak and Schoettle, 2011, Delbosc and Currie, 2013, Blumenberg et al. 2016).

Moreover, Millennials hold an in-depth understanding and intuitive knowledge of technology usage (Coombes, B. 2009); therefore, they were referred to as “digital natives” in the literature (Prensky, 2001). Millennials' open-to-innovation and technology-embracing attitudes presented them as early adopters and stable customers of shared mobility services, especially ridesourcing. The literature showed that young people were more likely to adopt ridesourcing services and have a considerably higher frequency of ridesourcing usage than older adults (Acheampong et al. 2020, Asgari and Jin 2020, Zhen 2015, Rayle et al. 2016, Clewlow and Mishra 2017, Circella et al. 2016, Gehrke et al. 2018, Deka and Fei 2019, Sikder 2019, Dias et al. 2017).

Despite the general agreement on the differences between Millennials and Generation Xers in view of their travel patterns, there is limited knowledge on the factors that cause these differences and the mechanism of their influences on travel behavior. Recent studies showed that only 10-25% of the differences in travel patterns between Millennials and Generation Xers could be explained by the demographic shifts of the Millennials, and about 35-50% of the differences could be explained by attitudinal changes and the rise of telecommunications and virtual mobility (i.e., online shopping, social media) (McDonald 2015, Rahimi et al. 2020a). Motivated by the above issue, this section investigates the differences between Millennials and Generation Xers, focusing on their potential differences in attitudes and mobility preferences and how these factors may contribute to their inclinations toward ridesourcing services.

Concentrating on the potential market of ridesourcing, the distinctive contribution of this study is twofold. First, this study investigates the choice behavior of Millennials and Generation Xers to identify whether and how their SED characteristics and mobility profiles may lead to different behavior toward the ridesourcing market. Second, as discussed above, Millennials and Generation Xers possess different attitudes that significantly impact their mode choice behavior. Hence, in this study, the attitudes and preferences of these generations toward emerging and traditional modes and their influence on the inclination toward ridesourcing services were explored.

Error component multinomial logit (MNL) and nested logit (NL) models were developed for both Generation Xers and Millennials, and their performances were compared. The results of error component NL models were presented in terms of the significant contributing factors. The findings of this study are expected to help better understand the generational differences in terms of their views toward mobility options and provide insights into the potential market of ridesourcing services. This knowledge may help us improve the design of shared mobility services and suggest policies to serve potential users.

7.2 Descriptive Analysis

This section compares Millennials' and Generation Xers' socioeconomic and demographic characteristics, trips attributes, and attitudinal factors. The dataset consists of 210 Generation Xers with 2,989 scenarios and 545 Millennials with 7,496 scenarios. Table 7-1 shows the descriptive statistics for Generation Xers and Millennials. As shown in Table 7-1, Millennials had a higher proportion of female users, they were more ethnically diverse, and they had a lower percentage of unemployed and retired users than Generation Xers. Generation Xer had higher proportions (58.7%) of lower-income groups (less than $50K) than Millennials (47.1%). Moreover, the number of household drivers was generally higher for Millennials than Generation Xers.

Table 7-1 Descriptive statistics

Attribute		Generation Xers	Millennials	Census 2010
		Share	Share	Share
Gender	Male	57.2%	51.2%	49.2%
	Female	42.8%	48.8%	50.8%
Ethnicity	White	77.0%	62.5%	63.7%
	Hispanic	13.9%	18.7%	16.3%
	Asian	1.5%	2.8%	4.9%
	Native American/American Indian	0.0%	0.7%	0.7%
	Black/ African American	7.6%	14.9%	12.2%
	Other	0.0%	0.4%	2.4%
Employment status	Full-time	52.1%	54.2%	NA
	Part-time	10.8%	15.9%	NA
	Unemployed	18.4%	16.0%	NA
	Student	0.0%	10.0%	NA
	Retired	11.0%	0.4%	NA
	Others	7.6%	3.4%	NA
Education	Less than 9th grade	0.5%	0.9%	5.2%
	9th to 12th grade, no diploma	1.5%	5.7%	8.3%
	High school graduate	26.2%	25.2%	28%
	Some college, no degree	32.0%	25.6%	23.7%
	Associate degree	6.6%	8.0%	7.7%
	Bachelor's degree	30.4%	27.6%	17.3%
	Graduate or professional degree	2.8%	7.0%	9.9%
HH income	0-$25K	26.7%	17.5%	23.1%
	$25K-$50K	32.0%	29.6%	23.5%
	$50K-$75K	21.6%	24.3%	17.8%
	$75K-$100K	11.8%	17.2%	12.1%
	$100K-$125K	1.8%	4.6%	13.1%
	$125K-$150K	2.5%	2.3%	-
	$150K-$175K	2.5%	1.7%	5.1%
	$175K-$200K	0.0%	1.6%	-
	More than $200K	1.0%	1.2%	5.3%
HH Drivers	0	5.4%	4.4%	-
	1	37.8%	30.9%	-
	2	45.3%	47.4%	-
	3	9.6%	12.3%	-
	4	2.0%	4.5%	-
	5 or more	0.0%	0.5%	-
Online Shopping Frequency	Never	3.6%	3.6%	-
	Less than once a month	23.2%	11.1%	-
	Once a month	18.1%	15.0%	-
	Once per two weeks	22.3%	17.4%	-
	Once a week	12.1%	22.3%	-
	More than once a week	20.6%	30.5%	-

7.2.1 *Attitudes and Personal Preferences*

The following figures illuminate the observed patterns in attitudes and preferences for Generation Xers and Millennials.

Figure 7-1 illustrates the pattern of general mobility attitudes for Generation Xers and Millennials. A higher proportion of Millennials believed that shared mobility increases their living quality and could help them save on their expenses. Millennials were more likely to prefer multitasking during their trips. Also, Millennials showed a higher interest in learning new technologies, used smartphone apps more regularly, and were more engaged in online activities.

Figure 7-2 presents a summary of the perceived benefits and concerns of shared mobility. In view of the benefits of shared mobility services, Millennials were less likely to consider the lower level of driving stress as a benefit of shared mobility, while they were more likely to choose multitasking as one of shared mobility’s main advantages. Data privacy was the primary concern for both generations, especially for Generation Xers. On the other hand, unreasonable fares and complicated service request procedures were more likely to concern Generation Xers than Millennials.

