EXPLORING THE DETERMINANTS BEHIND THE MODE PREFERENCE FOR AND FREQUENCY OF USE OF APP-BASED, ON-DEMAND RIDE SERVICES AND FIXED-ROUTE TRANSIT SERVICES BY TRANSIT-DEPENDENT POPULATIONS

by
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DISSERTATION

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ABSTRACT:

EXPLORING THE DETERMINANTS BEHIND THE MODE PREFERENCE FOR AND FREQUENCY OF USE OF APP-BASED, ON-DEMAND RIDE SERVICES AND FIXED-ROUTE TRANSIT SERVICES BY TRANSIT-DEPENDENT POPULATIONS

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In recent decades, the development of diverse types of transportation systems to meet the needs of people in all parts of a country is a trend in urban development that is in line with interest in the sustainable development of communities. This development has prompted transportation policymakers to adopt policies to improve the transportation conditions of the community, while citizens, in the face of these policies, make decisions in choosing the type of transportation system that is possible, and may be different from the policy makers' management programs. Therefore, paying attention to people's views and their awareness of their preferences can help policymakers in predicting travel behavior and thus aid policymakers in adopting proper management policies. In this regard, the present study, titled " Exploring the Determinants Behind the Mode Preference For and Frequency of Use of App-Based, On-Demand Ride Services and Fixed-Route Transit Services by Transit-Dependent Populations" examined the preferences of transit-dependent citizens from 48 cities in 27 U.S. states in 2019-2020. This study examines the travel behavior of transit-dependent individuals and their preferences for the use of traditional public transit services as compared to the app-based, on-demand ride services

(also known as ridehailing), as the new generation of transportation systems. Using random sampling and Cochran's formula, 385 people were selected as the sample and a questionnaire was given to these people using Qualtrics. Thirty-one participants were excluded from the final analysis for various reasons, such as the presence of paradoxical answers in the questionnaire, misspellings, and taking less than the standard response time to complete the questionnaire. Finally, 354 people were analyzed as the sample for this study. The data collected by the questionnaire were analyzed by SPSS and AMOS software, and the final analysis used the SEM model, testing two approaches including one in which the built environment variables were entered, and a second without entering these variables. The findings indicate the appropriate goodness of fit of the model. Theoretically, I have used two theories of the Planned Behavior by Icek Ajzen (Ajzen, 1991) to discuss the sample’s modal prefrences. This study may serve as one of the first comprehensive survey investigations which examines the determinants behind the modal preferences and the usage frequency of use of both ridehailing services and fixed-route transit by transit-dependent people in the form of a single model simultaneously.

The results showed that the overall preference for using private ride services has a positive effect on the percentage of ridehailing trips made by transit-dependent people, and the overall preference for using fixed-route transit services has an inverse effect on the percentage of ridehailing trips. Also, the effects of employment density, population density, preference for living in compact neighborhoods, and land use mix on the percentage of ridehailing trips were not confirmed. Moreover, the study of the direct effects of the independent variables in the model showed that the overall preference for using fixed-route transit is the strongest predictor of the percentage of ridehailing trips made by transit-dependent people, among the studied variables.

In contrast with the research literature, the study found that the built environment variables had no effects on the people's travel behavior. To explain this discrepancy between the research findings and the research literature, the status of the three built environment variables including population density, employment density, and land use mix in the residence of the sample, was examined. Through this examination, it was found that the residences of the sample population are at a very low level in terms of population density, employment density, and land use mix. Thus, it can be argued that it is possible that this ineffectiveness of the built environmental variables is due to the low density of the population and employment, as well as the low diversity of the land uses in the residence of the sample.

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1 CHAPTER ONE: INTRODUCTION

1.1 Introduction

America is a car-dependent society. According to the 2013-2017 American Community Survey, it is estimated that 76.4% of American workers aged 16 years and over have driven alone to work in 2017 (U.S. Census Bureau, 2019). The car dependency in the U.S. has substantially increased with the recent trends of the growth of urbanization. According to the U.S. Census Bureau, over 80% of all Americans live in an urban area (U.S. Census Bureau, 2016). The growth of urbanization has coincided with the emerging challenge of access to transportation as transit networks struggle under the increased demand for transit (Jiao & Bischak, 2018). The demand has outstripped the supply of transit networks and has led to inadequate transit coverage (Jiao & Bischak, 2018). Transit-dependent populations would determine transit demand in transportation underserved communities. According to the U.S. Department of Transportation's definition, transit-dependent populations are characterized as persons without private transportation, under age 18, over age 65, and/or below poverty or median income levels as defined by U.S. Census Bureau (U.S. DOT, 2012).

This study aims to investigate the determinants behind the mode preferences for and frequency of use of ridehailing services and fixed-route transit by transit-dependent people. App-based, on-demand ride services are provided by companies such as Uber, Lyft, and their competitors (Rayle et al., 2014). I focus on 48 populous cities, categorized as Urbanized Areas (UAs), across the United States. I also employ the Structural Equation Modeling (SEM) technique as the analytical method to explore the direct and indirect relationship between the explanatory variables and the outcome variables. I model the preferences and trip frequencies using a rich survey dataset, employing the Structural Equation Model (SEM) to constitute both direct and indirect effects, in order to provide new perspectives on the mode preferences for and frequency of use of these travel modes. I have selected populous cities as the study area for this research in order to provide a unique perspective on the patterns of preferences and use and travel behaviors. This study may serve as one of the first comprehensive survey investigations which examines the determinants behind of the modal preferences and the usage frequency of both ridehailing services and fixed-route transit by transit-dependent people in the form of a single model simultaneously.

1.1.1 Problem Statement

Over the past few decades, U.S. cities have experienced the relocation of urban-oriented populations at outer-urban and auto-oriented neighborhoods. The suburban or low-density physiography of these neighborhoods is associated with a philosophy of urban design that prioritizes the automobile, leading to limited access of public transit services. The existing trend of locating less wealthy population with a high dependency on transit in outer-urban areas results in increasing the demand for transit (Allen, 2018).

Transit-dependent people constitute a significant demographic of population. They have limited automobile access and there is not an adequate level of mass transit to service them (Jiao & Dillivan, 2013). These groups are often characterized as marginalized populations and have often been excluded from overall participation in society, with a lack of access to employment and retail (Jiao & Dillivan, 2013). As such, the impact of the lack of transit on these groups is adverse. The dependency of these groups on transportation is not limited to traveling to work (Sanchez & Brenman, 2010). They rely on transportation for other purposes such as obtaining medical care, getting to school, and shopping for basic needs, such as groceries (Sanchez & Brenman, 2010). Transit-dependent populations are often comprised of people with low incomes. (Sanchez & Brenman, 2010; U.S. DOT, 2012). Due to the orientation of transportation policies and public funds towards traveling by car, these populations face the challenge of economic inequities (Sanchez & Brenman, 2010; Sanchez et al., 2004; Clifton & Lucas, 2004; Garrett & Taylor, 1999; Welch & Mishra, 2013; Allen, 2017).

App-based, on-demand ride services are ubiquitous across the United States. The type of service provided by these companies is flexible. A passenger can take a ride with these services almost any time and anywhere. The drivers of these services are scattered in many places, as the required by the flexible nature of these service. They supply a substantial coverage area of service for transit-dependent people who have been deprived of access to mass and fixed-infrastructure transit. However, it is controversial if the app-based on-demand ride services could serve transit-dependents as a viable transportation option. Seventy percent of Uber and Lyft trips are made in nine large and densely populated metropolitan areas in the U.S. including Miami, Seattle, Boston, San Francisco, Philadelphia, Los Angeles, Washington DC, Chicago, and New York (Schaller, 2018). The number of trips made in these nine cities in 2017 constituted 1.2 billion trips (Schaller, 2018).

The lack of transportation equity and access may result in the segregation of poor and minority communities and make public transportation a central struggle in the larger theme of civil rights. Issues that must be considered include economic priorities at the regional level, and development and land-use practices associated with the continued disparities in public transportation (Allen, 2018). The poor are significantly more influenced by cuts in bus services and the workers with the lowest wages often have the longest commute, while the affluent have favored the expansion of transportation infrastructure (Euchne, 2016 as cited in Allen, 2018; Sanchez et al., 2003; Starkey & Hine, 2014; McKenzie, 2013). As such, fixed-route public transportation services, such as bus and rail, still serve as vital transportation options for transit-dependent people, despite the rapid expansion of app-based on-demand ride services. Additionally, transit-dependent people are faced with barriers that deter them from accessing app-based, on-demand ride services, which may significantly reduce their preference for and use of these services (Dillahunt et al., 2017; Shaheen, et al., 2017; Moran, 2016; Creger et al., 2018; Dillahunt & Veinot, 2018; Shirgaokar, 2018; Golub et al., 2018; Yan et al., 2019). Little is known about the influence of a combination of various factors, such as the residential preference and built environment, mobility-related travel attitudes, technology adoption, and the aforementioned barriers on the preference for and frequency of use of ridehailing services and fixed-route transit by transit-dependent people in the form of a single model simultaneously.

1.1.2 Research Objectives

This study seeks to address the abovementioned gap by conducting a survey to explore the modal preferences and usage frequency of transit-dependent people in 48 U.S. urbanized areas. These cities were choosing because ridehailing services occur mainly in urbanized areas and populous cities (Clewlow & Mishra, 2017). Therefore, in this study, 48 populous U.S. Urbanized Areas (UAs) have been selected as the study area based on the data obtained from the US Census Bureau. The Census Bureau identifies Urbanized Areas (UAs) as the areas of 50,000 or more people (U.S. Census Bureau, 2018). These urbanized areas have diverse populations, ranging from 192,364 (Tempe, AZ) to 8,398,748 (New York City), all of which are cities with more than 50,000 population.

In my research, I specified the factors that are expected to be determinant in the overall preference for these travel modes and frequency of use by transit-dependent people as the outcome variables, and I measured the associations between these determinant factors and the outcome variables. I developed a model that explores the direct and indirect effect of these factors on the outcome variable. Also, I specified the barriers deterring transit-dependent people from accessing app-based, on-demand services, and I evaluated the effect of these barriers on the overall modal preferences and use. I also explored the importance of the factors that may influence the decision making of people, including transit-dependent populations, in choosing fixed-route and on-demand services as the preferred mode. This dissertation tries to evaluate the overall mode preferences and use by residents of large cities in the U.S. and compare fixed-route transit and ridehailing services, while explaining the pros and cons of each mode especially for transit-dependent populations as the users.

1.1.3 Research Questions and Hypotheses

This study tries to answer the following questions:

What are the determinants behind the mode preference for the use of ridehailing services and fixed-route transit by transit-dependent people?

What are the determinants behind the frequency of the use of ridehailing services and fixed-route transit by these populations ?

What is the effect of the built environment variables on the percentage of ridehailing trips made by these populations?

The first hypothesis: *Population density, employment density, and land use mix (entropy) are determinant factors in identifying the percentage of ridehailing trips made by these populations.*

When built environment variables such as population and employment density are low in an area or land uses are not very mixed, people's preference can be affected in two ways. First, people who care about the travel time factor prefer to use app-based systems such as Uber to get to their destination faster because they are living in scattered areas. On the other hand, given the low-income status of the sample, those who care more about the cost of travel prefer to spend more time using traditional transportation systems such as buses, which are cheaper but slower. Research shows that ridehailing services offer more significant performance in dense urban areas, and higher population and employment densities, presumably attribute to more frequent trip requests. More frequent trip requests would lead to the attraction of more drivers to the area (Hughes & MacKenzie, 2016). But research also indicates that higher densities make destinations closer together, which inevitably results in shortening trip lengths and making transit use more comparative in comparison with automobile travel. (Yu et al., 2019; Porter et al., 2013). However, increasing land-use mix increases the likelihood of the adoption of ridehailing services (Yu et al., 2019).

The reason for the selection of these three built environment variables in this study is that population density, employment density, and land use mix were expected to be more important than other built environment attributes in travel behavior investigation. In a seminal meta-analysis, Ewing and Cervero (2010), summarized the empirical findings on the relationships between the built environment and travel. They figured out that among the built environment attributes, population density, employment density, and land use mix are ranked as the top three variables in terms of the total number of studies examining transit use and vehicle miles travels with respect to the built environment. As such, these three variables were expected to be more important than other built environment attributes in travel behavior investigation in my study.

The second hypothesis: *Preference for living in compact places (accessibility preference) is a determinant factor in identifying the percentage of ridehailing trips made by these populations.*

The research shows that residents who do not have the chance of living in their preferred residential type may have reduced travel satisfaction because the use of the preferred travel mode is restricted by the built environment. As such, these residents are forced to use substitute travel modes (Kamruzzaman et al., 2013). Also, research shows that in neighborhoods with proper fixed-route transport connections, a significant portion of people prefer to use fixed-route transit services than other modes (Van Wee et al, 2002). Therefore, it is important to figure out if residential preference is determinant in identifying the rate of the trips made by app-based, on-demand ride services by transit- dependent people.

The third hypothesis: *Importance of service availability in selecting the preferred travel mode from the viewpoint of passengers is a determinant factor in identifying the preference for using private ride services by these populations.*

The fourth hypothesis: *Importance of service time efficiency in selecting the preferred travel mode from the viewpoint of passengers is a determinant factor in identifying the preference for using private ride services and fixed-route transit services by these populations.*

The fifth hypothesis: *Preference for living in compact places (accessibility preference) is a determinant factor in identifying the preference for using private ride services and fixed-route transit services by these populations.*

1.1.4 Research Significance

One of the significances of this study relates to its concentration on transit-dependent people, as the target population. In addition to examining the determinants behind the modal preferences and the usage frequency of the fixed-route transit, this study also evaluates the determinants behind the preferences for and the usage frequency of the ridehailing services as a new generation of transportation systems which may be the response to the transit-dependent populations' transportation needs due to the wide range of services available in separate locations and areas where fixed-route services do not exist, or the existing ones are little, or inefficient. Also, the results of this study may engender visions for transportation policymakers who are interested in exploring the viability of app-based, on-demand ride services for transit dependent people. It could assist future researchers in investigating the factors through which the mobility of disadvantaged populations can be enhanced or exacerbated by incorporating ridehailing into transportation systems. This research also considers the attitudes of transit-dependent people into the investigation of their mode preferences by including robust attitudinal statements that pertain to the issues related to mobility by these two modes and related to users' concerns. This study is also significant because it seeks to answer a theoretical gap concerning the relationship between the built environment attributes and the transportation modal use and preferences. Previous research has shown that built environment attributes are determinant in predicting the travel behavior of people. The present study intends to investigate whether this effect still exists when these variables are at a low level in terms of population and employment densities and the diversity of land use in the area where low-income people live. The prominence of the present study is that it may be able to respond to this gap while strengthening previous work that explores the relationship between the built environment and travel behavior.

1.1.5 Dissertation Outline

The dissertation begins in Chapter two, the literature review, where I introduce fixed-route transit services and app-based, on-demand ride services into the transportation system in American cities. Then, I explain transit-dependent people and their characteristics, followed by discussing the barriers that deter these populations from accessing app-based, on-demand ride services. Afterward, I explore the determinants of travel modal usage and preferences, which is followed by the summary of the chapter.

Chapter 3 explains the methodologies applied in this dissertation. It begins with the research design and explains the steps of performing the data collection and analysis. Then, I explain the conceptual framework which shows the conceptual explanation of the expected relationship between variables, backed by theory. Next, the selected study area is introduced, and I also explain the sampling method. The next section is the survey design, which demonstrates the objectives of conducting the survey, and I explain the survey structure. Also, I describe the survey distribution and data cleaning. Thereafter, the data and variables are discussed, and I describe the type of data used in this study. Finally, I discuss the selected analytical method and the reasons for this choice.

In Chapter 4, I present the descriptive statistics of the results and the results of the Structural Equation Modeling analysis, and discuss the direct and indirect effects of the explanatory variables, including socioeconomic and demographic characteristics; adoption of technology; attitudes; accessing barriers to ridehailing services and built environment attributes on the outcome variables. Also, I examine the research hypotheses in this chapter.

Chapter 5 constitutes the discussion and conclusions, and I also present policy implications and recommendations.

2 CHAPTER TWO: LITERATURE REVIEW

This literature review begins with an introduction of the fixed-route transit services and the app-based, on-demand ride services into the transportation system in American cities. These introductions demonstrate a typology of fixed-route transit services and app-based, on-demand ride services and their components, in addition to the pros and cons of each mode, and the effect of on-demand services on fixed-route transit. Next, there is a focus on transit-dependent people and their characteristics, followed by the barriers that deter them from accessing ridehailing. I also examine the key determinants of the preference for and the frequency of use of the fixed-route transit and on-demand services, including socioeconomic and demographic characteristics; built environment and residential preferences; travel-related attitudes; and technology adoption. This chapter ends with a summary of findings and insights from the literature.

2.1 The Introduction of Fixed-Route Transit Services into the Transportation System in American Cities

Fixed-route transit occurs where adequate population or employment density exists to support more significant volumes of transit. It is a transportation system that provides service "on a repetitive, fixed-schedule basis, along a specific route with vehicles stopping to pick up and deliver passengers to specific locations; each fixed-route trip serves the same origins and destinations" (KFH Group, 2013, p. 11-54). Bus and rail transit are the recognized types of fixed-route transit service. The function of this mode in North America can be distinguished in two major roles. First, it accommodates riders who opt to use transit for travel, although other travel modes, particularly a motor vehicle, are available to them. These riders, also called choice riders, may opt for transit over the other travel modes due to several reasons, such as spending less, in particular for parking costs; productive use of travel time for other activities; and avoiding driving in heavy traffic. Transit particularly helps these riders within peak periods for work trips and it surges the quantity of riders who may commute by urban transportation systems. This role of transit makes it necessary for mobility in downtown areas of major cities and high-density employment districts (Kittelson & Associates, Inc, 2003).