Figure 7-3 summarizes the observed patterns in respondents’ motivations for and against private vehicle ownership. For both generations, private vehicles' convenience and flexibility and enjoy driving were the main reasons to own a private vehicle. In terms of reasons for not owning a private vehicle, both generations showed similar patterns. Affordability and operational/maintenance costs were the two primary reasons for not owning a vehicle. Notably, a significantly higher percentage of Millennials considered cost constraints as a barrier to own a vehicle. This might imply that Millennials are unwilling to make considerable investments in private vehicles, which may facilitate an environmentally friendly and sustainable transportation system in the future. Also, Millennials showed a higher likelihood of not owning a vehicle due to their daily trips in short distances. This is also consistent with the literature (Thompson and Weissmann 2012, Polzin et al. 2014), which indicated that the younger generations preferred urban lifestyle with more options for transit and non-motorized modes and proximity to daily activities.

Figure 7-4 summarizes the motivations for and desired features of AV. These sets of questions consider both the driving assistance technologies as well as autonomous features. Again, respondents could select multiple options. In view of motivations, lower levels of driving stress and safety improvement were the two main reasons for both generations. On the other hand, Millennials were more likely to consider better technology and multitasking as reasons to drive AVs. However, no need for parking and mobility for non-drivers were stronger motivations for Generation Xers. Both generations selected collision avoidance and improved fuel efficiency as the most desired features as their desired AV features. A higher percentage of Millennials selected self-driving and fully connected features compared to Generation

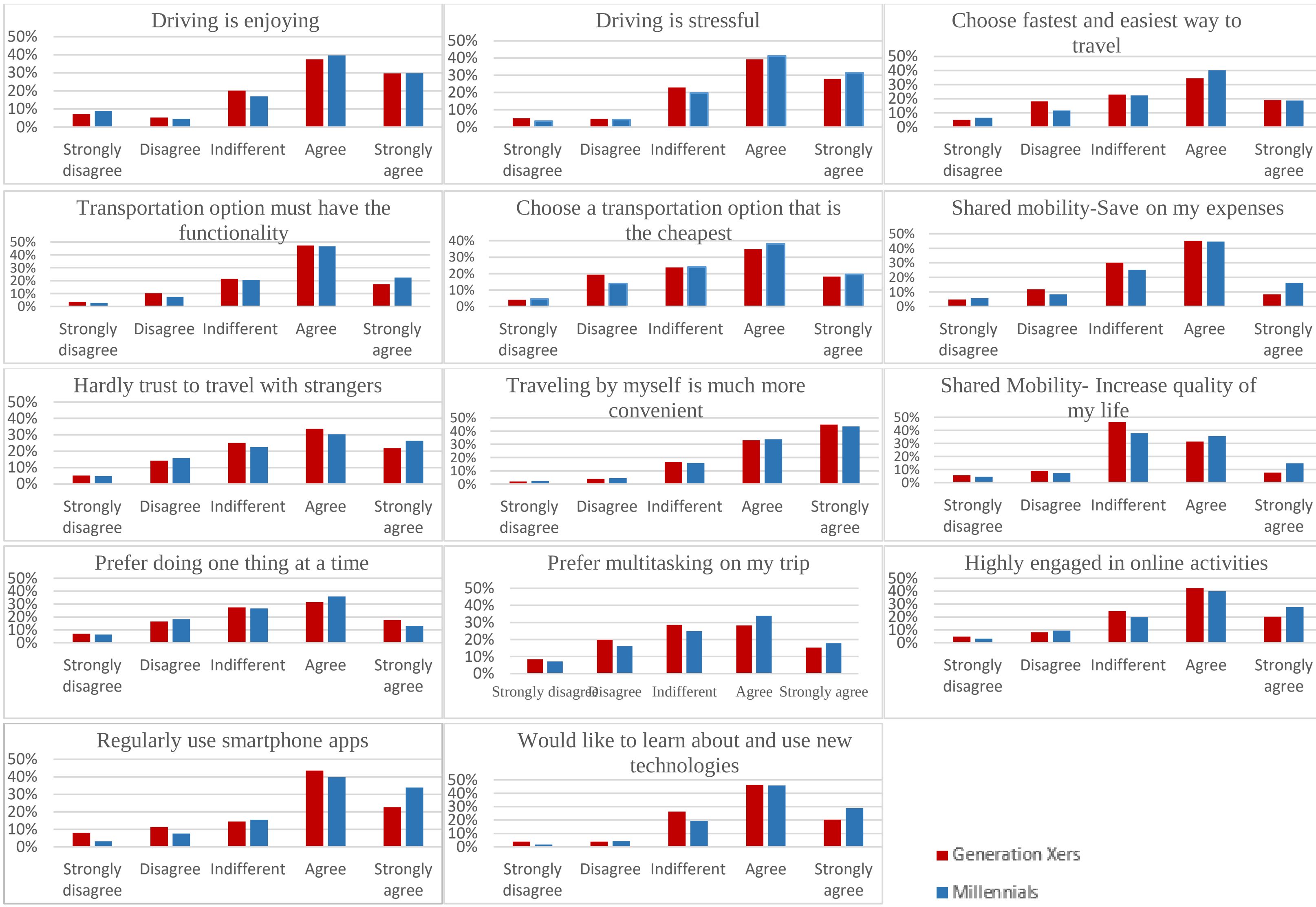


Figure 7-1 General mobility preferences for generation Xers and Millennials

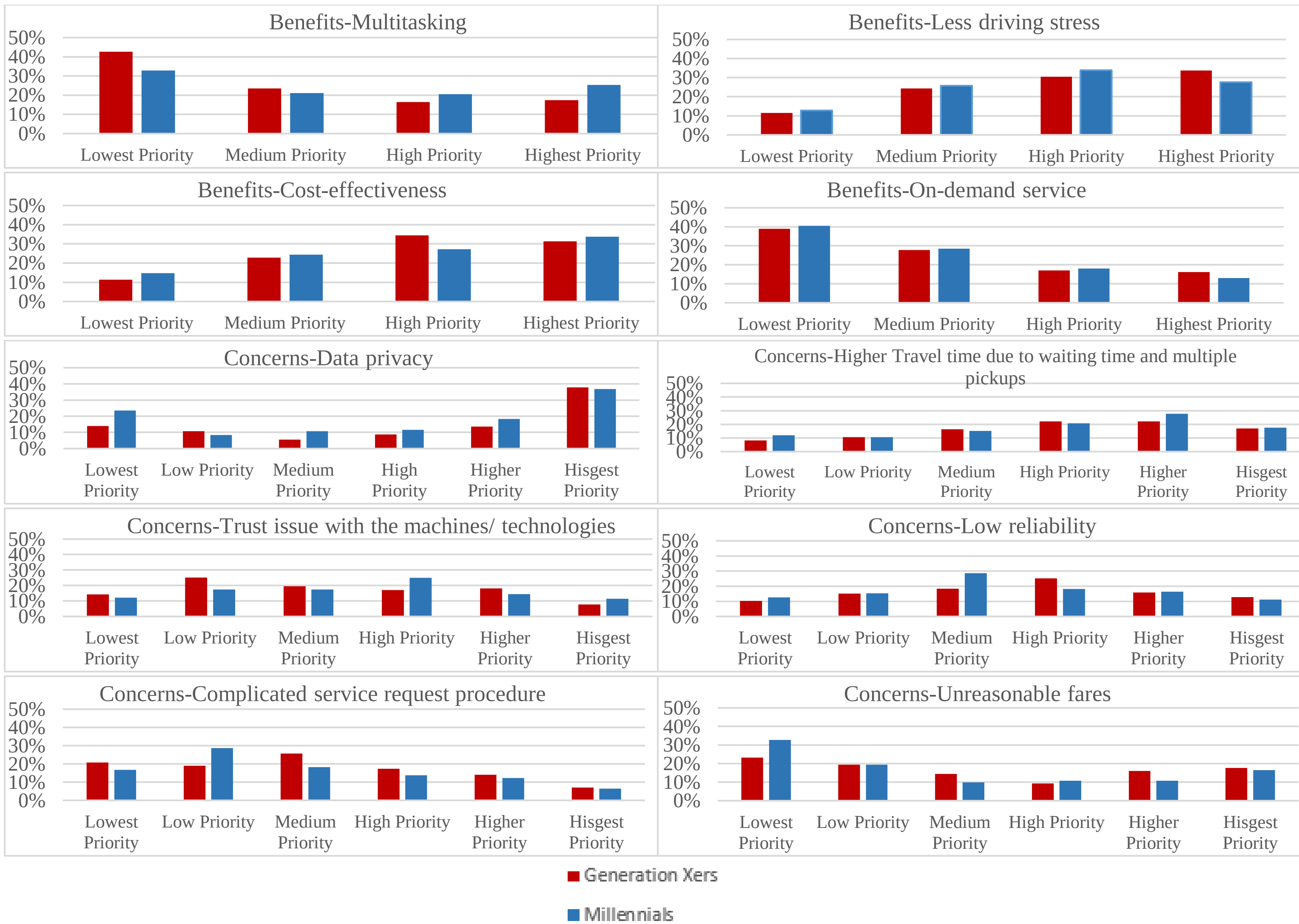


Figure 7-2 Perceived benefits and concerns of shared mobility for Generation Xers and Millennials

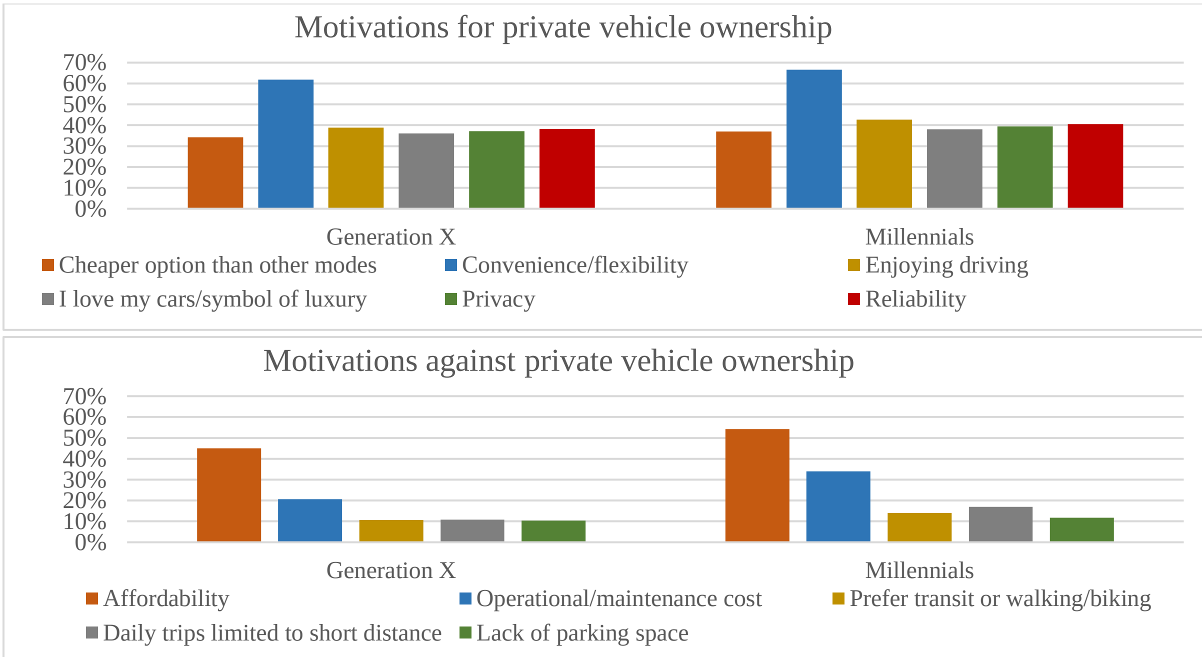


Figure 7-3 Motivations for and against private vehicle ownership for Generation Xers and Millennials