The second key role of transit is providing essential mobility services to people who are too poor, too young, too old, or individuals with physical and mental disabilities, who are unable to drive, as well as people without driver's license. These individuals are recognized as captive riders. In major cities of the North America, larger numbers of choice and captive riders are served by transit. Variations in factors such as population, employment and parking costs in central business districts, supplying bus and rail transit services, and geographic features would result in differences in the share of transit modes across urban areas (Kittelson & Associates, Inc, 2003).

2.1.1 Bus Transit

Bus transit is the most popular type of public transport in North America. In 2011, bus ridership formed 52% of all passenger trips by transit in the U.S., and 56% of transit trips on larger transit systems in Canada. An estimation for 2010 showed that over 1,200 bus systems were in operation in United States. High flexibility is a main characteristic of bus services. Distinct types of vehicles provide this service, and it can operate in a variety of environments. Also, this service can implement various stopping patterns (KFH Group, 2013).

2.1.2 Rail Transit

Distinct types of urban rail transit have been serving the U.S. cities just before the start of the 21st century. Traditional rail rapid transit and commuter rail lines have been working for a long time in many metro areas and later new regional rapid transit, light rail, and commuter rail systems were included in the U.S. rail transit system. At the beginning of the 21st century, over 20 U.S. cities were served by some types of urban rail service, and in most big cities such as New York, Philadelphia, Chicago, and Toronto rail transit systems were the main modes of traveling to or from the downtown areas (Thompson & Matoff, 2000).

Rail transit systems in North America transport over 5.4 billion passengers every year. The major rail transit submodes include heavy rail, light rail, commuter rail, and automated guideway transit (AGT). Minor rail submodes are constituted by monorails, funicular railways, aerial ropeways, and cable cars. The New York region has the most significant share of the use of rail transit countrywide. The number of passengers who were carried by rail transit operators in the New York City area in 2010 was more than 2.4 billion, which constituted over 62% of the entire passengers carried by rail transit across the country (KFH Group, 2013).

Heavy rail is the prevailing transit mode in the largest metro areas in North America. It has been provided, at least as a starter system, in most American cities with the essential population and job density to meet the supply of this transit mode. Light rail transit (LRT) allows increased capacity and higher speeds, which can be operated with single cars or multiple-car trains. Commuter rail is a long-distance transit service which uses trackage that is part of the general railroad system. This mode tends to work at peak commuting hours, but most of the mainlines of the larger commuter rail systems provide all-day service. Automated Guideway Transit systems (AGT), as their name implies, are fully automated, and the role of personnel is limited to supervision. The operation of the AGT systems is restricted to certain destinations, such as airports, government buildings, universities, and leisure and amusement parks. Monorail vehicles are characterized as being straddled or suspended from a single rail. Driverless monorails, such as the Jacksonville Skyway, are classified under the Automated Guideway Transit (AGT). Finally, cable cars are currently only being used in San Francisco. Lessening the costs of operations and increasing reliability were the reasons for the conversion of the most cable lines to electric street cars. However, lines were still operating in Seattle, San Francisco, and Tacoma in the 20th century, because the land of these cities were very steep for streetcars (KFH Group, 2013). Figures 13 through 18 display some recognized submodes of rail transit.

Figure 2. 1 Heavy rail transit in San Francisco Bay Area (Source: KFH Group, 2013)

Figure 2. 2 Diesel light rail (San Diego County) (Source: KFH Group, 2013)

Figure 2. 3 A commuter rail in San Francisco Bay Area (Source: KFH Group, 2013)

Figure 2. 4 An Automated Guideway Transit (AGT) as downtown people mover in Miami (Source: KFH Group, 2013)

Figure 2. 5 A Straddle Monorail in Seattle (Source: KFH Group, 2013)

Figure 2. 6 A cable car in san Francisco (Source: KFH Group, 2013)

2.1.3 Rail Transit vs Bus Transit

According to Henry and Litman (2014), rail transit stations could encourage intense development, although the numbers of stations are limited. Intense development is reflected in increased transit ridership per person, lessening car ownership per person, increased walking trips, increased resident density, employee density, and business activity density. Also, rail stations often encourage transit-oriented development, which can stimulate the reduction of additional vehicle travel. Rail transit tends to provide a higher prestige and service quality in terms of speed, comfort, and convenience than conventional bus transit. As such, it tends to attract more riders. Also, public support for rail transit tends to be stronger than for bus transit. Voters' enthusiasm for funding rail tend to be higher than for bus improvements.

However, rail investments on the grounds have been criticized from an equity perspective, which means that residents who belong to higher-income classes essentially benefit more from these investments. They attract the financial resources required for supplying essential bus service that transit-dependent populations and low-income individuals use. Rail funding often depicts an overall increase in transit funding rather than substituting for bus funding, because the funding for rail transit is often replaced by the funding for highway projects, and voters tend to be more enthusiastic in advocating for new financial resources for the improvement of rail, rather than bus service. However, some rail transit services still transport many lower-income passengers. Some of the outcomes of the improvements of rail transit services in the long term would be increasing bus service, improving the conditions of walking and cycling, more accessible land use, and an overall surge in the diversity of transportation system. These outcomes would come about by attracting more transit riders who would otherwise drive, surging the total demand for transit, and justifying more programs for the support of transit. Disadvantaged households can be beneficiaries of the outcomes of improving rail transit (Henry & Litman, 2014).

Bus transit can cover a more significant service area than rail transit. Therefore, the total ridership with bus can be greater than rail, especially for destinations located in sprawled areas. The number of destinations covered by bus transit is more than rail transit, which may include sprawled and suburban activity centers. In fact, bus transit is more suitable for reaching the destinations that are in sprawled areas with lower transit demand, due to the capacity of converging several routes onto one busway, which reduces the necessity of transferring. Meanwhile, rail transit is more suitable for serving concentrated destinations in corridors. Transit ridership per person with bus transit is fewer than rail transit, but the impact of this lower ridership on land use pattern is insignificant. Also, because of the higher load factors of rail transit, this mode has lower costs per passenger-mile than bus, but the costs per vehicle-mile with bus transit tend to be less than rail transit. Bus services are flexible because the change and the expansion of their routes are feasible. The operation of buses can happen in the existing roadways—as such, bus transit does not need particular facilities. Also, the capital costs of bus transit are lower than rail transit, and the operating costs per passenger-mile with bus is lower than rail in the occasions where there is low demand for transit. Bus transit is a more popular choice for transit-dependent people, thus improving bus services would bring more significant equity benefits. However, passengers like rail stations more than bus stations, and the demand for rail transit is more significant than the demand for bus transit. Rail transit has a positive effect on the value of properties near the stations, and compared to bus transit, rail transit has a more positive effect on land use (Henry & Litman, 2014).

2.1.4 What Does the Fixed-route Transit Bring to the City and the Household?

The mobility options for responding to the essential travel needs of transit-dependent people are limited in the United States. It creates persistent challenges for these populations and affects their quality of life. A community design and a land use pattern that does not support the development of public transit is the most significant reason for the failure of providing adequate transit services to these people in areas, which are mainly recognized with a sprawl pattern. This particular pattern increases the dependency on driving personal cars, which consequently lessens the use of transit. Also, the scattered distribution of job locations results in inadequate services in central business districts and corridors (Zhao & Gustafson, 2013). Mass transit brings mobility benefits to users. These benefits are the outcomes of additional personal travel that would not otherwise happen. Transit-dependent people, including the individuals who are not able to drive due to economic, social, and physical restrictions, gain most from these mobility benefits. Transit is a significant travel mode for non-drivers who belong to low- and median-income classes. For instance, the annual transport cost for a household with $20,000 annual income is about $2,500. A non-driver with this annual household income can only pay for about five taxi trips every week. Living in a community with decent transit service enables this person to buy a monthly transit pass and still pay for 2-3 taxi trips every week (Litman, 2015).

Low-income households challenge the spatial mismatch of jobs, due to a land-use pattern that quells the demand for transit, as well as insufficient capital and operating funding for transit properties. Workers from these households challenge the cost of housing, which is fast-growing and has reduced the current residence options with transit access to jobs. They also have problems with transit services with higher capacity than usual during the rush hour. Low-income workers are often involved in the service sector, with a schedule different from the 9 am-to-5 pm work schedule. Transit does not provide access to many of the service jobs. Moreover, housing affordability should not be decreased to the actual housing price. The cost of job accessibility and other destinations, as well as reductions in mobility that increase travel cost and extend travel time, are also significant in housing affordability. Limited access to cars and the costs associated with the maintenance of a personal car increase the dependency of low-income workers on public transit, while travel time with public transit is much longer than with personal automobiles, even when transit operates for the entire day (Zhao & Gustafson, 2013).

Inequal access to opportunities by transit is an issue in many of the large cities, even those with robust transportation networks. For instance, there are areas in New York City that suffer from poor service coverage by subway systems, although it has one of the most massive subway systems in the world (Regional Plan Association, 2019). Significant portions of NYC, including low income neighborhoods, are dependent on public transportation. These neighborhoods face the challenge of lacking access to any form of transit, which could drastically limit the access of residents to job opportunities. Over one-third of the city's populations do not live within walking distance of a transit station. This condition is particularly severe in Queens, where over sixty percent of residents do not live within walking distance of a subway station. There are many low-income neighborhoods across the city where transit-dependent people live. These neighborhoods constitute high population density, approximately 20,000 people per square mile, which justifies the need for subway and bus services for the transit-dependent people living there (Regional Plan Association, 2019).

Also, the results of a comprehensive study on the state of transportation equity in Dallas show that approximately 37% of Dallas population is not covered by transit in anytime of the day (Hamidi, 2017). The results indicate that in the transit dependent cores, where most of the transit dependent residents live along employment centers, approximately 32% of residents are not covered by transit. Also, the transit coverage for 26 % of city's population and 31% of residents living in the transit cores can depend on only one station, with the average daily 3-6 trips per hour. The study demonstrates that there is no coverage within walking distance by transit for over a third of the residents, in both the city and transit dependent cores, which means no transit is being used by this proportion of population. On average, the accessibility of about 30 % of the city's population and 41% of population in the transit dependent cores is limited to less than 1% of regional jobs in 45 minutes of transit. The most significant obstacle towards the consideration of transit as the major transportation mode for all Dallas residents, particularly transit-dependents and the low-income people, is the lack of adequate access to jobs by transit. It also displays that the lack of access to jobs along with the lack of access to a decent transportation system, integrated with spending roughly a quarter of household income on transportation, would result in holding households living in the transit dependent cores captive in places with fewer chances of upward mobility. Meeting the travel needs of all employees requires the operation of transit services twenty-four hours a day. Some communities do not provide this operation, and it does not meet the transit needs of employees who must work the second or third shift, after 11:00 PM and in the early hours of the morning. The restricted access and mobility of low-income households to affordable housing and jobs is the outcome of suburbanization and the land use patterns that do not support public transit, as well as increasing costs of developing transit services, car culture, and no significant increase in income for low-income working households (Zhao & Gustafson, 2013). Given that consumers of mass transit tend to be disadvantaged people, the increase of mass transit could bring equity benefits for disadvantaged households. The existence of mass transit in a community can contribute towards fulfilling the equity goals of a community. It helps the socially, economically, or physically disadvantaged households, through increasing the accessibility to employment opportunities, education, and public services, which contributes to increasing the social and economic opportunities for these populations (Litman, 2015).

Transit brings option value to the users. This means the value of having an option for the feasible prospective use. Transit may provide serious transportation services during emergency situations, such as disasters that restrict automobile traffic. It also increases public fitness and health through stimulating more walking or cycling trips. It lessens traffic congestion, increases traffic safety, and lessens air and noise pollution. It also leads to saving costs associated with maintaining roads and parking facilities (Litman, 2015). In addition, the potential benefits of transit for Transit-Oriented Development include lessening the additional vehicle travel, lessening the infrastructure costs, preservation of farmland and the natural environment, and enhancing accessibility especially for non-drivers. Transit can be also supportive and cost effective for government agencies and their activities. Transit accessibility enables the elderly and individuals with disability to live independently, which can result in lessening the costs allocated for care facilities. This would result in compensating parts of subsidies allocated for public transit through saving in other government budgets. Communities providing high-quality transit to households enable them to own fewer cars and drive less, and it tends to reduce a significant portion of household budgets specified for transportation (Litman, 2015).

Mass transit, however, may have some potential costs for both residents and cities, such as transit vehicle crowding, diminishing the activity of automobile business, challenges pertaining to more compact development, the need for subsidies for the increased capital and operating costs of materials, equipment and vehicles, and costs of infrastructure construction, such as improving the roadways (Litman, 2015).

Operating and capital costs constitute the costs of providing public transportation services. Operation and maintenance of vehicles, maintenance of stations and other facilities, general management and purchase of transportation from private operators constitute the operating costs. Capital costs include the purchase of equipment, including buses, railways and railway stations. Operating costs account for about two-thirds of public transportation costs, and the rest are capital expenditures. Fares and other operating income cover only 25 percent of the total cost, with the rest provided by federal, state, and local governments. The federal government supplies less than 10% of operating costs, but approximately 40% of the capital costs (Mallett, 2019). However, many transit costs are fixed, and transit services tend to experience economies of scale. As such, the marginal costs are not often significant (Litman, 2015).

2.2 The Introduction of App-Based, On-Demand Ride Services into the Transportation System in American Cities

App-based, on-demand ride services, also known as Transportation Network Companies (TNCs), or more informally, ridesharing, is a new generation of transportation service that has been introduced into the transportation systems by leveraging advances in technology (Rayle et al., 2014). TNC is a term used to define a transportation mode that connects drivers with passengers through technological devices. The type of services provided by TNC's is very similar to that of traditional taxis. A passenger orders a ride and pays for the service provided by a driver. Requesting a ride requires downloading a TNC's application on technological devices including smartphones, tablets, or computers and the payment process requires the travelers to register with a valid credit card (Moran, 2016).

The most popular service provided by app-based on-demand ride services in the U.S. is ridehailing or ridesourcing which is a private-ride service provided by privately-owned companies, wherein drivers provide passengers with a ride in a personal vehicle for a fee. UberX and Lyft are two famous examples of ridehailing service (Moran, 2016). Uber is a well-recognized TNC available in 263 cities and regions within the U.S. (Uber, 2019), and has a significant contribution to the U.S. economy with more than $17 billion in the Gross Domestic Product (EDR Group, 2017). Lyft currently provides its service in over 200 cities nationwide. In 2017, more than 28% of Lyft rides originated from the low-income areas, which often lack reliable public transportation, and about 47% of passengers used this service where public transit did not work (Lyft, 2017).

Ridesplitting, carpooling, taxi/car services are other examples of services provided by TNCs (Moran, 2016). A ridesplitting service is a ridesourcing service through which "TNC drivers can offer a shared ride for several riders who are sharing a similar route, for a discounted rate" (Moran, 2016, p. 3). Via, LyftLine, and UberPOOL are the examples of ridesplitting (Moran, 2016). Via provides service in New York, Chicago, Washington DC, West Sacramento, and Arlington, TX (Via, 2019). The results of a report commissioned by New York City's Taxi and Limousine Commission in 2018 show that the earning of Via driver partners in New York City is on average 43% more than Lyft drivers and 35% more than Uber drivers (Via, 2019). Taxi/car services such as UberBLACK and UberTaxi provide ride by professionally licensed drivers or chauffeurs. Travelers can also use Lyft Carpool as a type of carpooling service provided by TNC's, through which "a TNC facilitates a transaction between two commuters traveling a similar route" (Moran, 2016, p. 3).

2.2.1 What Does the App-based, On-demand, Ride Services Bring to the City and the Household?

App-based, on-demand ride services can pay off for municipalities and States. Ridehailing passengers in Chicago pay a 15-cent fee for every ride, which will be used for making the city's trains run faster and smoother through upgrading the tracks, signal and trains' electricity. In 2018, it was expected that the city of Philadelphia earned $2.6 million dollars for public schools through a 1.4% on ridehailing usage—this tax generated over one million dollars for the enforcement and regulation of the ridehailing industry. In South Carolina, municipalities and counties earned over one million dollars through a 1-percent ridehailing fee. In Massachusetts, during February 2018, a fee of 20 cents was determined by the officials for every trip made by app-based, on-demand ride services, and the revenue of this tax was designated to improving roads and bridges, compensating for the lack of funds dedicated to state transportation, and assisting taxi industry to adjust to new technologies and job training (Hu, 2018).

Although the expansion of ridehailing services has increased congestion, threatened taxi industries, and caused political and legal challenges for states and municipalities in regulating them, they serve as an unexpected advantage for municipalities, through saving them millions that would have otherwise been spent for transportation and infrastructure needs. Many municipalities and cities across the U.S. have designated fees and taxes on app-based, on-demand ride service companies or ridehailing passengers, or both. New York has a new surcharge on the trips made by app-based, on-demand ride services and taxi services, which can be turned into a central component of a congestion pricing plan for Manhattan. Also, a state task force, which has proposed fees of $2 to $5 on the trips made by app-based, on-demand ride services and taxi services in New York City, could create up to 605 million dollars per year for the failing subway. In 2015, South Carolina included a 1% fee to the trips made by app-based, on-demand ride services, which enabled it, to some extent, to set up a single regulatory framework. Adding this fee was also essential in hindering local officials from charging high fees to ridehailing vehicles parked outside. As an example, the city of North Charleston in South Carolina earned over $30,000 per year from this fee and used it for municipal operations. Supporters of the charges on ridehailing companies believe that these charges are justified, as these vehicles utilize public streets and resources, and redirect passengers and fares from public transit (Hu, 2018).

Research shows that female passengers are concerned about their sense of security from potential crimes in ridehailing vehicles and their drivers (Yan et al., 2019). They are uncomfortable with sitting with strangers in a small-sized vehicle and they fear that on-demand shuttles may travel to unsafe places. Installing security cameras, placing larger spaces between seats, and ensuring the driver are trained adequately are recommended for increasing the safety of on-demand ridesharing services (Yan et al., 2019). However, researchers observe safety of travel with app-based, on-demand ride services from various perspectives. Hailing a ride with these services could increase passengers' safety or at least a perception of safety, because both riders and drivers have "a digital record of the trip and reviews of one another" (Brown, 2018, p.137), which can also discourage discrimination against many passengers living in underserved neighborhoods or communities of color. Hailing rides by these apps can lessen the likelihood of drivers rejecting passengers due to characteristics such as race or gender. App-based, on-demand ride services stretch travel options to underserved areas because drivers do not know their passengers' destination before picking them up, and they cannot refuse to enter ill-favored neighborhoods (Moran, 2016). It means that travel to and within unfamiliar neighborhoods is more facilitated with the navigation systems of on-demand services (Brown, 2018). Ridehailing services may improve the perceptions of safety because riders and drivers can rate one another and ridehailing drivers particularly know that troublesome passengers are not eligible to use ridehailing platform. Also, the payment process with ridehailing services, at least in U.S., is cashless, which may increase the security of payment for both drivers and passengers, although it could be a barrier to low-income households because of their lack of access to debit/credit cards (Brown, 2018). However, there are partnership programs between ridehailing companies and local governments for helping low income households. For instance, the Pinellas County Transportation Disadvantaged (TD) Program, a partnership between Uber and the Pinellas County in Florida, has been created for supporting low-income households by subsidizing transportation for individuals who earn less income than the 150% of the federal poverty criteria. Low-income passengers who meet the eligibility criteria may request to hail a maximum of 23 free rides between 9:00 p.m. and 6:00 a.m. every month (Moran, 2016).

The literature calls for the complementary effect of app-based, on-demand ride services on the existing public transit system by improving last-mile transit access. The promotion of transit ridership and reducing operations costs are the possible outcomes of alternating low-ridership bus lines with these services (Yan et al., 2018). The technology-driven nature of app-based, on-demand services probably serves as a competitive advantage for these services over traditional ones. The results of a study in San Francisco indicate that travelers tend to substitute the taxi and public transport trips with most trips made by app-based, on-demand services (Rayle et al., 2014). Factors such as speed, convenience, and shorter waiting time for the arrival of ridesourcing vehicles, as well as the role of age, education, and travel behavior of individuals are determinant in tendency towards modal substitution (Rayle et al., 2014).

App-based, on-demand ride services, as a travel mode, have been widely explored in previous studies and travel behavior studies discuss the determinants of the mode choice (Lee et al., 2018; Vij et al., 2017; Kuppam et al., 1999; Clifton & Handy, 2003; Handy et al., 2004; Circella et al., 2017). These studies assess the shifts of travel modal preference over time, and the role of generational differences in being multimodal (Lee et al., 2018; Vij et al., 2017). Researchers investigate mode choice of on-demand ride services by takings various methods, such as designing a framework for a mode choice model for integrating on-demand services into regional travel models, as well as examining the factors that can limit the adoption of these services by passengers (Alemi et al., 2018; Henao, 2017).

Due to the scarcity of publicly available data, it has not yet been adequately assessed which travel modes are being substituted by on-demand ride services (Lavieri et al., 2018). Some survey-based studies examine the preference for on-demand services by passengers (Clewlow & Mishra, 2017; Dias et al., 2017; Rayle et al., 2016; Lavieri & Bhat, 2019; Asgari et al., 2018).

For instance, the results of a survey-based research in San Francisco display the substitutability of these services for the taxi, public transit and driving (Rayle et al., 2016). Also, the outcomes of the other survey-based research in the state of California highlights the strong impact of individuals' preferences for owning and using vehicles, limiting the ridehailing adoption among users and non-users (Alemi et al., 2018).

Millennials tend to be the frequent users of these services with a high likelihood of adoption (Alemi et al., 2018). The more usage of on-demand services results in a decreased rate of driving made by both frequent and non-frequent riders. Frequent riders, those who are more multimodal, those living in zero-/lower-vehicle households, and younger individuals, have a greater tendency towards using these services as a substitution for some travels that would have otherwise been made by active modes or transit (Alemi et al., 2018). Frequent users of these services are those who are more willing to pay to have less travel time, but the likelihood of being a frequent user is lower among individuals with stronger preferences for personal vehicle ownership, and those who have more significant concern about safety/security of on-demand services (Alemi, 2018). The most widely cited public safety concerns, which have called for some regulations by local governments, are drivers' background checks and insurance (Holloway, 2015). The background check is particularly significant in addressing the expectation of the customers of the safety of on-demand services. Dyer (2016) compares the background check standards for these services with taxicabs in Nevada and recommends implementing more comprehensive background checks and safety features by Uber to help the company to avoid prospective lobbying and lawsuit costs.

Having a tech-savviness lifestyle positively influences ridehailing in general and pooled ridehailing in particulate (Lavieri & Bhat, 2019). The likelihood of the adoption of on-demand services is higher in people who live technology-oriented lifestyles. It displays the association between familiarity with, and the adoption of modern technology in daily life, and the adoption of on-demand services (Alemi et al., 2018). Young, higher income and well-educated individuals tend to be the consumers of this travel mode. These are the individuals who work and reside in higher-density areas. Also, the likelihood of the usage of this mode is higher among households with one or more vehicles (Dias et al., 2017). The results of a survey-based nationwide study about mode choice behavior of participants concerning ridesourcing and automated vehicles (AV) highlights the potentiality of on-demand services, including AV technologies in becoming a viable travel mode for many travelers (Asgari et al., 2018). The results highlight the preference for single rides compared to shared rides by most drivers and passengers, but the preference for shared rides by transit users is more significant than exclusive services. It may specify the significance of cost for transit users in their mode choice decisions.

Urban Americans are regular users of app-based, on-demand ride services, which are used less regularly by individuals in the suburbs (Clewlow & Mishra, 2017). The results of a study concerning the adoption, use, and the effects of app-based, on-demand services in seven major U.S. cities signified a net decrease in transit use reported by the users of this mode (Clewlow & Mishra, 2017). More frequent users are those who disposed of a vehicle, and roughly half of the trips made by ridehailing services are those that would have otherwise been made by other modes including walking, biking, transit, or completely avoided. Also, there is not a smooth adoption of this travel mode across income classes and age groups, and the rates of vehicle ownership are similar between consumers of this travel mode and everyone else (Clewlow & Mishra, 2017). This displays the significance of factors such as vehicle ownership, income, and age in examining the adoption of on-demand services. These are the factors through which a significant portion of populations are characterized. These populations are called transit-dependent and their characteristics are discussed in the following section.

2.3 Transit-Dependent Population and Their Characteristics

According to the U.S. Department of Transportation, transit-dependent populations are characterized as persons without private transportation, under age 18, over age 65, or those living below poverty or median income levels, according to U.S. Census Bureau's definition (U.S. DOT, 2012). Transit-dependent populations have limited automobile access and there is not an adequate level of mass transit service to serve them (Jiao & Dillivan, 2013). The dependency of these groups on transportation is not limited to travel to work (Sanchez & Brenman, 2010). They rely on transportation for other purposes, such as obtaining medical care, getting to school, and shopping for basic needs such as groceries (Sanchez & Brenman, 2010). Transit-dependent populations are often low-income people (Sanchez & Brenman, 2010). Due to the orientation of transportation policies and public funds towards travel by car, these populations face challenging economic inequities (Sanchez & Brenman, 2010).

Transit-dependent populations constitute a significant demographic of people and the impact of the lack of transit on these groups is adverse. They are often characterized as marginalized populations from society and are often excluded from overall participation in society, for example, with a lack of access to employment and retail (Jiao & Dillivan, 2013). Exclusion creates a direct connection between transportation and the socioeconomic status of individuals (Gordon, 2010). A possible consequence of this relationship is poor transportation for the poor, as well as a decline in the poor's demand to receive strong transportation (Gordon, 2010).

The improvement of transit access for all requires reframing transportation as a civil right with civic organizations and transportation advocates at the local state, and national levels. Attempts towards enhancing the fairness of transportation policies require the recognition of the broad influence of these policies on civil rights, mobility, land use, and the environment. Evaluation of the fair distribution of the benefits and burdens of transportation policies to minority and low-income communities must be an essential part of every attempt made towards improving the fairness of transportation policies (Litman, 1999 as cited in Sanchez et al., 2003; Gutiérrez, 2014; Bullard, 2004; Kanter, 2015; Inwood et al., 2015; Baida, 2003; Gordon, 2010; Attoh, 2013; Allen, 2017). From a civil rights perspective, I can argue that people in need of transportation, such as low-income individuals, must not be charged for public transportation as a public service, because these people are paying taxes, and it is their right to use public transportation free of charge. App-based, on-demand ride services are ubiquitous across the country. The type of service provided by these companies is flexible, and a passenger can take a ride with these services almost anytime and anywhere. The drivers of on-demand services are scattered in many places, as the flexible nature of this service for driving requires. This flexibility provides a substantial covered area of service for transit-dependent populations deprived of access to public transit. However, app-based, on-demand ride services are private, and people must pay to use them. Having these services as a replacement for public transportation will no longer make transportation a public service, and people in need of transportation may question where the taxes they have paid have gone. Having public transportation as a free service can be perceived as a public right by people in need of transportation who must rely on it and replacing public transportation with on-demand services may negatively impact the perception of these individuals towards on-demand services.

The identification of transit-dependent populations serves as a useful tool for determining the unmet demand for transit. On-demand ride services can serve as a viable mode for transit-dependent populations. In a comprehensive study on the state of transportation equity in Dallas, Hamidi (2017) examined all types of transit-dependent populations, addressing socioeconomic characteristics such as age, income, and life cycle to figure out the hot spots of transit demand. She developed regression models to determine the relationship between transit demand and socioeconomic features of neighborhoods. Next, the spatial pattern of selected socioeconomic factors was assessed using spatial autocorrelation, which is applicable to measure if there is an underlying geographic clustering of the data based on both location and socioeconomic characteristics of block groups (Getis & Aldstadt, 2010 as cited in Hamidi, 2017). Then, the Z-scores of socioeconomic factors were measured and aggregated together to define transit demand for each block group. Finally, the resulting average of these criteria were implemented for hot spot analysis, and based on the outcome of this final step, statistically significant spatial clusters of high values (hot spots of transit demand) and low values (cold spots of transit demand) were specified. It indicates the significance of addressing socioeconomic and demographic characteristics of transit-dependents in specifying their demand for transit. Socioeconomic and demographic characteristics of riders are also key determinants of travel mode choice, along with travel attitudes, technology adoption, and built environment. The next section is a discussion of the barriers that deter transit-dependent people from accessing app-based, on-demand ride services, which is followed by a section exploring the key determinants of travel mode preference and frequency of use of ridehailing services and fixed-route transit.

2.4 Barriers That Deter Transit-Dependent People from Accessing App-based, On-Demand Ride Services

According to the literature, limited access to credit cards, cost, limited payment method, slow digital literacy, lack of access to smartphones, internet, or Wi-Fi, using a basic mobile phone with no internet capabilities, lack of access to a regular data plan, anxiety about and distrust of online payment methods, and the need of translation for transportation apps into languages other than English, are the major barriers that can deter transit-dependent people, especially low-income people, from accessing app-based, on-demand ride services (Dillahunt et al., 2017; Shaheen, et al., 2017; Moran, 2016; Creger et al., 2018; Dillahunt & Veinot, 2018; Shirgaokar, 2018; Golub et al., 2018; Yan et al., 2019).

Although ridehailing services have rapidly expanded in recent years, access by low-income adults to these services is still challenging, particularly for low-income communities of color (Creger et al., 2018). App-based, on-demand ride services are not still affordable to many riders for routine commuting and longer non-work trips, although they compete with public transit for shorter trips (Shaheen, et al., 2017). They are costly and riders may need to rely on credit cards (Dillahunt & Veinot, 2018). Access to smartphone and bank account are the prerequisites for using these services and these are important barriers to which low-income people often face. App-based, on-demand ride services like many other shared mobility services require debit/credit cards for payment. (Shaheen, et al., 2017). Thus, being unbanked or underbanked deters low-income people from accessing these services. Being underbanked means that a person may have a bank account but must rely considerably on cash or checks rather than bank services, such as credit cards. The rate of being unbanked and underbanked is generally higher among younger, less educated, low-income, and non-white populations. Due to banking restrictions, cash is still an important means of paying transportation fares. For riders who only use cash to pay for travel, this results in preventing them from using app-based, on-demand ride services (Brown, 2018).

Lack of access to a smart phone is another main barrier for access to ridehailing services. Smartphone access varies across households, and there is a significant positive association between smartphone access and the income level and educational attainment of people. Data plan limitations can restrict the use of app-based, on-demand ride services even among the households that own smartphones (Brown, 2018). Transit-dependent riders with the lack of access to regular data plan may fear being unable to hail a ride for their return trips, even if they could access Wi-Fi in their returning points. Populations with no access to the internet are the populations that have been left out by the “Digital Divide” (Shaheen, et al., 2017, p. 20). Like many other shared mobility systems, it is essential to access the Internet, in particular through a smartphone, in order to access to ridehailing services. Providing real-time data and location services by ridehailing apps requires access to high-speed data connections, and thus, locating riders and the process of real-time transactions is problematic with low speed internet (Shaheen, et al., 2017). Research also addresses logistical issues, such as the malfunction of the technology as a concern for transit-dependent riders when considering using ridehailing apps (Yan et al., 2019).

Low digital literacy is also a major barrier, because people with this challenge may need help from family members and friends for the process of downloading the app on the smartphone, creating account, and hailing the ride. They can feel discomfort using the ridehailing app or even the smartphone, due to low digital literacy (Dillahunt et al., 2017). Also, among transit-dependent people, low-income people and seniors are reluctant to connect personal financial information to mobility applications. Identity theft or losing funds from online or smartphone accounts may be a big concern for low-income riders, which deters them from using these services. Access to data and the internet is a significant barrier to low-income people, and they fear the risk of reducing data use or cancelling cellphone plans because of cost or data restrictions (Golub et al., 2018).

2.5 Key Determinants of Travel Mode Preference and Frequency of Use

There is a relationship between travel mode preference, mode choice, and frequency of use. Discussion of the demand for trips is a requirement for the analysis of trip frequency and mode choice. Demand approach allows the researcher to investigate questions concerning travel behavior, such as the effect of changing trip distance on the desire and ability to take trips by a particular travel mode. Discussion of the demand for trips can happen in a framework that the tools of microeconomics can provide. In this framework, it is significant to figure out to what extent the overall restrictions of resources necessitate compromising, among the existing alternatives, such as travel modes and to what extent the comparative desirability of these alternatives associates with the comparative costs. According to the demand approach, preferences over the goods in question is a factor based on which choice is taken. Preferences include attitudes and tastes towards travel modes and there is a correlation between individuals' preferences and their demographic and other personal characteristics (Crane, 1996). Also, frequent choice of a particular travel mode would lead to a habitual choice of this mode. This means that the increase in the usage frequency of a travel mode would result in the development of a habit of using this mode and lessons the likelihood of choosing substitute mode (Fujii, & Gärling, 2003). Given the relationship between travel mode choice, mode preference, and frequency of use, I have also considered mode choice in investigating the key factors influencing mode preferences and usage frequency.

Some previous studies have launched surveys to obtain measurable data for the evaluation of trips made by app-based, on-demand ride services (Treasure, 2018; de Souza Silva et al., 2018; Rayle et al., 2014; Rayle et al., 2016; Aarhaug & Olsen, 2018; Clewlow & Mishra, 2017; Murphy, 2016; Yan et al., 2018; Chen, 2018; Asgari, et al., 2018; Lewis & MacKenzie, 2017; Pike et al., 2017; Henao, 2017; Smart et al., 2015). In these studies, data was collected through various methods, such as phone-based, and Internet-based questionnaires or a mix of survey and qualitative data collection methods, such as interviews and focus group discussions (Aarhaug & Olsen, 2018; Murphy, 2016; Henao, 2017). The study of Rayle et al. (2016) in San Francisco was a notable example of conducting an intercept survey. Survey-based studies have evaluated travelers' preference for using app-based on-demand ride services (Clewlow & Mishra, 2017; Dias et al., 2017; Rayle et al., 2016; Lavieri & Bhat, 2019; Asgari et al., 2018), and they have apprised the substitutability of these services for other travel modes, although these investigations have not been extended due to limited access to the essential data to be used by the public (Lavieri et al., 2018). This study may serve as one of the first comprehensive survey investigations which examines the determinants behind the modal preferences and the usage frequency of both ridehailing services and fixed-route transit by transit-dependent people in the form of a single model simultaneously.

The following section discusses socio-economic and demographic characteristics, built environment and residential locations, mobility-related attitudes, and technology adoption as the key determinants of travel modal preferences and the usage frequency of ridehailing services and fixed-route transit.

2.5.1 Socio Demographic Characteristics, Travel Behavior and Modal Preferences

Demographic characteristics of individuals are well cited in the investigation of ridehailing demand in the literature of on-demand ride services (Dias et al., 2017; Alemi et al., 2018; Lavieri et al., 2017; Henao & Marshall, 2017; de Souza Silva et al., 2018; Clewlow & Mishra, 2017; Yan et al., 2018; Chen, 2018; Lewis & MacKenzie, 2017; Henao, 2017). Sociodemographic variables are among the traditional determinants that influence travel behavior and have significantly remained related to the most aspects of travel (Alemi, 2018; Hanson, 1982). Mode choice depends on both the built environment and socioeconomic characteristics, although most likely the role of socioeconomics characteristics is more significant (Ewing & Cervero 2001; Ewing & Cervero 2010). The inclusion of sociodemographic variables in transportation mode choice models can improve the statistical assessment of the model and it can increase its descriptive capacity (Bernetti, et al., 2008). Variables such as the vehicle per capita and household income are determinant in the mode choice of passengers (Ewing & Cervero, 2001), and research control for the socioeconomic characteristics of individuals, serve to explain the shift in mode choice for various distance travels (Limtanakool et al., 2006).