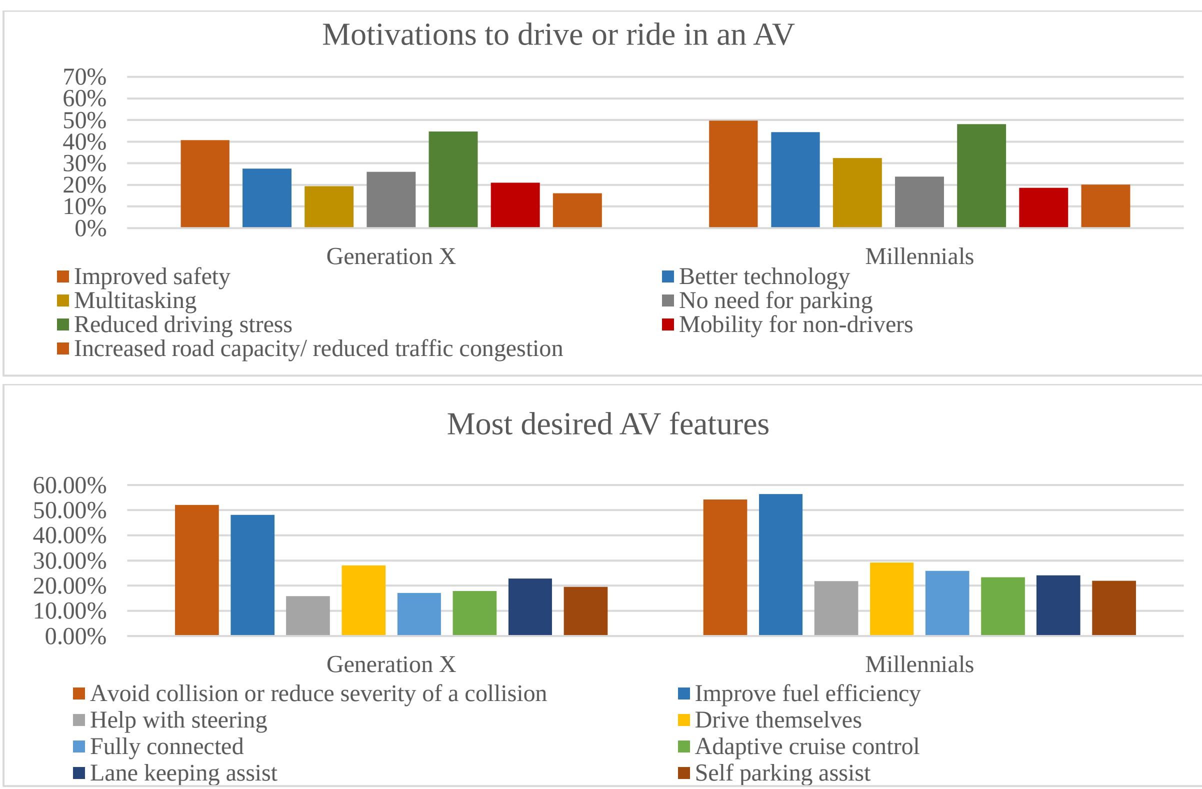


Figure 7-4 Motivations for and desired features of AV for Generation Xers and Millennials

7.3 Results

Similar to previous chapters, the results are presented in two different parts. First, the results of factor analysis are discussed. Then, the results of the error component nested logit will be presented for Millennials and Generation Xers.

7.3.1 *Factor Analysis Results*

Table 7-2 presents the results of the factor analysis. The eigenvalue larger than one was considered to specify the number of factors. Highlighted cells show the indicators associated with each identified factor; green cells represent a positive association with the factor, while blue cells reflect a negative association. All indicators are presented in Figure 7-1 through Figure 7-4. T-tests results showed significant differences between the two groups.

Table 7-2 Derived attitudinal factors

General mobility preferences	Factors			
	F1	F2	F3	F4
Shared mobility-Save on my expenses	0.719	0.194	-0.115	0.06
Choose a transportation option that is the cheapest	0.677	0.039	0.119	0.156
Choose fastest and easiest way to travel	0.615	0.2	-0.095	0.339
Shared mobility- Increase quality of my life	0.612	0.317	-0.078	0.172
Prefer multitasking on my trip	0.54	0.392	0.038	-0.225
Driving is stressful	0.53	0.009	0.472	-0.261
Transportation option must have the functionality	0.435	0.232	0.313	0.332
Regularly use smartphone apps	0.172	0.802	0.06	-0.005
Highly engaged in online activities	0.158	0.784	0.079	0.124
Would like to learn about and use new technologies	0.238	0.742	0.092	0.117
Hardly trust to travel with strangers	-0.096	0.012	0.786	0.178
Traveling by myself is much more convenient	0.008	0.166	0.771	0.152
Prefer doing one thing at a time	0.115	-0.091	0.185	0.771
Driving is enjoying	0.121	0.254	0.102	0.546

Perceived benefits and concerns of shared mobility	Factors					
	F5	F6	F7	F8	F9	F10
Concerns- Complicated service request procedure	-0.703	-0.148	-0.112	0.117	0.03	-0.283
Concerns- Unreasonable fares	-0.701	0.269	0.175	-0.005	-0.012	-0.093
Concerns-Trust issue with technologies	0.655	-0.01	-0.039	-0.101	0.112	-0.534
Benefits- Cost-effectiveness	-0.052	0.95	0.014	-0.106	-0.181	-0.045
Benefits- Multitasking	0.106	-0.629	-0.077	-0.626	-0.436	0.038
Concerns- Low reliability	0.15	-0.011	0.879	0.086	-0.079	0.003
Concerns- Data privacy	0.436	-0.077	-0.719	-0.028	-0.09	0.023
Benefits- On-demand service	-0.095	-0.118	0.094	0.941	-0.247	-0.027
Benefits- Less driving stress	0.03	-0.119	-0.023	-0.156	0.97	0.032
Concerns- Higher travel time	0.205	-0.067	-0.031	-0.057	0.061	0.897

Motivations for and against private vehicle ownership	Factors			
	F11	F12	F13	F14
Own a vehicle – Reliability	0.776	-0.191	0.087	0.055

Own a vehicle – Privacy	0.77	-0.112	-0.022	0.043
Own a vehicle – Enjoying driving	0.586	0.339	-0.164	0.022
Own a vehicle – I love my cars/symbol of luxury	0.528	0.352	-0.082	-0.368
Don’t own a vehicle – Prefer transit or walking/biking	-0.134	0.67	-0.141	0.027
Don’t own a vehicle – Daily trips limited to short distance	0.015	0.56	0.081	0.069
Own a vehicle – Cheaper option than other modes	0.202	0.246	0.664	-0.187
Don’t own a vehicle – Affordability	-0.073	-0.036	0.64	0.068
Don’t own a vehicle – Lack of parking space	0.147	0.265	-0.521	-0.124
Don’t own a vehicle – Operational/maintenance cost	-0.023	0.271	0.044	0.801
Own a vehicle – Convenience/flexibility	0.465	-0.198	-0.012	0.421
Motivations for and desired features of AV	Factors			
	F15	F16	F17	F18
Desired features- Avoid collision	0.685	-0.089	-0.009	-0.06
Motivation-Improved safety	0.667	-0.042	0.12	-0.129
Desired features- Lane keeping assist	0.661	0.142	-0.043	0.076
Desired features- Self parking assist	0.564	-0.007	0.033	0.181
Motivation-Increased road capacity/ reduced traffic congestion	0.556	-0.098	0.01	0.154
Motivation- Reduced driving stress	0.492	0.009	0.326	0.263
Desired features- Adaptive cruise control	0.411	0.395	0.187	-0.127
Desired features- Help with steering	-0.039	0.66	-0.035	-0.022
Desired features- Fully connected	-0.067	0.615	0.035	0.253
Desired features- Improve fuel efficiency	0.138	-0.275	0.757	0.033
Motivation- Better technology	0.024	0.395	0.651	-0.12
Motivation-Multitasking	-0.007	0.317	0.37	0.198
Desired features- Drive themselves	-0.014	0.021	0.209	0.646
Motivation- Mobility for non-drivers	0.24	-0.037	0.001	0.578
Motivation- No need for parking	0.001	0.223	-0.17	0.554

Table 7-3 presents the list of all factors, including the labels and description of the factors, the percent of explained variance by each factor, the total explained variance for each category, and the eigenvalues for each factor.