Travel mode preferences are also related to the socioeconomic and demographic characteristics of individuals and their households, such as such as age, sex, income, and household size, as well as vehicle ownership (Van Wee et al, 2002). There is a relationship between the comparative usefulness of cars to public transport and mode preference. Preference for cars is stronger among residents who own a car, higher-income people, and individuals living in larger households. It is also strong among men and people younger than 46. People who own a car, people who have a higher income, and people with larger family size have an above-average car preference (Van Wee et al, 2002).

The socioeconomic background of individuals is applicable in specifying the users of on-demand services, and this information is useful in specifying the effect of the adoption of on-demand services on the established travel modes (Clewlow & Mishra, 2017). Investigating the basic demographics of individuals, as well as their previous and alternative modal choices is taken as a method for the comparison between on-demand services and other traditional alternatives (Rayle et al., 2016). Age, gender, household income, having children in the household, individual's status as student, ethnicity, race, vehicle availability, household size, and household composition are among the determinant variables in examining the likelihood of the adoption of on-demand services and mode choice (Yan et al., 2018; Alemi et al., 2018; Hampshire et al., 2017; Lavieri & Bhat, 2019; Rayle et al., 2016). The income level of mass transit users is significantly lower than automobile commuters. Bus ridership can be predicted based on the socioeconomic characteristics of the riders, and there is an indirect relationship between car availability in the households and riding the bus. Also, having fewer cars than drivers per household is related to the increased use of bus services (Flannelly & McLeod,1989). Individuals younger than age 60 years are less likely to change their transportation towards the transit mode, in comparison with older adults (Bernetti, et al., 2008).

In survey-based studies, the socio-economic and demographic information of respondents and their households, such as sex, employment, educational status, income level, living expenses, and access to vehicle, are significant in determining the likelihood of choosing travel modes by respondents (Asgari et al., 2018; Yan et al., 2018). Research controls for the sociodemographic characteristics of the ridehailing travelers to estimate the variation of ridehailing adoption with respect to built environment attributes, and to evaluates the impact of the ridehailing adoption on the overall patterns of travel across a variety of sociodemographic characteristics (Alemi et al., 2018).

Users of on-demand services differ in their sociodemographic characteristics. The results of a study on the frequency and the adoption of ridehailing in California shows that about half of the frequent ridehailing users are more probable to reside in low /medium-income households, and are between the ages of 25 and 34—and the likelihood of adoption to on-demand ride services is increased with highly educated, older millennials (Alemi et al., 2018). Also, a larger proportion of frequent ridehailing consumers reside in households in which no vehicle exists, but it is not proven if the number of vehicles available in the household affect the higher usage or the adoption of users (Alemi et al., 2018). There is a positive correlation between personal vehicle usage and economic status (Yan et al., 2018), and income and vehicle access are significant attributes of driving. Higher spending likely increases the tendency of students to live near campus, and higher rent on campus offsets the need to drive. The likelihood of selecting non-driving travel alternatives is higher between students than faculty and staff, although there is not a significant difference between males and females in terms of using motorized versus non-motorized modes (Yan et al., 2018). Research highlights that the availability of on-demand ride services could be beneficial for university students due to a lower rate of vehicle ownership in this group than working people. Restricted parking regulations and an inflated cost of parking in universities are the other reasons that can make on-demand services a viable option for university students (Lavieri et al., 2017). The need to have a smartphone, credit cards, and bank account, as well as linguistic isolation, are the obstacles to which lower-income communities encounter to choose ridehailing as a travel mode (Hughes & MacKenzie, 2016; Pike et al., 2017).

The adoption of on-demand services and their usage can be modeled as the functions of sociodemographic characteristics of riders (Lavieri & Bhat, 2019). The literature calls for the use of census level sociodemographic data at the trip origins for estimating the characteristics of ridehailing users (Lavieri et al., 2017 as cited in Hampshire et al., 2017). Also, the socioeconomic and demographic background of riders, including gender, age, work status, educational attainment, and race/ethnicity, along with household annual income and household composition, are applicable in creating a regional profile of on-demand services (Clewlow & Mishra, 2017). Concerning race/ethnicity, there are relationships between belonging to a certain ethnicity and privacy concerns with pooled ridehailing (Lavieri & Bhat, 2019). Race and gender are recognized as key demographic variables in access to on-demand services (Ge et al., 2016). Research displays a pattern of racial discrimination against African American customers in the form of longer waiting times and trip cancellations by drivers, particularly in low-density areas (Ge et al., 2016).

The literature review indicates that there are consistencies between the type of socioeconomic and demographic characteristics that feature transit-dependent people, such as income, and age, as well as access to a vehicle and those characteristics that feature the users of fixed route and on-demand ride services. It shows the significance of including these characteristics in exploring the modal preferences for and the use of these modes by transit-dependent populations. However, there appears to be some areas of disagreement in the results of studies applying socio-economic and demographic characteristics of riders. According to Dias et al. (2017), ridehailing users tend to be high-income individuals, but the results of Alemi et al. (2018) study on the frequency and adoption of ridehailing in California shows that about half of the frequent ridehailing users are more likely to reside in low-/medium-income households. The income status of individuals is associated with the income level of their households, especially in low income families with large household sizes. In these households, all family members earn money and spend it together. Therefore, personal income is not a good criterion for survey-based studies that aim to focus on low-income populations to investigate mode choice, mode preference and usage. Also, disability is an issue that may seriously limit or prevent individuals from some travel activities, such as using shared app-based ride services. The issue of disability can serve as an important variable for exploring ridehailing as a preferred mode by transit-dependent people, but it is not very much explored in previous studies concentrating on mode preference for on-demand ride services.

The next section discusses the effect of the built environment on the mode preference for and use of fixed-route transit services and app-based on-demand ride services.

2.5.2 Built Environment and Travel Mode Choice

2.5.2.1 D-Variables, Mode Preference, and the Use of Fixed-Route Transit Services

The possibilities of moderating travel demand by altering the built environment have always been a significant topic in urban planning discussions (Ewing & Cervero, 2010). Such impacts used in travel studies have often been themed with words which start with the letter D, thus arose the term “D-Variables.” Three of these include density, diversity, and design, were originally highlighted by Cervero and Kockelman (1997), later followed by distance to transit and destination accessibility. The sixth D, which has been studied less, is demand management, including parking supply and charge. The seventh D would be the word "Demographics", and while not related to the environment, it has administrated as confounding effects in travel studies (Ewing & Cervero, 2010).

Density, which more precisely can be defined as a measurement of the volumetric mass, is the mass of a unit volume of a material substance per unit of area. Gross or net can be considered as the area, and the variables can be employment, population, dwelling units etc. Population and employment, which are the variables of interest, are generally calculated to roll up the overall activity density per area (Ewing & Cervero, 2010).

A diversity index is a quantitative measure that pertains to the number of various land-uses in a given area, and the degree to which they are depicted in employment, floor area, or land area. Entropy measures of diversity are extensively applicable in travel studies. Entropy's low values demonstrate single-use environments, while more varied land uses are specified with higher values of this index. Ratios, including jobs-to-housing or jobs-to-population are used, but less frequently (Ewing & Cervero, 2010).

Street network features within an area are connected to design, which are different from aggregated urban grids of extremely interrelated, straight streets, to thin suburban networks of curving streets, forming loops and lollipops. The average block size, the ratio of four-way intersections, and the number of intersections per square mile, are the measures which are usually considered. Design is sometimes gauged as sidewalk coverage, average street widths, average building setbacks, or other physical variables that distinguish auto-oriented environments from pedestrian-oriented ones as well (Ewing & Cervero, 2010).

Destination accessibility, which can be regional or local, measures ease of availability to trip attractions (Handy, 1993 as cited in Ewing & Cervero, 2010). Regional accessibility has been simply defined as the distance to the central business zone, as well as the number of jobs or other attractions easily accessed within a given travel time, which tends to be higher at central locations, and lowest at circumferential ones (Ewing & Cervero, 2010). The local accessibility is defined as the distance from home to the nearest store (Handy, 1993 as cited in Ewing & Cervero, 2010). Distance to transit is usually calculated as an average, which can be related to the shortest street routes from where people live or work, to the closest rail station or bus stop. Further, it may be calculated as transit route density, distance amongst transit stops, or the number of stations per unit area (Ewing & Cervero, 2010).

Population density, the density of housing units, and employment density shorten travels, which encourages public transit, and lessens dependency on the private car (Sun et al., 2017). Researchers have addressed increased network connectivity and grid-like street patterns as the contributing factors that would generally encourage taking public transit (Sun et al., 2017). In terms of accessibility to transit, the results of a study in Shanghai, China, showed that individuals' relocation to suburban areas closer to metro stations could lessen job accessibility and increases the likelihood of substituting non-motorized commuting with transit commuting (Cervero & Day, 2008 as cited in Sun et al., 2017).

The demand for transit is affected by the types and mix of land uses (TCRP Report 16, 1996). High residential density, compact cities with mixed land use, and suitable accessibility are recognized as the factors that can increase travel with public transit (Yu et al., 2019). There is an association between higher density and individuals’ motivation for reducing car use and selecting public transit as a travel mode (Yu et al., 2019). Concerning destination accessibility and distance to transit, research highlights the relationship between increasing car use and long-distance to a destination or the inconvenience of walking to bus stops (Yu et al., 2019). Higher densities make destinations closer together, which inevitably results in shortening trip lengths and makes transit use more comparative in comparison with automobile travel (Porter et al., 2013).

2.5.2.2 D-Variables, Mode Preference and the Use of App-Based, On-Demand Services

The literature cites built environment attributes, such as employment density (jobs/acre), road network density, and transit stop density (stops/mile), that are applicable in exploring the geographical distribution of trips made by ridehailing service across neighborhoods (Brown, 2018). Higher accessibility to Uber is correlated with higher road network density, population density, and less travel time to work (Wang & Mu, 2018). Travel time is a key predictor of the ride-splitting behavior of passengers (Chen et al., 2017). Increasing the regional accessibility and land-use mix increases the likelihood of the adoption of on-demand services. The likelihood of using this travel mode is more significant among individuals who have more long-distance business trips and have a more significant proportion of long-distance trips made by plane (Alemi et al., 2018). On-demand services offer more significant performance in dense urban areas and higher population and employment densities, presumably attributed to more frequent trip requests. More frequent trip requests would lead to the attraction of more drivers to the area and the reduction of waiting time (Hughes & MacKenzie, 2016).

There are existing strategies concerning land use, which are created to make the residents closer to their destinations and provide them lasting alternatives to driving, which would result in driving less. In fact, and more precisely, when there is more accessibility, it would lead to people to drive less. Accessibility to new areas enhanced by strategies that incorporate mixed-use zoning and permit for retail, and other commercial applications within close adjacency to residential zones and street connectivity ordinances, would guarantee more direct routes between residential and commercial regions (Handy et al., 2005). There is an association between more significant land-use mix and regional accessibility by car and the higher likelihood of the adoption of on-demand ride services (Alemi, 2018). Those who are concerned about the environment want to decrease their auto travel and would prefer to live in higher-density zones, due to the ease of access to work. Those who are concerned about better accessibility, and having flexible and convenient auto travel, choose the lower-density form of living, and that is the factor that makes it easy for people to use the car as a symbol of status (Schwanen & Mokhtarian, 2010). Researches refer to low residential location density and individuals' privacy concerns as the key part of the impediments to the adoption of pooled ride-hailing, with non-Hispanic Whites with sensitivity to their privacy than members of other races (Lavieri & Bhat, 2019).

2.5.2.3 Residential Location and Mode Preference

Residential location is a choice that one chooses with the long-range in mind. This choice has an effect on daily travel choices. (Domencich & McFadden, 1975 as cited in Handy & Mokhtarian, 2004). Travel-related decisions have been classified into three distinct groups: long-range decisions, medium-range decisions, and short-range decisions. Residential location, along with housing type and employment location, is classified as a long-range, or major land use/locational decisions. Automobile ownership and the usual mode of travel to work, variables that are very interdependent, particularly for the household's primary worker, are categorized as medium-range decisions. Finally, non-work travel decisions are categorized as short-range decisions. Medium-term travel-related decisions are conditional on long-range decisions, and short-range ones are conditional on both medium and long-range decisions. (Ben-Akiva & Atherton, 1977). It highlights the importance of considering residential location as a major variable in both travel behavior studies.

The residential location choice of riders is a determinant in the prospective rates of the adoption of on-demand services and the effect of this adoption on using other travel modes (Alemi et al., 2018). It is expected that the adoption rate of on-demand services is more significant among those who are residing in cities and large metropolitan areas, where the usage of these services is widespread. Also, frequent ridehailing users are more likely to reside in urban neighborhoods (Alemi et al., 2018). The literature calls for employing various methods for identifying the residential location of riders. Alemi et al. (2018) geocoded the home address for everyone in their dataset, then categorized the residential neighborhood into three classes including predominantly urban, suburban or rural. Yan et al. (2018) obtained the residential preference variables by asking respondents about the importance of travel modes when they moved to their current residence, and these variables were found to be major determinants of mode choice. Lavieri & Bhat (2019) defined residential location based on a survey item, in which the respondents figured out the type of neighborhood they resided in, and they classified residential locations as either rural areas, small towns, central areas/downtown, or suburban areas.

The relationship between the preference for and use of travel modes can be explained, with respect to the relation of these concepts, with the residential location of people and the built environment. Residents who do not have the chance of living in their preferred residential type may have reduced travel satisfaction because the use of preferred travel mode is restricted by the built environment. As such, these residents are forced to use substitute travel modes. (Kamruzzaman et al., 2013). Determining the impact of the built environment on travel behavior requires the investigation of personal attitudes and preferences (Van Acker, 2010). Research shows that in neighborhoods with proper public transport connections, a significant portion of people prefer to use public transport (Van Wee et al, 2002). The importance of mode preferences is stronger for public transport lovers than for car lovers, because from a spatial perspective, the road network is more developed than rail (and bus) networks, and the accessibility to destinations by public transport varies more than the accessibility to destinations by car. Also, the likelihood of choosing a residential location in harmony with travel mode preference is lower among the individuals who prefer to travel by cars than those with a preference for public transport. Considering travel mode preferences of people in land-use policies would assist people who prefer using public transport to travel according to their preferences (Van Wee et al, 2002).

2.5.3 Mobility-Related Attitudes

Mobility-related attitudes of individuals is well cited in travel behavior studies (Spears et al., 2013; Choo & Mokhtarian, 2004; Molin et al., 2016; Cao et al., 2008; Circella et al., 2016; Lyon, 1981; Lyon, 1982; Lyon, 1984; Circella et al., 2008; Redmond & Mokhtarian, 2001; Diana & Mokhtarian, 2008; Handy et al., 2006; Etezady et al., 2019; Kuppam et al., 1999; Clifton & Handy, 2003; Circella et al., 2017). Attitudes, values, preferences, and perceptions can strengthen associations among individuals (Vinayak et al., 2018). Geographical proximity no longer serves as the sole factor which determines the interdependence between people. The likelihood of close social interaction is higher between people with similar attitudes and lifestyle preferences, and close social interaction subsequently reinforces the impacts of attitudes and preferences (Vinayak et al., 2018). The change in passengers' attitudes about information and communications technology has greatly influenced the change in public transportation. Individuals’ interactions and information exchange on transportation choices or observing the behavior of other individuals in their close vicinity can also influence behavioral choices (Shaheen & Cohen, 2018).

Using a specific travel mode and the tendency towards using it mutually affect one another (Kroesen et al., 2017). Attitudes for travel, personality, and lifestyle are significant to vehicle mode choice. For instance, those who might be interested in living in urban areas characterized with higher-density mixed uses are also more interested in driving expensive cars or SUVs, which indicates that having the desire for living in urban districts may not be in relation with an interest in fuel-efficient transportation, as a new urbanist commentator might desire. The lack of preference for travel is related to their preference for driving a luxury car, a preference that likely arose due to the desire to make an unpleasant activity more tolerable. The worse travel conditions get, the more some will try to make up not by shortening travel, but by improving their experience, via obtaining a more expensive vehicle, for example. Those who believe they do travel a lot in long distances are less likely to go by compact cars (Choo & Mokhtarian, 2004).

Transit policies must not merely concentrate on designing and developing spatial plans, but also should consider subjective implications (Van Acker, 2010). Living in a high-density and mixed-use area close to the center of the city or village is related to lower car usage and using more public transportation, as well as an increase in activities such as walking and cycling. However, these spatial influences on modal selections are generally small, and other influences are of more significance (Van Acker, 2010). As an example, modal choices are not only directly affected by high density and more diversity, but principally indirectly through the interplay with other aspects, such as car ownership. Also, some people select a residential neighborhood by themselves so that it would be in harmony with their residential and travel attitudes and preferences. To others, however, the enjoyment of travel dominates their modal choices, and it does not matter where they live in. In such conditions, the primary purpose of spatial planning strategies, like lessening car usage through densification, is not frequently gained (Van Acker, 2010).

The likelihood of the use of app-based transportation services is more significant for individuals who use these services frequently, and those who have utilized taxi and carsharing services in the past (Alemi et al., 2018). Also, the tendency of the quicker adoption of these services is observable among individuals with a stronger attitude towards supporting the environment—these individuals tend to be variety-seeking and technology-embracing (Alemi et al., 2018). Aiming to explore the determinants of the continues intention of the mobile taxi booking (MTB) application service, Weng et al. (2017) surveyed 387 users of this service in Kuala Lumpur, Malaysia. They used the Technology Continuance Theory (TCT) to explore the subjective factors, such as attitudes and perceptions that motivate passengers towards the continuous usage of the taxi app. They considered attitudes, perceived risk, perceived ease of use, and perceived usefulness as predictor variables to better understand the contentious intention of using MTB apps. TCT is a theoretical model proposed by Liao et al. (2009), which represents and explains users' behavior concerning technology continuance. The findings emphasized the substantial impact of perceived usefulness, attitude, and satisfaction on the continuance intention of using the MTB App.

Consideration of the behavioral experiences of people in access to transit is significant in the investigation of the role of attitudinal factors in the preference for on-demand services as a travel mode by transit-dependent people. One can imagine the experience of transit-dependent individuals: they live in transportation underserved communities, in which they have no access to transit, but they are able to receive an on-demand service, as an alternative travel mode. This alternative might serve as a satisfactory choice. However, if these individuals change their residential location and move to places that offer decent public transit, they obtain a behavioral experience of access to transit that they did not have before. Experiencing transit can change their subjective knowledge and attitude towards on-demand services. Based on this new knowledge, they might not find the on-demand ride services as a satisfactory choice, and they might demand transit. The experience of a particular travel mode can form one's subjective knowledge about it. Transit-dependent people in transportation underserved communities do not have the subjective knowledge of transit or adequate transit, because no transit exists in these areas—or the existing transit is limited or inefficient. They might receive a substitute choice, such as ridehailing services, but they have not had the chance to experience using transit or adequate transit to be able to compare such experiences to ridehailing. Therefore, the behavioral experiences of transit-dependent people in their access (or lack thereof) to fixed-route public transit can influence their travel attitudes, which influence their preference for, and use of app-based, on-demand ride services.

2.5.4 Technology Adoption

App-based, on-demand ride services imply a transportation service that connects drivers with passengers through app-based technological devices. Thus, technology adoption must be included as a variable in exploring the transit-dependents' mode preference for and their use of this travel choice. The activity-travel choices of individuals who own smartphones significantly differ from those who do not own these devices (Astroza et al., 2017). Obtaining travel information by these devices makes the effect of smartphone ownership on activity-travel choice more significant. There is a correlation between owning and using a smartphone and increasing the likelihood of using multiple options for travel (Astroza et al., 2017). Given the rapid expansion of technology, and the widespread use of the smartphone, the significance of including the impacts of technology in travel forecasting models for predicting travel demand in the context of substitute scenarios, becomes even more prominent (As,troza et al., 2017).

The emergence of app-based, on-demand ride services as a new generation of travel modes is the result of the integration of transportation and information technology (Yan et al., 2018). Following the advances in the information and communication technologies (ICTs), the travel and lifestyle of people have changed. Due to the fast emergence of mobile apps and web payment methods, on-demand ride services have rapidly become widespread (Asgari et al., 2018). These services are now equipped with the essential enabling technologies and features, such as digital maps and GPS technologies, providing ridehailing users with waiting times based on real-time information (Clewlow & Mishra, 2017). The integration of transportation and information technology may increase access to shared mobility, and populations challenging the lack of adequate travel options are the potential beneficiaries of increasing access to shared mobility (Feigon & Murphy, 2016). Transit-dependent populations could be one of these potential beneficiaries.

The expansion of technology companies providing ridehailing platforms is the consequence of the connection between drivers and passengers, through mobile smartphone applications, and social networks and real-time information, which are determinants in making this connection (Henao, 2017). However, access to information technology is recognized as an obstacle towards the widespread adoption of new shared mobility options, because such access is a precondition to using many of these shared modes. It is more observable among lower-income individuals and those who are not familiar with using new technology (Feigon & Murphy, 2016).

Among transit-dependent people, the elderly might be the individuals who do not feel as comfortable using ridehailing services, due to the technology-based nature of this travel mode.

Research quantifies the associations between the use of ridehailing services and various explanatory variables, including technology adoption, to examine the frequency and the adoption of these services (Alemi et al., 2018). The extent of individuals' familiarity with modern technology and the adoption of these technologies in their daily life would determine an increase in the likelihood of the adoption of this travel mode. As such, technology adoption should also serve as a useful variable in exploring the mode preference for and the use of on-demand ride services. Riders' adoption of ridehailing as a technology-based mode can be explained in the context of the Technology Acceptance Model (TAM). According to TAM, the role of perceived ease of use and perceived usefulness are significant in the acceptance or rejecting of a technology. People's beliefs about the usefulness of a system in enhancing their performance would determine perceived usefulness, and the degree to which they believe that using that system would require minimal effort, would determine perceived ease (Davis, 1989). It is expected that transit-dependent individuals who are more familiar with modern technologies are more likely to have mode preference for and use of this travel choice.

2.5.5 Summary

Transit-dependent populations form a significant demographic of people, and the impact of the lack of transit on these groups is adverse. They are often characterized as marginalized populations from society and tend to be excluded from overall participation in society and suffer from the lack of access to employment and retail. They have limited automobile access and there is not an adequate level of mass transit service to them. The dependency of these groups on transportation is not limited to travel to work. They rely on transportation for other purposes, such as obtaining medical care, getting to school, and shopping for basic needs such as groceries. Transit-dependent populations are often low-income people. Due to the orientation of transportation policies and public funds towards travel by car, these populations face challenging economic inequities.

Transit dependent people in the U.S. are faced with very limited mobility options for responding to their essential travel needs, which affects their quality of life. A community design and a land use pattern that does not support the development of public transit has led to the failure of providing adequate transit services to these people, particularly in areas with a sprawl pattern. This pattern increases people's dependency on driving personal cars, which consequently reduces their use of transit. A land-use pattern that quells the demand for transit, and insufficient capital and operating funding for transit properties, has led to the spatial mismatch of jobs, and low-income household are now more vulnerable than others, due to this mismatch. These households and workers challenge the cost of housing, which is fast-growing, and has reduced the current residence options with transit access to jobs. They also have problems with transit services with higher capacity, which usually operate during the rush hour. The restricted access and mobility of low-income households between affordable housing and jobs is the outcome of suburbanization, and the land use patterns that do not support public transit, as well as increasing the costs of developing transit services, car culture, and no significant increase in income for low-income working households.

Urban Americans are regular users of app-based, on-demand ride services; whereas, these services are used less regularly by individuals in the suburbs. In major U.S. cities, the more frequent users of app-based, on-demand services, are those who disposed of a vehicle, and roughly half of the trips made by ridehailing services are those that would have otherwise been made by other modes, including walking, biking, transit, or completely avoided. Also, there is not a smooth adoption of this travel mode across income classes or age groups. The likelihood of the adoption of on-demand services is higher among those who live technology-oriented lifestyles. This displays the association between familiarity with and the adoption of modern technology in daily life and the adoption of on-demand services. Young, higher income and well-educated individuals tend to be the consumers of this travel mode. These are the individuals who work and live in higher-density areas.

The socioeconomic background of individuals is applicable in specifying the users of fixed-route transit services and app-based, on-demand services. It is useful in specifying the effect of the adoption of on-demand services on the established travel modes. Age, gender, household income, having children in the household, an individual's status as student, ethnicity, race, vehicle availability, household size, and household composition, are among the determinant variables in examining the likelihood of the adoption of on-demand services and the mode choice and mode preferences.

The demand for transit is also affected by the types and mix of land uses. High residential density, mixed land use, and suitable accessibility are the factors that can increase travel with public transit. Also, there is an association between higher density and motivation for lessening car use and selecting public transit. Ridehailing services offer more significant performance in dense urban areas. Higher population and employment densities presumably is associated with more frequent trip requests for ridehailing, while increasing the regional accessibility and land-use mix increases the likelihood of the adoption of these services. There is also a relationship between the residential location of people and their travel mode preferences and usage. Residents who do not have the chance of living in their preferred residential type may have reduced travel satisfaction because their use of preferred travel modes is restricted by the built environment. As such, these residents are forced to use substitute modes of travel.

The likelihood of the use of ridehailing services is higher among individuals who use these services frequently, and those who have used carsharing services in the past. Research quantifies the associations between the use of on-demand services and technology adoption, to examine the frequency and the adoption of these services. The extent of individuals' familiarity with modern technology and the adoption of these technologies in daily life would determine the likelihood of their ridehailing adoption. The role of perceived ease of use and perceived usefulness are also significant in the acceptance or rejecting of a technology. Individuals' beliefs about the usefulness of a system in enhancing their performance would determine perceived usefulness, and the degree to which they believe that using that system would be free of effort would determine perceived ease.

3 CHAPTER THREE: METHODOLOGY

3.1 Research Design

Following the development of the research questions and hypothesis, explaining the research significance, and literature review, it is essential to select the appropriate methods that can answer the research questions. The survey is the selected method, and the following steps explain the execution of the data collection and analysis.

Step one: In order to design my survey, I reviewed the existing survey-based studies that have emphasized the fixed-route transit services and app-based, on-demand ride services from various aspects. The survey must be original and comprehensive enough for the purposes of this dissertation. I reviewed previous surveys to figure out the most important factors concerning the preference for and use of traditional and technology-based travel modes.

Step two: I designed my survey based on the procedures performed in step one.

Step three: I determined transit-dependent people as the target population of this study. As such, I needed to design the sample for data collection, based on the socio-economic and demographic characteristics of these populations. I collected the data concerning the mode preference and usage frequency by running the survey, and I obtained the data concerning the built environment variables. This study uses the following types of built environment data: secondary, online, and publicly available.

Step four: Using ArcGIS software, I determined the population centroid of the respondents’ zip codes. Then, I buffered around each centroid to examine the status of the built environment attributes. I used built environment data to measure the status of population and employment density, and the land-use mix around population centroids.

Step five: I conducted Structural Equation Modeling (SEM), a statistical analysis, in order to model and investigate the direct and indirect effects of the explanatory variables on the outcome variables.

Step six: I analyzed the results and engaged with the literature to figure out if the results answer the research questions, and whether the findings validated or invalidate the hypotheses. I then explained the policy implications and recommendations. These two will be presented in Chapters 4 and 5 respectively.

3.2 Conceptual Framework & Reference to Theory

As explained in chapter two, the concept of travel mode preference is related to mode choice. The concept of mode choice has usually been employed as an application of consumer choice theory, which relates to the belief that individuals make rational choices between options, acting or serving in place of other options competing together, in order to maximize personal utility or net benefit (Cervero, 2002). Decisions made by travelers concerning commuting between the origin and destination points depends on the weight they give to the relative travel times, costs, and other characteristics of modes (Cervero, 2002). The consumer choice theory assumes the consumer as an individual, with thorough and transitive preferences, will choose the most preferred package from the affordable set, defined by the standard linear budget constraint (Hands, 2009). In the context of budget constraint, which had been introduced by the theory of household consumption (and was later taken over by the general equilibrium theory), budget is a significant factor that serves to designate the plan for revenues and expenditure of any economic unit. The budget constraint restricts the set of possible decisions (Kornai, 1980).

The theory of planned behavior and the technology acceptance model serve as a theoretical context for the explanation of the adoption of riders to the fixed-route transit and ridehailing. The theory of planned behavior considers behavior as the result of rational choices and emphasizes the effect of reasoned influences such as perceptions, attitudes and preferences on behavior (Ajzen, 1991 as cited in Van Acker, 2010). The technology acceptance model signifies the role of perceived ease of use and perceived usefulness in the acceptance or the rejection of a technology. Individuals' belief concerning the usefulness of a system in enhancing its performance would determine perceived usefulness. Also, the degree to which they believe that using that system would be free of effort would determine perceived ease (Davis, 1989). According to this model, one's attitude towards using a system determines that person's actual use of that system.

The theory of planned behavior can be applied as a strong theoretical basis for discussing the system of preferences for the use of transportation modes. The main mechanism of the theory of planned behavior assumes that one's actual accomplishment of the behavior is influenced by one's intention towards adopting a specified course of action. This theory comes from the perspective of psychologists, who regarded intentions as mediators between attitudes and actions (Haugtvedt et al., 2018). In research on consumer behavior, researchers have identified the causal sequence as a hierarchy of beliefs, attitudes, and intentions (Ajzen, 2008). The most popular theoretical models in this field are the theory of reasoned action (Aschenbrenner et al., 1989) and its successor, the theory of planned behavior (Ajzen, 1991). Therefore, according to the theory of planned behavior, it can be argued that travel behavior of individuals is influenced by their preferences for using each of these transport systems. On the other hand, this theory also discusses the factors that influence the intentions of individuals.

According to the theory of planned behavior, the intention to perform a particular behavior is influenced by three major factors, which are discussed as follows. The first factor is “behavioral beliefs,” which refers to the individual’s beliefs about the possible consequences of behaviors. These beliefs lead to a favorable or unfavorable attitude toward various behaviors. The second factor is “normative beliefs,” which refers to the normative expectations of others that lead to perceived social pressure or subjective norms. The final factor is “control beliefs,” which “provide the basis for perceptions of behavioral control” (Ajzen, 1991, p.189). Control beliefs are a set of beliefs that “[deal] with the presence or absence of requisite resources and opportunities” that ultimately “determine intention and action” (Ajzen, 1991, p.196). Control beliefs lead to perceived behavioral control, which refers to the perception of the ease or difficulty of performing behavior. The combination of attitudes toward behavior, subjective norms, and behavioral control perceptions, leads to the prediction of a behavioral intentions (Ajzen, 1991). Planned Behavior Theory is used as a conceptual framework for selecting the appropriate policies and understanding the impact of interventions on individuals' behavior. These beliefs are the informational foundation of behavior, and the causes of behavior can ultimately be found in these beliefs. Therefore, a change in these beliefs can lead to a change in behavior (Heath & Gifford, 2002).

Among the three factors in the theory of planned behavior in the analysis of the system of preferences, control beliefs are effective in analyzing the conceptual model. Under this factor, the three variables “the importance of service time efficiency in modal preference”, “accessibility preference”, and “the importance of service availability in modal preference” are expected to be as variables affecting people's preferences in using transportation modes in the model. Time as a key factor that eases the travel process is considered in the intent and preference of transit dependent people to use a particular travel mode. Importance of service availability is also expected to affect the individuals' preference for using a particular travel mode. The importance of the index of availability becomes more significant, especially in relation to the type of service provided by private ride services such as Uber, as the most available mode of transportation and easing travel behavior. As mentioned, control beliefs lead to perceived behavioral control, which refers to the perception of the ease or difficulty of performing behavior. Thus, this effect can also be explained under the theory of planned behavior. Overall, the timeliness, speed, and availability are all attractive factors for transportation by a particular travel mode, and they are critical in increasing the preference for using this mode.

Theory of Planned Behavior can be viewed as a rational approach to consumer behavior because it assumes that goals and behavior in this domain rationally follow the one's behavioral, normative, and control beliefs (Haugtvedt et al., 2008). This theory has been used as a framework for selecting the proper policies and understanding the impact of interventions on individuals' behavior (Heath & Gifford, 2002). Based on this theory, it can be expected that the use of transportation modes depends on the financial ability of individuals. In fact, planned behavior theory deals with the determining role of people's financial level in making a rational decision proper to the financial level. Therefore, transit-dependent people choose a certain mode of transportation according to their household income. Income and employment status are among the factors influencing the use of transportation systems that fall under the economic situation of individuals. Household size and studentship are other factors influencing the use of travel modes that fall into the category of socio-demographic characteristics. In addition to these factors, transportation modal use may be also subject to some personal limitations that limit individuals' arbitrary control on preferences. One of the limitations that is expected to be an influential variable in the model is disability.

Residential preference or the preference for living in compact and accessible or sprawl neighborhoods is also expected to affect modal preferences. Residents who do not have the chance of living in their preferred residential type may have reduced travel satisfaction because the use of preferred travel mode is restricted by the built environment. As such, these residents are forced to use substitute travel modes (Kamruzzaman et al., 2013).

Determining the impact of the built environment on travel behavior requires the investigation of personal attitudes and preferences (Van Acker, 2010). Research shows that in neighborhoods with appropriate public transport connections, a significant portion of people prefer to use public transport. (Van Wee et al., 2002). Built environment variables are expected to affect travel behavior and modal preferences. It could be understood by mentioning two examples. When built environment variables such as population and employment density are low in an area or land uses are not very mixed, people's preference can be affected in two ways. First, people who care about the travel time factor prefer to use app-based systems such as Uber to get to their destination faster because they are living in scattered areas. On the other hand, given the low-income status of the sample, those who care more about the cost of travel prefer to spend more time using traditional transportation systems such as buses, which are cheaper but slower.

The conceptual model below illustrates these relationships.