Table 7-3 **Statistical results of the factor analysis**

Category	Factor	Description	% of var.	Cumulative % of var.	Eigen value
General mobility attitudes	Service quality	Associated with the consideration of service quality (including travel time and cost, convenience, and multitasking) in mode choice.	18.853	18.853	2.639
	Pro-technology	Refers to respondents' involvement in online activities, frequent use of smartphone applications, and enthusiasm to know about and utilize new technologies.	16.4	35.253	2.296
	Travel with strangers	Represents respondents' trust issues with traveling with strangers.	11.707	46.96	1.639
	Joy of driving	Correlated with the respondents' joy of driving and reluctance to do multitasking.	9.838	56.798	1.377
Attitudes toward shared mobility	Trust and data privacy concerns	Represents trust concerns about technologies and is negatively related to the shared mobility fare and request process.	16.922	16.922	1.692
	Cost-effectiveness	Indicates the beliefs in the cost-efficacy of shared mobility and reluctance to multitask.	14.312	31.234	1.431
	Reliability concerns	Correlated with respondents' concerns about shared mobility reliability and negatively correlated with data privacy concerns.	13.502	44.736	1.35
	Pro-On-demand service	Indicates people's interest in on-demand services and their reluctance to do multitask.	13.48	58.216	1.348
	Driving stress relief	Associated with the beliefs in lower driving stress when using shared mobility.	12.567	70.783	1.257
	Travel time concerns	Represents respondents' concerns about higher travel time when using shared mobility because of several pickups and waiting times. It is negatively associated with the trust issues with the technology	11.841	82.624	1.184
Vehicle ownership	Pro-private vehicle	Indicates the inclination toward private cars because of their privacy, reliability, the joy of driving, and fondness for cars.	19.259	19.259	2.118
	Pro-alternative modes	Refers to the inclination toward other modes, such as transit, walking, or biking. Short-distance trips significantly contributed to this factor.	11.771	31.03	1.295
	Travel cost concerns	Represents the travel cost as a critical reason for owning/not owning a car. Lack of parking space is negatively associated with this concern.	10.831	41.861	1.191
	Ownership	Refers to concern about ownership	10.055	51.916	1.106

Category	Factor	Description	% of var.	Cumulative % of var.	Eigen value
	cost concerns	and maintenance costs as the main reason for not owning a private car.			
AV features	Driving assistance & safety	Associated with the propensity toward AVs because of collision avoidance, self-parking, and reduced driving stress.	16.486	16.486	2.473
	Automation	Indicates the inclinations toward steering and fully connected features.	9.294	25.78	1.394
	Efficiency & technology	Reflects the desire for higher fuel efficiency and better technology.	9.114	34.894	1.367
	Mobility for non-drivers	Represents the tendency toward automatic driving features, particularly for non-drivers.	8.961	43.855	1.344

7.3.2 *Model Results*

Since the main objective of this study is to understand the potential differences between Generation Xers and Millennials regarding their propensity toward ridesourcing services, separate error component models were developed for these two generations. Both MNL and NL structures were explored. For NL models, the nest was defined for shared and exclusive ridesourcing services.

A complete model with all the independent variables was defined for each generation. At the 90% significance level, the models were optimized by eliminating insignificant variables while considering the improvement in the model's performance (evaluated using log-likelihood value). The variables not selected in the first run of optimization were reevaluated to obtain a fully optimized model.

Table 7-4 compares the goodness-of-fit measures for MNL and NL models for the two generations. A higher log-likelihood ratio test (LRT) and a lower value of Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are preferred. Accordingly, for Generation Xers, the NL model outperformed the MNL model in all measures. For Millennials, the performances of the two models were close.

Table 7-4 Comparison of MNL and NL models' performance

Generation	Model	Performance measures		
		LRT	AIC	BIC
Generation Xers	MNL	636.9	9028.2	9101.9
	NL	652.5	9010.6	9080.9
Millennials	MNL	7656.1	16567.5	16759.3
	NL	7663.1	16559.5	16753.0

In the following sections, the focus was on interpreting the results of the NL models for Generation Xers and Millennials.

As shown in Table 7-5, for both generations, the estimated means and standard deviations of travel time and travel cost were significant (at the 99% significance level), suggesting the presence of heterogeneity. As expected, high driver availability, which was specified only for private vehicle passengers, showed a significant positive value implying that higher vehicle availability would result in a higher probability of choosing the passenger mode over other modes. Furthermore, for both groups, the significant positive value of the nest coefficient indicated a positive correlation between shared and exclusive ride services.

7.3.2.1 Generation Xers

In view of general attitudes toward mobility options, individuals who care about the service quality of their travel modes were more likely to choose shared rides over conventional modes. It implies that rational users who consider the utility of their travel mode adopt shared ride services when they believe that it helps them save expenses, increase their living quality, ease driving stress, and provide multitasking opportunities. As expected, users who do not prefer to travel with strangers were less likely to use ridesourcing services compared to conventional modes. Trust issue with strangers is one of the primary concerns discouraging people from using ridesourcing services, consistent with findings of the literature (Ma et al. 2019, Alemi et al. 2019).

Table 7-5 Model results for Millennials and Generation Xers

Generation Variable	Generation Xers Coefficient	Millennials Coefficient
Constant		
Exclusive rides	-0.024	17.3***
Shared rides	-0.583*	23.0***
Private vehicle/public transit (base)	-	-
Alternative-specific variables		
High availability (Specific to private vehicle passenger)	0.932 ***	-0.081*
Nest coefficient		
Ridesourcing nest coefficient	0.959 ***	0.478 ***
Attitudinal factors		
General mobility preferences		
Service quality (Specific to shared rides)	0.223**	1.120***
Pro-technology (Specific to shared rides)	-	0.058***
Travel with strangers (Specific to exclusive rides)	-0.192**	-
Travel with strangers (Specific to shared rides)	-0.405***	-0.718***
Joy of driving (Specific to shared rides)	-	-0.507***
Perceived benefits and concerns of shared mobility		
Cost-effectiveness (Specific to exclusive rides)	-0.123***	-
Cost-effectiveness (Specific to shared rides)	-	0.907***
Pro-on-demand service (Specific to exclusive rides)	-	0.491**
Driving stress relief (Specific to exclusive rides)	-	0.625***
Travel time concerns (Specific to exclusive rides)	0.149**	-0.323*
Motivations for and desired features of AV		
Driving assistance & safety (Specific to shared rides)	-	-0.400*
Mobility for non-drivers (Specific to exclusive rides)	0.169***	-0.782**
Mobility for non-drivers (Specific to shared rides)	0.329*	0.114*
Socioeconomic and demographic attributes		
Gender (Base: Male)		
Female (Specific to exclusive rides)	-	1.80***
Ethnicity (Base: White)		
Hispanic (Specific to exclusive rides)	-	-2.430***
Hispanic (Specific to shared rides)	-	-1.960***
Black or African American (Specific to exclusive rides)	-	-2.020***
Black or African American (Specific to shared rides)	-	-2.150***
Employment (Base: Part-time)		
Full Time (Specific to exclusive rides)	0.589***	-
Unemployed (Specific to exclusive rides)	-	-2.570***
Student (Specific to exclusive rides)	-	-1.710***
Education (Base: Bachelor's degree)		
High school graduate (Specific to exclusive rides)	-	-3.220***
High school graduate (Specific to shared rides)	-	-3.510***
Some college, no degree (Specific to exclusive rides)	-	-2.00***
Some college, no degree (Specific to shared rides)	-	-3.840***
HH Income (Base $25K-$50K)		
$0K-$25K (Specific to Shared Rides)	-0.343*	-2.270***
$50K-$75K (Specific to Exclusive Rides)	0.58***	-1.30**
$75K-$100K (Specific to Shared Rides)	-	-2.230***
$150K-$175K (Specific to Exclusive Rides)	1.26***	-
HH Drivers (Base: One driver)		
Two drivers (Specific to exclusive rides)	-	-2.09***
Three drivers (Specific to exclusive rides)	-	-2.380***