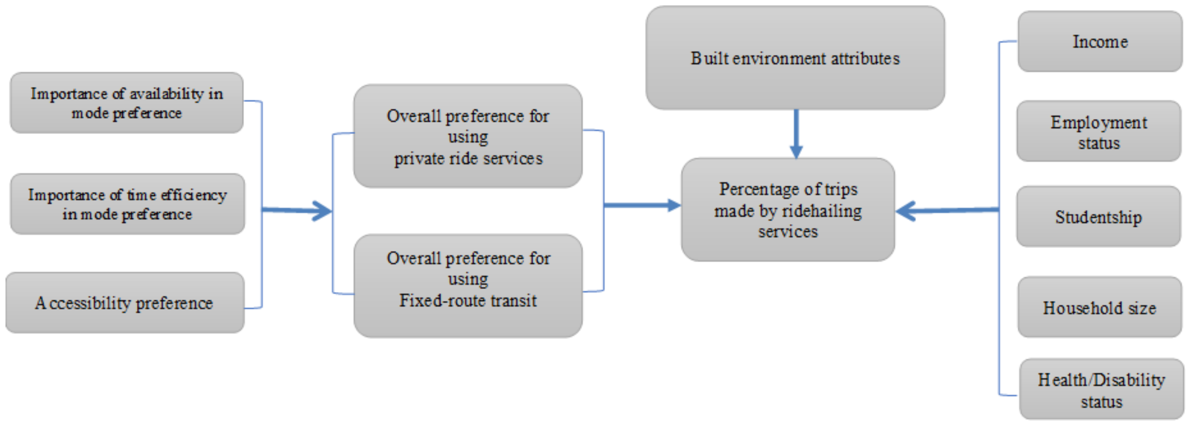

Figure 3. 1 Conceptual framework: The effect of the explanatory variables on the overall mode preference and usage frequency (Borrowed from the work of Etminani-Ghasrodashti, R., & Hamidi, S. (2019))

3.3 Study Area

This study focuses on 48 populous U.S. Urbanized Areas (UAs) as the study area, which are displayed in figure 3.2 and described in tables 3.1 through 3.4. The Census Bureau defines Urbanized Areas (UAs) as the areas of 50,000 or more people (U.S. Census Bureau, 2018).

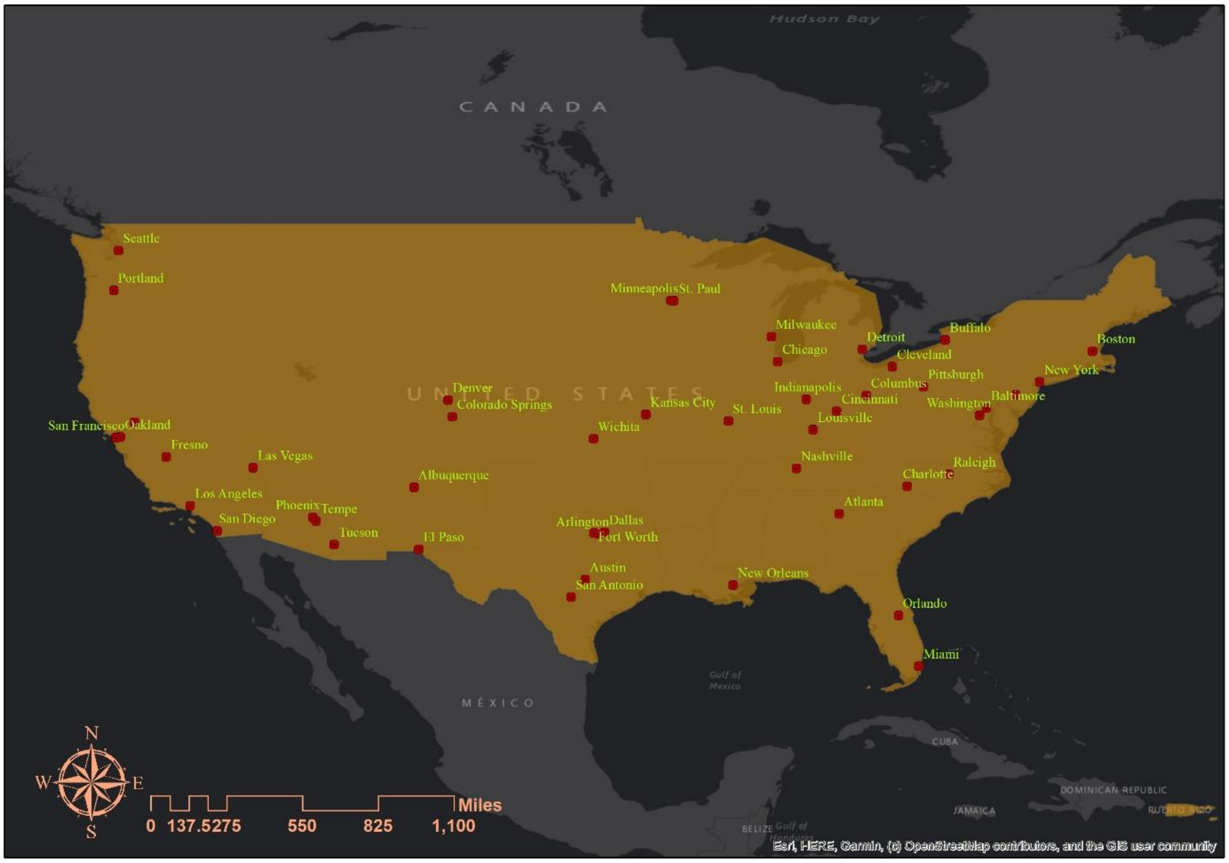

Figure 3. 2 Study Area (Source: Esri, 2019 https://www.esri.com/en-us/home)

Category	Fact	Minimum	Maximum	Average	Median
Population	Population estimates, July 1, 2018, (V2018)	192,364	8,398,748	973,357	632,381
Age and Sex	Persons under 5 years, percent	4.40	7.90	6.52	6.55
	Persons under 18 years, percent	13.40	28.00	21.69	21.65
	Persons 65 years and over, percent	8.70	16.70	12.10	12.25
	Female persons, percent	47.00	53.00	51.02	51.20
Race and Hispanic Origin	White alone, percent	14.60	80.80	57.71	60.40
	Black or African American alone, percent	3.20	78.60	24.52	23.35
	American Indian and Alaska Native alone, percent	0.10	4.60	0.71	0.40
	Asian alone, percent	1.10	34.20	6.76	4.40
	Native Hawaiian and Other Pacific Islander alone, percent	0.00	1.70	0.17	0.10
	Two or More Races, percent	1.80	7.00	3.77	3.50
	Hispanic or Latino, percent	3.10	80.90	23.32	17.35
	White alone, not Hispanic or Latino, percent	10.30	70.50	42.43	42.40
Computer and Internet Use	Households with a computer, percent, 2014-2018	79.40	95.20	88.51	89.40
	Households with a broadband Internet subscription, percent, 2014-2018	59.30	89.30	79.01	79.65
Education	High school graduate or higher, percent of persons age 25 years+, 2014-2018	76.50	94.60	85.99	86.35

	Bachelor's degree or higher, percent of persons age 25 years+, 2014-2018	14.60	62.80	36.74	35.35
Income & Poverty	Median household income (in 2018 dollars), 2014-2018	29,008	104,552	54,698	54,452
	Per capita income in past 12 months (in 2018 dollars), 2014-2018	17,338	64,157	32,653	30,107
	Persons in poverty, percent	10.90	36.40	19.59	19.10
Geography	Population per square mile, 2010	1,265.40	27,012.50	5,489.54	3,971.50

Table 3. 1 Summary of the descriptive statistics of the selected cities as the study area (source: U.S. Census Bureau QuickFacts, 2020)

Category	Fact	Albuquerque city, New Mexico	Arlington city, Texas	Atlanta city, Georgia	Austin city, Texas	Baltimore city, Maryland	Boston city, Massachusetts	Buffalo city, New York	Charlotte city, North Carolina	Chicago city, Illinois	Cincinnati city, Ohio	Cleveland city, Ohio	Colorado Springs city, Colorado	Columbus city, Ohio	Dallas city, Texas	Denver city, Colorado	Detroit city, Michigan
Population	Population estimates, July 1, 2018, (V2018)	560,218	398,112	498,044	964,254	602,495	694,583	256,304	872,498	2,705,994	302,605	383,793	472,688	892,533	1,345,047	716,492	672,662
Age and Sex	Persons under 5 years, percent	6.10	6.70	5.70	6.70	6.50	5.10	6.80	6.80	6.50	7.30	6.50	6.60	7.30	7.70	6.30	7.30
	Persons under 18 years, percent	22.80	26.00	18.50	20.80	20.90	16.20	22.70	23.90	21.20	21.90	22.70	23.40	22.50	25.40	20.20	25.10
	Persons 65 years and over, percent	14.60	10.20	11.40	8.70	13.20	11.20	12.40	10.00	12.00	12.20	13.50	13.10	10.00	10.10	11.40	13.30
	Female persons, percent	51.20	50.80	51.30	49.30	53.00	51.90	52.40	52.00	51.40	51.80	51.80	50.00	51.20	50.40	49.90	52.70
Race and Hispanic Origin	White alone, percent	73.50	61.50	40.30	73.50	30.40	52.60	47.40	49.50	49.40	50.30	39.80	78.30	59.50	62.50	76.50	14.60
	Black or African American alone, percent	3.20	22.50	51.80	7.80	62.50	25.30	36.70	35.10	30.10	42.70	49.60	6.20	28.50	24.30	9.40	78.60
	American Indian and Alaska Native alone, percent	4.60	0.40	0.20	0.60	0.30	0.30	0.50	0.40	0.30	0.10	0.50	0.70	0.20	0.30	1.00	0.30
	Asian alone, percent	2.80	6.90	4.20	7.30	2.60	9.60	5.60	6.50	6.40	2.00	2.40	3.00	5.70	3.40	3.80	1.60
	Native Hawaiian and Other Pacific Islander alone, percent	0.10	0.10	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.10	0.00	0.30	0.10	0.00	0.10	0.00
	Two or More Races, percent	4.50	3.10	2.40	3.30	2.50	5.10	4.00	2.80	2.70	3.60	4.30	6.00	4.30	2.50	3.60	1.90
	Hispanic or Latino, percent	49.00	29.20	4.30	34.30	5.10	19.70	11.60	14.00	29.00	3.70	11.60	17.70	5.90	41.70	30.30	7.60
	White alone, not Hispanic or Latino, percent	39.40	39.10	37.60	48.30	27.50	44.50	43.80	41.90	32.80	48.20	33.70	68.70	55.90	29.00	53.70	10.30
Computer and Internet Use	Households with a computer, percent, 2014-2018	88.80	93.50	88.40	93.90	84.00	89.70	83.20	92.90	85.80	84.20	79.40	93.40	90.90	85.30	91.80	79.40
	Households with a broadband Internet subscription, percent, 2014-2018	78.10	82.40	78.10	85.80	72.30	83.60	70.30	85.40	75.90	75.30	65.80	88.70	83.60	73.50	83.70	59.30
Education	High school graduate or higher, percent of persons age 25 years+, 2014-2018	89.70	84.80	90.30	89.10	84.90	86.40	83.90	88.90	84.50	87.60	79.60	93.30	89.50	76.50	87.10	80.00
	Bachelor's degree or higher, percent of persons age 25 years+, 2014-2018	34.70	29.50	49.90	50.40	31.20	48.50	26.60	43.50	38.40	36.10	16.60	39.00	35.70	32.30	47.90	14.60
Income & Poverty	Median household income (in 2018 dollars), 2014-2018	51,128	58,502	55,279	67,462	48,840	65,883	35,893	60,886	55,198	38,542	29,008	61,324	51,612	50,100	63,793	29,481
	Per capita income in past 12 months (in 2018 dollars), 2014-2018	29,210	27,513	43,468	40,391	29,700	42,010	23,397	36,426	34,775	29,156	20,085	32,539	27,967	32,804	41,196	17,338
	Persons in poverty, percent	17.60	15.70	21.60	14.50	21.80	20.20	30.30	14.00	19.50	27.20	34.60	12.60	20.40	20.50	13.80	36.40
Geography	Population per square mile, 2010	2,907.60	3,811.30	3,154.30	2,653.20	7,671.50	12,792.70	6,470.60	2,457.10	11,841.80	3,809.80	5,107.20	2,140.60	3,624.10	3,517.60	3,922.60	5,144.30

Table 3. 2 Detailed descriptive statistics of the selected cities as the study area (source: U.S. Census Bureau QuickFacts, 2020)

Category	Fact	El Paso city, Texas	Fort Worth city, Texas	Houston city, Texas	Indianapolis city (balance), Indiana	Kansas City, Missouri	Las Vegas city, Nevada	Los Angeles city, California	Louisville, Kentucky	Miami city, Florida	Milwaukee city, Wisconsin	Minneapolis city, Minnesota	Nashville, Tennessee	New Orleans city, Louisiana	New York city, New York	Oakland city, California	Orlando city, Florida
Population	Population estimates, July 1, 2018, (V2018)	682,669	895,008	2,325,502	867,125	491,918	644,644	3,990,456	620,118	470,914	592,025	425,403	669,053	391,006	8,398,748	429,082	285,713
Age and Sex	Persons under 5 years, percent	7.50	7.90	7.70	7.30	6.90	6.50	6.00	6.50	5.80	7.60	6.70	6.80	6.00	6.50	6.30	6.90
	Persons under 18 years, percent	26.90	28.00	25.00	24.70	23.10	24.10	21.00	22.70	17.30	26.10	20.10	21.20	20.20	20.90	19.80	20.90
	Persons 65 years and over, percent	12.40	9.60	10.30	11.90	12.60	14.50	12.10	14.50	16.70	10.20	9.50	11.50	13.50	14.10	12.90	10.20
	Female persons, percent	51.10	51.10	50.00	51.80	51.40	50.00	50.40	51.60	50.70	51.80	49.30	51.80	52.40	52.30	51.60	51.80
Race and Hispanic Origin	White alone, percent	80.80	64.10	57.60	61.40	60.10	62.20	52.40	69.90	75.20	44.60	63.80	63.20	34.00	42.70	36.10	60.70
	Black or African American alone, percent	3.80	19.00	22.50	28.30	29.00	12.20	8.90	23.50	17.70	38.80	19.40	27.90	59.70	24.30	23.60	25.40
	American Indian and Alaska Native alone, percent	0.50	0.50	0.30	0.30	0.40	0.90	0.70	0.20	0.20	0.60	1.40	0.20	0.20	0.40	0.90	0.20
	Asian alone, percent	1.40	4.20	6.90	3.20	2.70	6.60	11.60	2.70	1.10	4.30	6.10	3.60	2.90	13.90	15.70	4.30
	Native Hawaiian and Other Pacific Islander alone, percent	0.20	0.10	0.10	0.10	0.10	0.80	0.20	0.10	0.00	0.00	0.00	0.10	0.00	0.10	0.60	0.00
	Two or More Races, percent	2.70	3.30	2.10	3.20	3.50	4.90	3.60	2.70	1.80	4.00	4.60	2.60	1.80	3.50	6.80	3.20
	Hispanic or Latino, percent	80.90	35.00	44.80	10.20	10.20	32.90	48.60	5.40	72.50	18.80	9.60	10.40	5.50	29.10	26.90	31.10
	White alone, not Hispanic or Latino, percent	13.20	39.50	24.60	55.20	55.10	44.20	28.50	65.80	10.70	35.30	59.80	55.40	30.60	32.10	28.20	37.30
Computer and Internet Use	Households with a computer, percent, 2014-2018	84.50	91.00	87.20	85.50	87.40	90.40	89.80	86.50	81.50	83.00	91.50	90.80	81.80	87.50	90.00	93.20
	Households with a broadband Internet subscription, percent, 2014-2018	75.00	80.80	77.00	76.50	78.60	78.50	80.70	79.20	64.10	72.10	81.60	82.30	69.60	79.40	81.10	84.10
Education	High school graduate or higher, percent of persons age 25 years+, 2014-2018	79.60	81.70	78.30	85.50	89.60	84.40	77.00	88.90	77.00	83.40	89.70	88.30	86.20	81.60	81.60	90.20
	Bachelor's degree or higher, percent of persons age 25 years+, 2014-2018	24.70	28.60	32.10	30.40	34.30	23.90	33.70	29.20	27.90	24.20	49.40	39.70	36.80	37.40	42.50	36.70
Income & Poverty	Median household income (in 2018 dollars), 2014-2018	45,656	59,255	51,140	46,442	52,405	54,694	58,385	51,307	36,638	40,036	58,993	55,873	39,576	60,762	68,442	48,511
	Per capita income in past 12 months (in 2018 dollars), 2014-2018	21,927	28,330	31,576	27,119	31,143	29,304	33,420	29,681	27,078	22,605	37,071	33,139	30,177	37,693	40,628	29,930
	Persons in poverty, percent	20.00	16.00	20.60	19.10	16.50	15.80	19.10	16.60	24.30	26.60	19.90	16.50	24.60	18.90	17.60	18.20
Geography	Population per square mile, 2010	2,543.20	2,181.20	3,501.50	2,270.00	1,459.90	4,298.20	8,092.30	1,836.60	11,135.90	6,188.30	7,088.30	1,265.40	2,029.40	27,012.50	7,004.00	2,327.30

Table 3. 3 Detailed descriptive statistics of the selected cities as the study area (source: U.S. Census Bureau QuickFacts, 2020)

Category	Fact	Philadelphia city, Pennsylvania	Phoenix city, Arizona	Pittsburgh city, Pennsylvania	Portland city, Oregon	Raleigh city, North Carolina	Sacramento city, California	San Antonio city, Texas	San Diego city, California	San Francisco city, California	Seattle city, Washington	St. Louis city, Missouri	St. Paul city, Minnesota	Tempe city, Arizona	Tucson city, Arizona	Washington city, District of Columbia	Wichita city, Kansas
Population	Population estimates, July 1, 2018, (V2018)	1,584,138	1,660,272	301,048	653,115	469,298	508,529	1,532,233	1,425,976	883,305	744,955	302,838	307,695	192,364	545,975	702,455	389,255
Age and Sex	Persons under 5 years, percent	6.80	7.40	4.90	5.40	6.10	6.70	7.10	6.10	4.50	4.90	6.50	7.40	4.40	6.20	6.50	7.40
	Persons under 18 years, percent	22.00	26.50	15.10	18.10	21.20	23.50	25.30	20.10	13.40	15.10	19.70	25.20	14.90	21.40	17.80	25.40
	Persons 65 years and over, percent	13.20	10.30	14.60	12.30	10.20	12.70	11.80	12.30	15.10	12.30	12.60	10.10	10.00	13.90	11.90	13.60
	Female persons, percent	52.70	50.20	51.10	50.50	51.60	51.20	50.60	49.70	49.00	49.60	51.60	50.70	47.00	50.20	52.50	50.70
Race and Hispanic Origin	White alone, percent	41.20	72.30	66.90	77.10	58.50	47.20	80.50	64.80	46.70	68.00	46.20	56.70	67.80	72.40	41.00	74.60
	Black or African American alone, percent	42.30	6.90	23.20	5.80	29.00	13.40	6.90	6.50	5.20	7.00	46.90	16.00	6.50	5.10	46.90	11.10
	American Indian and Alaska Native alone, percent	0.40	2.10	0.20	0.70	0.40	0.80	0.80	0.40	0.30	0.60	0.20	0.90	2.70	3.50	0.30	1.00
	Asian alone, percent	7.20	3.70	5.70	8.10	4.50	18.90	2.80	16.70	34.20	15.10	3.20	18.40	8.90	3.20	3.90	5.00
	Native Hawaiian and Other Pacific Islander alone, percent	0.00	0.20	0.00	0.70	0.10	1.70	0.10	0.40	0.30	0.30	0.10	0.00	0.40	0.20	0.00	0.10
	Two or More Races, percent	3.00	3.80	3.50	5.50	3.00	7.00	2.80	5.20	5.40	6.80	2.30	5.00	4.60	5.10	2.90	4.30
	Hispanic or Latino, percent	14.50	42.60	3.10	9.70	11.00	28.70	64.20	30.10	15.20	6.60	4.00	9.60	22.40	43.20	10.90	17.00
	White alone, not Hispanic or Latino, percent	34.60	43.00	64.80	70.50	53.30	32.50	24.80	42.90	40.60	64.50	43.20	51.40	56.80	44.50	36.20	63.00
Computer and Internet Use	Households with a computer, percent, 2014-2018	84.10	89.10	86.80	93.30	95.20	92.00	87.90	94.50	91.90	94.40	82.80	90.60	94.20	89.70	89.80	86.10
	Households with a broadband Internet subscription, percent, 2014-2018	73.70	79.90	78.80	86.70	87.80	83.20	76.60	89.30	86.00	88.90	70.90	83.30	86.00	80.90	80.00	77.90
Education	High school graduate or higher, percent of persons age 25 years+, 2014-2018	83.90	81.50	92.40	92.20	91.70	84.70	82.00	87.90	88.50	94.60	86.90	86.30	92.50	84.90	90.60	87.90
	Bachelor's degree or higher, percent of persons age 25 years+, 2014-2018	28.60	28.20	42.90	49.00	50.40	32.60	25.90	45.30	57.10	62.80	35.00	40.10	44.60	26.80	57.60	30.00
Income & Poverty	Median household income (in 2018 dollars), 2014-2018	43,744	54,765	45,831	65,740	63,891	58,456	50,980	75,456	104,552	85,562	41,107	55,085	54,210	41,625	82,604	50,867
	Per capita income in past 12 months (in 2018 dollars), 2014-2018	26,557	27,870	31,972	38,674	36,875	30,487	25,091	39,066	64,157	55,789	28,478	30,036	29,786	22,645	53,321	27,723
	Persons in poverty, percent	24.90	19.40	21.40	14.90	13.70	18.30	18.60	13.80	10.90	11.80	24.20	19.90	21.30	23.40	16.80	16.20
Geography	Population per square mile, 2010	11,379.50	2,797.80	5,521.40	4,375.20	2,826.30	4,764.20	2,879.80	4,020.40	17,179.10	7,250.90	5,157.50	5,484.30	4,050.20	2,294.20	9,856.60	2,400.40

Table 3. 4 Detailed descriptive statistics of the selected cities as the study area (source: U.S. Census Bureau QuickFacts, 2020):

These cities were chosen because on-demand ride services occur mainly in urbanized areas and populous cities (Clewlow & Mishra, 2017). Therefore, in this study, 48 American populous cities have been selected based on the data obtained from the US Census Bureau. These urbanized areas have diverse populations, ranging from 192,364 (Tempe, AZ) to 8,398,748 (New York City), all of which are cities with more than 50,000 population. I selected these cities as the study area, as they demonstrate a diverse environment and a diversity of transit provisions. Including a diversity of fixed-route and app-based, on-demand ride services would increase the scale of this research, and it serves to make the study outcomes more generalizable. This study includes large cities with robust transportation networks such as New York City, Boston, San Francisco, Washington, D.C., and Dallas, as well as cities with limited public transportation systems, such as New Orleans, and Arlington, TX, which may restrict the accessibility of residents to both local and regional opportunities..

Unequal access to opportunities by transit is an issue in many of these cities even those with robust transportation networks such as New York City that suffer from poor service coverage by subway systems, although it has one of the massive subway systems across the world (Regional Plan Association, 2019). In addition, according to a nationwide study by Schaller (2018), in 2017, New York area, Washington DC metro area, Chicago , Boston, Los Angeles, Philadelphia, Miami, Seattle and San Francisco accounted for 1.2 billion trips, or 70% of trips made by ridehailing across the country, while these places held 23% of the nation’s total population. The study reported higher rates of using on-demand ride services in these urban centers than in the rest of the United States. These services constituted 215 million trips in the New York area and a total of 1.0 billion trips in the Chicago, Boston, Miami, Los Angeles, Seattle, San Francisco, Philadelphia, and Washington DC metro area. These are the nation's largest and most densely populated urban centers, where the ridehailing use is concentrated. This study indicates that 38% of all trips made by app-based services are in the center city of these metro areas, 26% are in urban-density census tracts outside the central cities, and 7% are in suburban or rural areas. New York area, Washington DC metro area, Chicago, Boston, Los Angeles, Philadelphia, Miami, Seattle, and San Francisco are recognized with their high densities of population and employment, widespread transit systems, and a considerable number of households with no motor vehicle in their possession. These cities are also recognized to have high levels of entertainment and social activities, which attract many business and leisure passengers. High frequent usage of ridehailing among the residents of these urban centers relates to various factors, such as density, the rates of car ownership, and transit usage. In 2017, there are 45 trips made by ridehailing per person in the central cities of Chicago, Boston, Miami, Los Angeles, Seattle, San Francisco, Philadelphia and Washington DC metro area. Trip rates are lower but still significant in urban tracts outside the center city, and much lower in suburban and rural tracts. The rates of trips made by ridehailing in the New York metro area are lower than for the other eight large metro areas, essentially because taxicabs constitute a roughly equal number of trips as the number of trips made by ridehailing in the New York area. However, taxi usage in the other eight urban centers was approximately 15-20% of total ridership by ridehailing and taxi. Considering the total trip volumes of services provided by New York taxi, ridehailing and the other for-hire services in this urban center, trip rates for all for-hire services are comparable in the New York metro area as in Washington DC metro area, Chicago, Boston, Los Angeles, Philadelphia, Miami, Seattle, and San Francisco. In general, there are substantial clusters of trips made by ridehailing in the core of these nine urban centers, and a significant rate of the trips made by on-demand services are outside the most congested downtown core neighborhoods. It means that annual trips made by ridehailing per resident are higher in the central city and urban districts of large metros than elsewhere across the United States.

In examining the socio-economic and demographics characteristics of the study area in tables 3.1 to 3.4, these highlights were observed. In terms of racial distribution in cities, cities with higher proportions of black or African American communities have lower rates of a computer at home and Internet use than other cities. Meanwhile, such a racial distinction is not seen among the other races to that extent. For example, in cities with a predominantly black population, such as Detroit (78.60%), Baltimore (62.50%), and Atlanta (51.80%), the percentage of the households with a computer are 79.40%, 84.00%, and 88.40%, respectively. In these cities, the percentage of the households with a broadband Internet subscription are 59.30%, 72.30%, and 78.10%, respectively. Moreover, large and technologically advanced cities such as New York City, Washington D.C., Los Angeles, and Chicago all have higher rates of education, a computer at home, and Internet use, than other cities. Subject to these factors, which are considered a privilege for modern urban life – especially in the United States, which is dominated by a competitive neoliberal capitalist system – these cities are also ranked higher in terms of the residents' income rates.

The choice of these 48 cities has other advantages for my study. First, I considered the factor of spatial distribution. In terms of the distribution of territorial spaces, I have selected cities in such a way that they cover a wide variety of natural and climatic regions of the country, mountainous and plain areas, port and dry areas, etc. and participate in sampling. As a result, the research findings can be applied in all types of regions in terms of climatology, geomorphology, and topography, because different climates make different urban spatial structures possible, including in transportation. In turn, all these factors affect the citizens' travel behavior.

Second, I have tried to include diverse cultural regions of the country in the sample. That is the reason that I have sampled cities with populations of diverse racial groups. Diverse cultural geographies create diverse cultures, and therefore different behaviors. As a researcher who came to the field of urban planning with a background in social sciences, these issues have always been present in my mind and have influenced my research.

The third factor is one that should be considered in any sampling of American cities, and I have considered it in this study. One cannot speak of the city of the modern age, especially of late modern capitalism, while ignoring the key factor of the political economy of space. The importance of this factor is emphasized by economic geographers, including David Harvey (2013). America, with the largest national economy and the leading global trader worldwide (USTR, 2020), has a variety of cities in terms of economic viabilities, from poor cities like New Orleans to New York City, the most economically powerful metropolitan worldwide (Florida, 2012). In a world where economics, though not the only factor, is one of the most principal elements in the direction of urban development, this factor can also directly affect the state of urban transportation.

Overall, given that the descriptive statistic tables represent the features of the urbanized areas selected as the study area, cities with different economic, political, and geographical contextual characteristics have been covered in my sampling of American cities. This has provided a representative example of the spatial complexities and entanglements of urban life in the United States.

3.4 Sample

I conducted a survey for data collection and analysis, performed through the online distribution of questionnaires, aggregating, and analyzing the obtained data. I intended to examine the modal preferences of many respondents, and the survey served as the most applicable technique of data collection, instead of other techniques such as interviewing or observations.

I used Qualtrics for sampling and launching the survey. Qualtrics is a superior enterprise survey technology solution worldwide. For over five years, this company has provided online samples and cooperated with more than 20 online panel providers. This partnership has supplied a network of quality respondents with significant diversity to their global client base. There have been over 15,000 projects completed by Qualtrics Panels Team across a variety of fields in the U.S. and throughout the world (Qualtrics, 2014). Most of the Qualtrics' samples originate in traditional, actively managed, double-opt-in market research panels. It is the company's preferred method, but they also use social media occasionally to gather participants. It is feasible for the company to access other types of sources to fulfil the requirements of a certain target group, upon the request of their clients (Qualtrics, 2019).

In the sampling process, Qualtrics avoids duplication and verifies the validity by checking every respondent's IP address and utilizing advanced digital fingerprinting technology. Also, to maintain the integrity of the survey data and to counter the likelihood of the duplication of respondents across sources, every Qualtrics strategic panel partner utilizes deduplication technology. Qualtrics is a panel aggregator and leverages numerous sample sources to best fit the needs of the research. The Qualtrics panel partners select respondents on a random basis with a high probability of qualifications for a survey. Exclusions such as participation frequency and category exclusion occur during the process of achieving the representative sample. The next step is proportioning each sample from the panel base to the general population, followed by randomizing before survey distribution.

Qualtrics utilizes their pre-targeting to hone in on the respondents that are in the study area. From there, they set quotas according to the key demographics the client would like to segment (i.e., age, gender, income). Once in the study area, they randomly reach out to the individuals in that region and consequently have their demographic questions silo them into different quotas. It would be a convenience sample once they narrow into the given zip codes or regions, because they will be working with online panelists. Once a demographic quota is hit, they then start strategically sampling for the remaining open quotas. An appropriate example of this is, if they have 51% of respondents report their gender as "female", they will then send more survey invitations to individuals that identify as "male" based upon their pre-profiled information. Before launching, they would need to solidify what segments the client would like to specifically construct quotas around, to ensure the effectiveness of the instrument.

The target population of this study is the total number of transit-dependent people in the 48 cities, as the study area, across the U.S., which is unknown. I measure the sample size based on the following Cochran’s formula:

$$n=\frac{Z^2pq}{d^2}$$

Where:

n = sample size,
Z(Z statistic for a level of confidence) = 1.96
p=q= expected prevalence or proportion =0.5

d= precision = 0.05

Z statistic for a level of confidence: For the conventional level of confidence of 95%, Z value is equal to 1.96. Expected proportion (p) is the proportion (prevalence) that a researcher estimates by the study. The scale of "p" is from 0 to 1, and the variation in the sample size depends on the value of "p". If prevalence is 50%, then "p" is equal to 0.5. "p" is the probability of an attribute in society, and "q" is the probability that this attribute does not exist, each of which must be considered 0.5. Precision (d) is the optimal probability of precision. In proportion of one; if 5%, d is equal to 0.05) (Daniel, 1999 as cited in Naing et al., 2006).

This formula is applicable when the population size is unknown. The results of the sample size calculation would be around 384.16. Therefore, a rounded sample of 385 respondents will be required for conducting the survey.

3.5 Survey Design

In this survey, I filtered the eligible participants based on the inclusion criteria explained in the section of the survey structure. It was followed by investigating the extent to which respondents use fixed-route transit services and app-based, on-demand ride services as their actual travel mode, and the extent to which they would prefer to use fixed-route services and ridehailing as the main mode of transportation. Then, I explored if they have any of the barrier(s) that seriously limit or prevent them from using app-based ride service, and the level of their familiarity with and use of modern technologies. It was followed by obtaining data concerning the residential neighborhood of respondents and examining their attitudes towards the issues related to travel by fixed-route transit and ridehailing. The survey questionnaire terminated with the questions concerning the socioeconomic and demographic characteristics of respondents. These steps are explained in detail in the following section, survey structure.

3.5.1 Survey Structure

After consultation for feedback with my dissertation committee members, concerning the structure and the content of the survey, I submitted the survey to the IRB (Institutional Review Board) at UTA for approval. The survey is designed in five sections, including informed consent; screening questions; transportation (actual); active transportation; transportation (preferred); burden/access; residential neighborhood; attitudes; and the background section. The following paragraphs describe these sections.

Section one: The first section of the survey is the Informed Consent. In this section, I introduce myself and the subject of the survey. Respondents are informed that the data collected will be anonymous and personally identifiable information will not be collected or accessed. At the end of this section, they are asked to indicate their voluntary agreement to participate in the online survey.

Section two: Respondents who specify their voluntary agreement to participate may proceed to the second section, which displays the inclusion criteria questions. Individuals can choose to participate in this research study if they are 18 years old and over, they do not own a car, they have used an app-based ride service (such as Uber/ Lyft), they have used traditional public transit even if such services are not available in their current residence, they reside in one of the cities that has been defined as the study area, and they currently belong to one of the following categories of households:

One or two persons with less than $14,999 annual income

One, or two persons with $15,000 to $24,999 annual income

One, or two persons with $25,000 to $34,999 annual income

Two, three or four persons with $35,000 to $49,999 annual income

Three or four persons with $50,000 to $64,999 annual income

More than four persons with less than $65,000 annual income

The inclusion criteria was determined based on two major characteristics of transit-dependent people, including being low-income and not owning a private car (U.S. DOT, 2012). Due to survey limitations, individuals under age 18 cannot participate in the survey, but those over age 65 can participate. Concerning the car ownership question, I initially asked if the participants have access to car(s) in their household, because it is likely that they might be in a household that they do not personally own car but there are cars in the household that they may use. I was informed by the Qualtrics around a week after data collection that the incident rate of participation in survey was very low, because the filter question that asked about people's access to cars in the household. They let me know that targeting participants in terms of car accessibility in the household is very difficult, and thus encouraged me to consider car ownership. As such, I had to replace car accessibility in the household with car ownership. However, there is a question in the survey which asks participants to specify the numbers of vehicles available in their household, through which I can measure the relationship between car accessibility in the household and mode preference, and frequency of modal usage.

Concerning the inclusion criteria of household size and the annual household income, using 2013-2017 American Community Survey 5-Year Estimates data, I considered the maximum and minimum of low household income categories in these cities and combined them into main income classes, to increase the chance of collecting data from low-income residents. I considered household income rather than personal income, because I am sampling low-income populations and low-income people are likely to have large household sizes. In these households, all family members bring money and spend it together. Therefore, personal income was not a suitable variable for the purpose of this study and sampling.

It must be noted that to ensure that only eligible individuals participate, Qualtrics has pre-targeting information from the participants (which they filled out when they initially join the panel). With that, Qualtrics also use a third-party system called relevant ID that uses publicly sourced information to verify the participant.

Section three: The questions in this section ask about the actual transportation habits of participants in their daily travels. Daily travels usually include work and non-work trips. I have categorized work/school trips as work trips, and participants specify if they are currently employed and/or a student. Those who answer yes to this question specify information about their daily travel to work/school. They also specify the main way they make this trip for a typical trip from home to work/school including bus, rail, app-based on-demand private ride services, app-based, on-demand ride-sharing services, and walking/biking. This section also asks all participants to specify in a typical month how often they take traditional public transit service, private ride services, and ride-sharing services from their home to a work place or school location, a church or civic building (ex. library), a service provider (ex. bank, post-office), a restaurant or coffee place, a store or place to shop, and a place to exercise (ex. a gym or a park). Participants were also asked to specify their overall use of these modes.

Section four: The questions in this section ask about the active transportation. The type of answers provided in this section reveals information about the respondents' lifestyle, such as how many times in a month they took a walk or a stroll around their neighborhood, or how often they exercised or walked from their residence to a local store.