Generation	Generation Xers	Millennials
Three drivers (Specific to shared rides)	-1.17***	-1.960***
Online shopping frequency (Base: More than once a week)		
Less than once a month (Specific to exclusive rides)	-	-0.898**
Less than once a month (Specific to shared rides)	-	-2.170**
Once a month (Specific to shared rides)	-	-1.570**
Once per two weeks (Specific to exclusive rides)	0.51**	-1.450**
Random parameters		
Travel time		
Mean	-1.24***	-1.45***
Standard deviation	1.06***	-1.21***
Travel cost		
Mean	-2.01 ***	-2.15 ***
Standard deviation	0.82***	1.1***
Number of observations	Respondents =210 Observations=2,989	Respondents =545 Observations=7,496

*** Significant at 1% Level, ** Significant at 5% Level, * Significant at 10%

Regarding perceived benefits and concerns of shared mobility, results showed that those who believed in shared mobility's cost-effectiveness were less inclined to choose exclusive rides. In contrast, those concerned about higher travel times were more likely to choose exclusive ride services than other modes. The findings are reasonable, as exclusive services usually have higher fares but provide convenient door-to-door services that help save parking time for private vehicles or walking time for the first/last segments of the transit trip.

As expected, individuals with stronger motivation or desire for self-driving features and mobility for non-drivers were more likely to choose both exclusive and shared rides over conventional modes. The positive correlation indicates a promising market of ridesourcing services for non-drivers, such as dependent children who cannot drive yet, users with disabilities, or those without access to private vehicles. Ridesourcing provides better utility and service quality for these travelers, making these services more attractive than transit services (Henao 2017).

Looking into the socioeconomic and demographic characteristics, full-time workers were more likely to choose exclusive rides than other modes compared to part-time workers. The positive impacts could be associated with the time constraints and tight work schedule or affluent lifestyle. Individuals with low income (i.e., less than $25K) were less likely to use ridesourcing services over traditional modes, probably due to more financial constraints or not having access to smartphones or credit cards. In contrast, those with higher income levels were more likely to choose exclusive rides than other modes. The literature supports these findings (Young and Farber 2019, Sikder 2019, Dias et al. 2017, Asgari and Jin 2020, Barbour et al. 2020, Grahn et al. 2019, Dias et al. 2017, Deka and Fei 2019, Clewlow and Mishra 2017).

Furthermore, households with three drivers, which could indicate a higher number of household vehicles, were less likely to switch from traditional modes to shared rides. The negative correlation is consistent with findings in the literature regarding the negative associations between vehicle access and ridesourcing usage (Sikder 2019, Alemi et al. 2019, Gehrke et al. 2018). Individuals who shopped once every two weeks were more likely to prefer exclusive rides over other modes than those with different online shopping frequency levels.

7.3.2.2 Millennials

Like Generation Xers, Millennials who cared about service quality were more likely to use shared rides, and those who had concerns about traveling with strangers were less likely to use shared rides. Unlike the Generation Xers, the concerns of traveling with strangers did not affect Millennials' propensity toward adopting exclusive-ride services. Millennials with pro-technology attitudes were more likely to use shared-ride services. Familiarity with technology was noted with positive impacts on adopting shared mobility (Acheampong et al. 2020, Simmons 2018, Dias et al. 2017, Alemi et al. 2019). Millennials who enjoyed driving were less likely to choose shared rides than other modes.

In view of perceived benefits and concerns of shared mobility, Millennials who had concerns about higher travel time of shared mobility were less likely to use exclusive rides. The negative association infers that Millennials were more likely to use the conventional modes under time constraints, probably because they see them as more reliable and time-efficient options.

Furthermore, Millennials who appreciated the benefits of on-demand service and driving stress relief were more likely to prefer exclusive ridesourcing services, while those who care about the cost-effectiveness of shared mobility were more likely to prefer shared-ride services compared to those who do not perceive these features as benefits of shared mobility services.

Regarding AV features, similar to Generation Xers, the desire for mobility for non-drivers encouraged Millennials to use shared rides; however, unlike the previous generation, Millennials who shared the same attitude were less likely to choose exclusive rides over other modes. This may be due to the financial constraints with non-drivers, who do not see exclusive rides as a viable option for regular use. From another perspective, this might also indicate that Millennials were less likely to be bothered by sharing rides with others.

Also, Millennials who look for driving assistance and safety features were less likely to prefer shared rides over conventional modes. This might indicate their desire to still participate in driving activities to some degree.

Considering socioeconomic and demographic characteristics, female users were more likely to adopt exclusive services compared to male users. Hispanic and African American individuals were less likely to use ridesourcing services (both exclusive and shared services) over traditional modes compared to Whites. As expected, unemployed individuals and students were less likely to adopt exclusive rides than other modes, probably due to their higher costs. Similarly, people with lower education levels (less than a bachelor's degree) were less likely to adopt ridesourcing services than conventional modes.

Regarding the pattern associated with the household income, very low-income individuals (less than $25K) and middle-income individuals ($75K-$100K) were less likely to choose shared ride services over traditional modes. Moreover, lower-middle-income ($50K-$75K) and middle income ($75K-$100K) Millennials were less likely to use ridesourcing over traditional modes. Furthermore, as the number of household drivers increased (compared to the base category: one driver), users were less likely to use ridesourcing options over traditional modes. In view of online shopping frequency, a lower frequency than the base frequency (i.e., more than once a week) was associated with a lower probability of using ridesourcing services over private vehicles or public transit.

7.4 Discussion and Policy Implications

Ridesourcing services have grown considerably in the past few years, and they provide great societal, environmental, and economic benefits by providing mobility for non-drivers, potentially promoting shared mobility, and reducing vehicle ownership and vehicle emissions, especially in shared ridesourcing form. This study focuses on the role of attitudes toward mobility options in ridesourcing adoption, and particularly the differences between the two generations, which could provide information for planners, service providers, and policymakers to develop specific strategies and programs that facilitate the growth of shared mobility.

In terms of similarities, for both generations, individuals who care about the service quality of their mode favor shared ridesourcing services over private vehicles or public transit. It indicates that shared mobility could be a viable option for those who believe it would save their expenses and travel time, increase the quality of life, ease driving stress, and provide multitasking opportunities. Publicizing ridesourcing capabilities in decreasing travel time (e.g., private vehicle parking time or public transit access/egress and waiting time) could create a more positive perception of these services. Marketing plans focusing on driving avoidance in stressful situations (e.g., heavy traffic, peak-hour, driving under the influence) or multitasking ability (especially for commuters) could also be highly effective in attracting individuals who care about the utility of their travel mode.

For both generations, issues on traveling with strangers discourage the use of ridesourcing services. However, there were also notable differences. This issue prevented the use of both exclusive and shared rides for Generation Xers, while it only showed significant negative impacts on Millennials' use of shared rides. It indicates that while traveling with strangers is a major barrier toward the adoption of ridesourcing, Millennials were less likely to be bothered by this concern in their mode choice decisions. Some policies and strategies to address this concern may include imposing strict regulations for hiring drivers (checking for mental health and driving abilities), use of security cameras in ridesourcing fleet, drivers' training sessions to improve their driving skills and attitudes, and responsive customer service (in case of any problem with the driver or other passengers).

Among the latent factors directly related to attitudes toward shared mobility, cost-effectiveness showed significant impacts for both groups. Generation Xers, who believed in the cost-effectiveness of shared mobility, were less likely to choose exclusive rides, while Millennials with the same belief were more likely to choose shared ride services than other modes. This suggests that the current fares for exclusive rides may still be high compared to driving private vehicles; therefore, reducing the fare of these services, providing reward programs, and offering deep discounts could encourage people to the more frequent use of these services. Future integration of these services with AV technologies may help reduce cost and make shared mobility a more cost-effective and attractive mode.

The concern about the higher travel time of ridesourcing services showed opposite effects for Generation Xers and Millennials. It encouraged the use of exclusive rides rather than private vehicles or transit among Generation Xers but negatively affected Millennials' propensity to choose ridesourcing services. It may imply that Generation Xers, who were more time-sensitive or on a tight schedule, would use an exclusive ride to save parking time or walking time to the destination. In contrast, Millennials may give a higher penalty for waiting times as they prefer to be on the move. Policies to improve service quality and reliability could affect the users' perceptions toward ridesourcing services, especially for Millennials. Marketing strategies may focus on the convenience of ridesourcing trips (providing door-to-door trips and multitasking ability) or their abilities to decrease travel time by eliminating private vehicles' parking time or transit's waiting time.

Similar findings were also observed for the desire toward mobility for non-drivers. While the desire for mobility for non-drivers showed a positive effect on the adoption of shared rides over traditional modes for both generation groups, it had opposite effects on the choice of exclusive ride. For Generation Xers who believed in the benefits of AVs in providing mobility for non-drivers, they had a positive inclination to use exclusive services over traditional modes, while Millennials with the same attitude were less likely to choose exclusive ride over traditional modes, probably due to lifestyle preferences or cost considerations. Non-drivers could represent dependent children who cannot drive yet, users with disabilities, or those without access to private vehicles. These users could be attracted to ridesourcing services since it gives them autonomy and freedom for their daily activities. Regular adoption of ridesourcing, especially single-ride services, could be costly for non-drivers, and promotions and reward programs might be practical tools to attract these uses.

In addition, some factors showed unique impacts on Millennials' mode choice behavior. Particularly, technology savviness encouraged the adoption of shared rides, while the joy of driving tended to discourage the use of shared ride services over private vehicles or public transit. Moreover, for Millennials, the benefits of on-demand service and driving-stress relief encouraged the use of exclusive ride services over private vehicles or public transit. Advertising campaigns, focusing on the on-demand aspect of these services (e.g., book a ride in advance) and driving avoidance in stressful situations (e.g., rush hours, nights, driving under the influence of alcohol and drugs) could be practical to attract users with these attitudes.

CHAPTER 8

CONCLUSIONS

This research presents the findings of a comprehensive study focusing on mode choice behavior in the era of ridesourcing services. Data from a stated preference survey conducted in the U.S. in 2017 was used for this dissertation. The survey targeted 2010 Census representative samples based on various demographic characteristics, including gender, age, household income, ethnicity, and education.

The primary focus of this dissertation was on identifying the role of attitudes in individuals' decisions to choose between ridesourcing services and conventional modes. A comprehensive set of questions were designed to derive the attitudinal factors. These questions captured the respondents' general mobility preferences, perceived benefits and concerns of shared mobility, motivations for and against private vehicle ownership, motivations to drive or ride in an Autonomous Vehicle (AV), and the most desired AV features. Moreover, respondents were asked to select one dominant travel mode for their regular daily activities (commute, shopping, and social trips) and under different situations (i.e., running late, the need to be on time, unavailability of a reliable vehicle, being new to the area, and having parking issues) to capture their mode-dependency attitudes.

Besides the attitudinal factors, different sociodemographic attributes and online shopping-related factors were considered the potential independent variables. Due to the panel structure of the data, error component multinomial and nested logit models were developed to analyze the mode choice behavior.

8.1 Summary and Conclusion

The findings of this dissertation can be categorized under three major research efforts, including (1) investigation of transit riders' and visitors' mode choice of ridesourcing, (2) exploration of the role of experience in the propensity toward ridesourcing, and (3) examination of the generational differences in propensity toward ridesourcing services.

Regarding the factors that affect the decision to switch to ridesourcing for transit riders and visitors, error component multinomial logit model results showed some similarities between the two groups. For instance, for both groups, technology savviness and being a fan of on-demand service were likely to encourage the use of ridesourcing. In contrast, people who preferred alternative modes (transit, walking/biking) were less likely to use ridesourcing. However, the model results confirmed the initial hypothesis that there are significant disparities between the two market segments, especially regarding attitudinal factors. For transit riders, the decision to shift to ridesourcing is highly affected by the perceptions of time and cost as well as inclinations toward technological applications. In particular, concerns about the higher travel time of ridesourcing encouraged the use of ridesourcing for transit riders. Moreover, transit riders who cared about mobility for non-drivers were inclined to use exclusive services. On the other hand, the attachment to private vehicles was acted as an inhibitor for transit riders to adopt shared rides. For visitors, traveling with strangers and the joy of driving were major barriers to using ridesourcing. On the other hand, visitors would use ridesourcing when they desire driving assistance and safety features, seek to reduce driving stress, and believe that ridesourcing provides higher utility in terms of travel time, travel cost, reliability, convenience, and stress relief.

For the first time, this dissertation explored the role of previous ridesourcing experience in the propensity toward the future adoption of these services. The study focuses on understanding the differences in mode choice behavior between those who have used ridesourcing services (users) and those who have never adopted them (non-users). Regarding the similarities between the two groups, it was shown that individuals interested in using technology-based platforms and services had higher probabilities of choosing exclusive rides regardless of having ridesourcing experience or not. In terms of attitudinal differences, data privacy and trust concerns were not barriers to adopting ridesourcing for previous users, while non-users were inherently anxious about sharing trips with strangers. Moreover, users were more likely to prefer other modes over private vehicles; however, non-users highly depended on their cars and enjoyed the utilities associated with the vehicles. Car-dependent people usually overestimate private vehicles' utility and can be highly reluctant to use other modes. Regarding mode dependency attitudes, in general, users showed higher inclinations toward regular or irregular use of on-demand services than the other group. Private vehicle drivers with ridesourcing experience are more likely to use exclusive rides than shared rides, while for non-users, private vehicle passengers have a positive impact on adopting exclusive services. Moreover, for people with ridesourcing experience, both irregular and regular users of public transit and ridesourcing showed a positive tendency toward adopting these services again. Contrarily, for non-users, transit riders were not motivated to adopt ridesourcing services.

Regarding Millennials' and Generation Xers' mode choice behavior, this dissertation investigated the attitudinal differences between these generational cohorts and examined how these attitudes may influence their decisions toward ridesourcing services. In terms of the effects of these attitudes on mode choice behavior, results from the nested logit models revealed some similarities between the two generations. For instance, the belief that shared mobility saves expenses and travel time, increases the quality of life, and provides multitasking opportunities encouraged the adoption of shared rides for both generations. Furthermore, while both Millennials and Generation Xers who were concerned about traveling with strangers were less likely to adopt ridesourcing services, Generation Xers showed more concerns on this issue, which negatively affected their propensity to use even exclusive rides. On the other hand, distinct behaviors were observed between Millennials and Generation Xers. For instance, concerns about the higher travel time of ridesourcing encouraged the use of exclusive rides rather than private vehicles or transit among Generation Xers but negatively affected Millennials' propensity to choose ridesourcing services. Moreover, Generation Xers, who believed in the cost-effectiveness of shared mobility, showed a negative inclination toward exclusive rides. In contrast, Millennials, with the same belief, preferred the adoption of shared rides over traditional modes. In General, for Generation Xers, the mode choice of ridesourcing was highly impacted by the perceived time and cost benefits of shared mobility. On the other hand, while travel cost is a determining factor for Millennials, their mode choice was more likely to be influenced by their attitudes or desire toward technology, on-demand services, and driving stress relief.

8.2 Research contributions

The contribution of this dissertation to the travel behavior literature can be listed as follows:

- Investigating the propensity toward ridesourcing services at a reduced fare to estimate the tradeoffs between these services and conventional modes beyond cost constraints while taking into account the future introduction of AVs to the market.

- Examining the role of attitudinal factors in the decision to switch from traditional modes to ridesourcing services.
- Identifying the factors behind the distinct mode choice behavior of various market segments and the mechanism of their influences on ridesourcing adoption.

This research presented in this dissertation delineates the potential market of ridesourcing and highlights underlying attitudes that significantly influence mode choice behavior involving these services. The findings from this dissertation provide an in-depth understanding of the distinct behavior of various user segments and generation groups toward shared mobility services. The findings can assist in developing strategies and policies with a focus on individuals' needs and concerns. This consideration can be especially helpful for planners and service providers to design customized programs that are more effective in promoting sustainable transportation systems than generalized policies.

8.3 Research Limitations and Recommendations

This dissertation is subject to several limitations. The designed scenarios are based on the stated preference method, which might not fully resemble real-world situations. Future studies can incorporate revealed preference scenarios to confirm and expand findings from this dissertation. For example, in this dissertation, the cost of ridesourcing was reduced such that factors affecting its adoption can be investigated beyond cost consideration. Future studies may employ revealed preference-based scenarios in which the current cost of ridesourcing fares can be considered. Moreover, since the stated preference scenarios are based on hypothetical situations, the availability of ridesourcing services was not verified across the sampling areas due to vast geographic coverage. Future studies can use revealed preference scenarios to obtain information about the availability of different ridesourcing and transit services in each respondent's living area. In addition to the state of Florida and the metro areas covered in the survey used for this dissertation, researchers are encouraged to apply the same models to other datasets to test the transferability of the findings.

For simplicity, the level of multitasking for this dissertation is defined as a fixed attribute. To provide additional insights, future studies may ask respondents to choose between a list of their activities during their trip and ask about the utilities of the time spent during the trip through questions answered with a Likert-scale (e.g., ‘‘In relation to its value to you, how useful is the time during your trip?’’). A similar procedure was applied by other studies (Singleton 2018, Berliner et al. 2015, Circella et al. 2015) to determine the importance of multitasking during a trip by measuring the general value of trip-based multitasking (Singleton 2018). The last limitation of this dissertation is the lack of information on explicit attitudes related to environmental concerns. These attitudes could provide further insight into the shift toward ridesourcing and may further strengthen the analysis.

It should be noted that as data for this study were collected before the COVID-19 pandemic, it does not reflect the impact of the outbreak on individuals' mode choice behavior and attitudes toward ridesourcing services. COVID-19 substantially affected the adoption of ridesourcing services as well as individuals' attitudes and perceptions toward these services (Morshed et al. 2021). We can anticipate that people, especially those who already use cars as their regular mode, are more likely to be attached to their private vehicles due to hygiene concerns and maintaining social distance (Shakibaei et al. 2021).

Moreover, the concern about traveling with strangers probably is deepened during the pandemic. On the other hand, although ridesourcing services can adopt strategies like installing barriers between drivers and passengers and providing sanitizers and thermometers to ensure the passengers of a safe trip, these measures probably would increase the fare of these services (Morshed et al. 2021). Therefore, people may not perceive shared mobility services as cost-efficient travel modes for a long time. Future studies are encouraged to investigate the potential impact of the pandemic on the adoption of ridesourcing, especially people’s attitudes toward these services.

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