Section five: The questions in this section ask users about their preferred transportation modes. Participants answer their preferences for using private ride services, ride-sharing services, and traditional public transit services. They indicate the extent to which they prefer to use each of these modes as their main mode of transportation in the absence of private vehicle, and for destinations that are not within a walkable distance to a workplace/school, a store or place to shop, a restaurant or coffee place, as well as their overall preference for using each mode. In this section participants specify the importance of various factors in choosing the preferred travel mode among app-based, on-demand ride services and traditional public transit services. These factors affect their decision making for choosing the preferred mode. It must be noted that some of these factors are the barriers that deter transit-dependent people from accessing app-based, on-demand ride services. Participants also specify the importance of various factors in choosing their preferred travel mode between private ride services and ride-sharing services. The next question includes four statement investigating participants' residential preferences, through which I can use to determine if there is a relationship between residential preference and modal preference.

Section six: The questions in this section ask about the barriers that the literature describes as seriously limiting or preventing transit-dependent people from using app-based, on-demand ride services including:

Access to Credit/Debit card

Access to a smart phone

Access to Internet at home

Have a mobile data plan

Unaffordable fares

Feeling the need for assistance initiating rides via the phone apps

Unwilling to connect personal financial information to phone

Need for translation for transportation apps into languages other than English

Discomfort with sharing personal information

Concern about identity theft

Unable to use these services when phone battery runs out or have no internet access

Need training for using online methods

Participants also specified the level of their familiarity with and use of modern technologies by selecting one of the following statements to describe themselves:

A tech-savvy person

Can complete errands such as shopping, paying bills and registrations using online technology

Can do basic internet tasks like checking emails

Need someone to help me navigate the internet

Section seven: The questions in this section ask about the residential neighborhood of participants. They specify the type of housing unit in which they currently live, and when they moved to their current residence.

Sections eight: The questions in this section ask about participants' attitudes towards the issues related to traveling by app-based on-demand ride services and fixed-route transit services. These statements are listed in table 3.6.

Section nine: The Questions in this last section ask about socioeconomic and demographic characteristics of respondents and their background. It includes questions about their gender, age, the composition of individuals in different age groups in their household, race/ethnicity, educational background, current status as a student, employment situation, approximate total annual combined income of all the working adults in household, homeownership, possessing a valid driver's license, the numbers of vehicles available in their household, miles traveled on their vehicles, and physical or mental disabilities that could seriously limit or prevent them from doing travel activities.

3.6 Data Collection

3.6.1 Survey Distribution

After the final approval of the survey by the dissertation committee, I sent an IRB protocol and I got the IRB approval from the UTA. Qualtrics handled the recruitment of participants, the distribution of the approved surveys, and data collection. Qualtrics does not ask for any personal information, such as name, contact information or home address—thus the respondents will not be individually identifiable. There are no perceived risks for participating in the survey, and participants can quit the questionnaire at any time they want. If participants decline, Qualtrics will not follow up with them but they will not be compensated, and they will just be removed from the study. Given that the study area is widespread and populous, and it is difficult for the researcher to travel across the area for data collection, the Qualtrics panel partners will be hired by this company for data collection. The following paragraphs describe the recruitment of participants and data distribution and collection.

Qualtrics sent an email to potential respondents to participate in a survey. The email invitation provides information about the purpose of the survey, the expected length of the survey, and the types of available incentives. Participants had the choice to unsubscribe at any time. The survey invitation does not provide specific details about the survey contents to avoid self-selection bias (Qualtrics, 2014). Qualtrics provides respondents with various incentives for participating, such as cash, gift cards, and vouchers and redeemable points. The length of the survey is a factor that will affect whether respondents will receive an incentive. To ensure the highest quality data, and to guarantee proper participation of respondents in the survey, Qualtrics offers alternatives for more attention checks. Qualtrics' measures include replacing participants who straight-line through surveys or complete the survey in less than a third of the average time expected for completion.

Panelists participate from a variety of sources. They may be airline customers who were selected to join in reward for SkyMiles, retail customers who have decided to participate to get points at desired retail outlets, or general consumers who choose to participate for cash or gift cards, etc. After inviting participants to complete the questionnaire, Qualtrics informs them of the compensation. Because compensation for respondents will vary, it is not suitable to inform them in the cover letter how much they will be compensated. Instead, based on the company's recommendation, I made sure that the Informed Consent section informed participants that they will be compensated the amount they agreed upon before they entered the questionnaire.

Although maintaining the confidentiality and security of compensation is not something Qualtrics handles directly (that is handled by the vendor), the company is aware that compensation will be confident and secure.

Qualtrics recruits participants from various sources, such as targeted email lists and social media. Confirming the validity of the names, addresses, and dates of birth of the consumer panel members typically happens through third-party verification measures before their participation. Business-to-business (B2B) participants are subject to measuring extra quality control, such as LinkedIn matching. The obtained data will be completely anonymous. Therefore, there will be no situations where respondents might be embarrassed, exposed, or stigmatized. Qualtrics sends panel members an email invitation or prompts them on the respective survey platform to begin the completion of a given survey. The typical survey invitation is generic and simple. It supplies a hyperlink, which will take participant to the survey, in addition to mentioning the incentive offered.

Expected follow-ups for each participant over the entire duration of data collection depends on the participant. Some participants answer in the first try. Qualtrics usually sends three reminders to participants. It usually takes one to two reminders for people to answer. Qualtrics does not get a lot of people in the first try. Completion of the survey questionnaire in this study will take about 10 minutes. Upon request, the Qualtrics' project manager can inform the client of the response rate after the data collection is complete. The response rate is the percentage of the target that receives a survey invitation and responds to the survey invitation by initiating the survey. The incidence rate is the percentage of individuals who initiate the survey that can pass through the survey screeners and are eligible to complete the survey.

3.6.2 Data Cleaning

Data cleaning was essential for this study. Following data collection, I needed to clean the data, to ensure that all participants responded the questions with no error in their answers. The following paragraphs explain some priorities and techniques that were applied for data cleaning.

As mentioned, completion of the surveys takes about 10 minutes. I checked the duration of completing the surveys, which is provided by the Qualtrics and recorded in the data set. Participants who completed the survey too quickly (less than 5 minutes) most likely had not read or answered the questions carefully and appropriately. These respondents' entries will be removed from the dataset. I ran spell check for text entry questions, and I also moved the cases in which participants exhibited straight-lining, which is defined as the selection of the initial choice/response to every question, regardless of the question (Qualtrics, 2019).

Two surveys with the exact same answers in separate submissions were assumed to be duplicate records. I identified these duplicate rows and removed them. I also checked for the Christmas-tree pattern, which occurs when participants select the choices in a diagonal pattern without paying careful attention to reading the questions.

Finally, I removed cases with contradictory answers. For instance, in the section of socio-economic and demographic characteristics there is a question asking respondents to specify the number of persons, including themselves, in the following age categories in their household: Under 18 years old, 18 to 24, 25 to 34, 35 to 44, 45 to 54, and 55 or older. This question measures both the composition of age groups in household and household size. The household size in this question should be consistent with the household size asked in screening question three. Contradiction in reported answers indicate that participants have not read the question before selecting their response or have used automated response methods to respond. These cases were moved of the dataset.

3.7 Variables

3.7.1 Dependent Variable

The dependent variables of interest are the overall preferences for and the use of ridehailing services and fixed-route transit. The overall preferences were rated in the survey on a scale from 1 (Not prefer at all) to 9 (Strongly prefer). The overall frequency of use were rated on a scale including never, less than once per month, once or twice a month, about once every 2 weeks, about once per week, and two or more times per week. The following three dependent (endogenous) variables were examined in the final SE model.

Overall preference for using private ride services (such as Uber/Lyft) as the main mode of transportation (in absence of private vehicle and for destinations that are not within a walkable distance)

Overall preference for using traditional public transit services (such as bus, light rail) as the main mode of transportation (in absence of private vehicle and for destinations that are not within a walkable distance)

Percentage of ridehailing trips which indicates the percentage of the sum of the overall use of private ride services and ridesharing services in the sum of the overall use of private ride services, ridesharing services, and traditional transit.

3.7.2 Explanatory Variables

The following paragraphs describe the explanatory variables considered in this study. It was required to recode all nominal and ordinal data and transfer them into dummy variables to be examined in the SEM models. Table 3.5 also displays the explanatory variables.

Categories	Variables	Description
Socio-economic & Demographic	Gender	Female (code 1)/non-female (code 0)
	Age	Age
	HHSize	Household size
	Race/Ethnicity	White (code 1)/Non-white (code 0)
	Edubachler	Educational background: Respondent has a bachelor education or over (code 1), or not (code 0)
	Studentship	Being Student (code 1) /Not being student (code 0)
	FullTime_Worker	Employment status as a full-time worker (code 1)/Not a full-time worker (code 0)
	Income	Approximate total annual combined income of all the working adults in household
	House Ownership	House Owner (code 1); Not House Owner (code 1)
	Singlefamily	Living (code 1) /Not Living in the Single-Family Detached Houses (code 0)
	Dis_No	Any physical or mental disabilities that seriously limit or prevent you from travel activities. Disabled (code 1) or non-disabled/healthy (code 0)
Residential Preference	accessiblityprefenrece	Accessibility preference
Built Environment	PopDensity	Gross population density in persons per square mile.
	EmpDensity	Gross employment density
	Entroy	Land use mix (Entropy)
Technology Adoption	Techfamilier	level of familiarity with and use of modern technologies tech familiar (code 1) or non-tech familiar (code 0)
Mobility-Related Attitudes	Preferenceforprivate	Preference for using private ride services over ridesharing services
	Preferencefortraditional	Preference for traditional public transit services over the app-based ride services
Barriers	Barriers	Barriers That Deter Transit-Dependent People from Accessing App-based, On-Demand Ride Services
	Bar_TechReq	Barrier of Technology Requirements: *Access to a smart phone; Access to Internet at home; Have a mobile data plan*
	Bar_Afford	Barrier of Affordability: *Access to credit/debit card; Unaffordable fares; Unable to use these services when phone battery runs out or have no internet access*
	Bar_DigLit	Barrier of Digital Literacy: *Feeling need assistance initiating rides via the phone apps; Need translation for transportation apps into languages other than English; Need trainings using online methods*
	Bar_TechSec	Barrier of Technology Security: *Unwilling to connect personal financial information to phone; Discomfort with sharing personal information; Concern about identity theft*
Household Car Ownership	Household Car Ownership	Having Car(s) in the Household (code 1); Not Having Car(s) in the Household (code 0)
Possession of a valid driver's license	Possession of a valid driver's license	Possession of a valid driver's license (code 1); Not possession of a valid driver's license (code 0)
Vehicle Miles Travelled	VMT	Vehicle Miles Travelled Per typical week (including weekends)
Service Time Efficiency	Pref_TimeEfficSrv	Importance of service time efficiency in selecting the preferred mode from the viewpoint of passengers
Service Availability	Availability	Importance of service availability in selecting the preferred travel mode from the viewpoint of passengers
Pctridehailtrips	Pctridehailtrips	Percentage of ridehailing trips
Modal Use	Freqtotprivate	Overall use of private ride services (such as bus or Uber/Lyft)

	FrqtotRshare	Overall use of ridesharing services (such as UberPool, Via, GoLink)
	FreqtotTransit	Overall use of fixed-route transit services (such as bus or light rail)
Modal Preference	Prefprivate_overal	Overall preference for using private ride services (such as Uber/Lyft)
	Pref_Ridshar_overal	Overall preference for using ride-sharing services (such as UberPool, Via, GoLink)
	Pref_Pub_overal	Overall preference for using traditional public transit services (such as bus, light rail)

Table 3. 5 Sociodemographic and demographic variable, explanatory variables and dependent variables

Residential Preference

Also, "accessiblitypreference" in table 3.5 refers to the variable of residential preference, which measures the preference of respondents for living in a compact and accessible neighborhood. The higher the value of this variable, the more respondents would like to live in compact and accessible neighborhoods. This preference was evaluated based on four statements in the survey concerning the preference of respondents for these two types of residential neighborhoods.

Barriers That Deter Transit-Dependent People from Accessing App-based, On-Demand Ride Services

The other key variable in this research is the "Barriers That Deter Transit-Dependent People from Accessing App-based, On-Demand Ride Services" or in brief "Barriers". The survey includes twelve statements, obtained from the literature, that may seriously limit or prevent transit dependent people from using app-based services.

These barriers consist of four categories including the Barrier of Technology Requirements (Bar_TechReq), Barrier of Affordability (Bar_Afford), Barrier of Digital Literacy (Bar_DigLit) and Barrier of Technology Security (Bar_TechSec), each of which has three factors (see table 3.5). Given that the respondents had the choice to select as many barriers as they are facing to use ridehailing services, I summed the number of barriers that each respondent had selected to have a ratio variable. There is also a “Barriers” variable itself as a separate variable, which is the sum of all the barriers that a respondent chooses from these 12 barriers.

Mobility-Related Attitudes

This variable has been examined through fifteen statements included in the survey which refer to the attitude and perception of respondents towards the issues related to travel by fixed-route transit and ridehailing such as travel security, technology embracing, shared mobility, travel burden; cost; and time. Table 3.6 presents these attitudinal statements.

To what extent do you agree or disagree with the following statements?
I feel carefree to travel using app-based ride services any time of the days.
I usually feel nervous when using app-based ride services because I think the driver may have unreported criminal records.
Getting around is easier than ever with my smartphone
Learning how to use new technologies is often frustrating
Technology creates as least as many problems as it does solutions.
I feel uncomfortable when I travel with others using ride-sharing services (such as UberPool, Via, GoLink)
I believe that ride-sharing services (such as UberPool, Via, GoLink) offer me affordable fares
I believe that using private ride services (such as Uber/Lyft) is an economic burden to me because of their unaffordable fares.
Owning a private car can reduce my travel burden
Access to traditional public transit services (such as bus/rail) can reduce my travel burden
We need more traditional public transit services (such as bus/rail) because it is the most affordable option.
I prefer to use app-based ride services (such as Uber/Lyft), even if it is likely to need to reduce data use because of cost.
I prefer to use traditional public transit services (such as bus/rail) even if I have to have a longer waiting time.
I think I waste my time when a rideshare vehicle is strolling to pick up or drop off other passengers.
Although using app-based ride services are more expensive than using traditional public transit services (such as bus/rail), I prefer to use app-based ride services to avoid the low speed of bus and rail.

Table 3. 6 Attitudinal statements

I have factorized these statements into two categories: first, statement indicating preference for private ride services over ridesharing services, and second, statements indicating preference for public transit over app-based ride services. Thus, two new variables concerning mobility-related attitudes have been generated for the analysis including the preference for using private ride services over ridesharing services “preferenceforprivate”, and the preference for traditional public transit services over the app-based ride services (preferencefortraditional).

Technology Familiarity

This variable has been examined through four statements listed under a question asking participants to describe their level of familiarity with and use of modern technologies (see appendix I, survey, Q 6.2). The statements present a variety of choices from being a tech-savvy to being someone who needs assistance to navigate the internet. To create the dummy variable of "techfamilier” from these statements, the subjects who select the statement one or two are considered tech familiar and those who select the statements three or four are considered non-tech familiar.

Built Environment

Built environment attributes are key factors which are expected to influence modal use and preferences. I expect that the built environment attributes directly affect the respondents’ use and preferences. I created 1.25-mile network buffers with ESRI GIS around the population centroid of the zip code of each respondent to measure the built environment attributes.

I then examined various radiuses for buffers around the population centroids to figure out the most appropriate radius for measuring employment density, population density, and entropy. Smaller radiuses such as 0.5-mile buffer served for measuring built environment variables in smaller areas such as neighborhoods (Brownson et al., 2004). The literature defines a half-mile as a walkable distance (Sallis et al., 2004), and the neighborhood has been defined as a 0.5-mile radius or a 10-minute walk from the residents' home in which the physical and social environments could be assessed (Brownson et al., 2004). Given that the area where the built environment variables were going to be measured was via zip code, which is larger category than neighborhoods, the radius must be larger than 0.5-mile. Based on my examination, I realized that a 1.25-mile buffer can serve as the most exact radius for measuring these variables because this radius covers the largest areas inside the zip codes around the pop centroids.

I was going to measure the built environment variable in the exact home address of the respondents or the nearest intersection to their place of residence. Based on the Qualtrics' policy, this information is personal, and the company cannot include these questions in the survey. It was a limitation to my study. To measure the pop centroids of each zip codes, I obtained the information of the block groups centroids across the U.S. from the Census 2010 website. Then, I determined the block group centers within each specific zip code through geoprocessing. Next, I measured the mean center of each block group, which stands for the population centroid of each zip code.

Network buffers needed to be selected, in order to increase the accuracy of measuring the built environment around the pop centroids of each zip codes. Euclidian buffers "appear as perfect circles when drawn on a projected flat map" through which "straight-line distances are calculated between two points on a plane" (Flater, 2011, p. 34). However, with a network buffer around a point, not only the distance can be specified, but also the maximum distance that could be traveled along a network is signified. Network buffers provide a service area which covers the roads reachable within the specified distance. As mentioned, the specified distance in this study is 1.25 miles. I performed the spatial join tool in ESRI GIS to measure the built environment attributes for each buffer area. The following paragraphs introduce the selected built environment variables in this dissertation and their measurements.

Land-Use Mix

There is a correlation between land-use mix and the possibility of adopting ridehailing services. Increasing land-use mix increases the likelihood of adopting these services. (Alemi et al., 2018). Entropy measures of diversity, as a selected built environment attribute, is extensively applicable in travel studies. Entropy's low values demonstrate single-use environments, and its higher values specify higher level of variety in land uses (Ewing & Cervero, 2010). The entropy index is most commonly representative of land-use mix and quantifies homogeneity of land use in a given area. Entropy's value stands between zero and one, where zero specifies homogenous land use, and one represents the equal distribution of the tract of land throughout the entire land use types (Bordoloi et al., 2013).

I calculated the entropy for 1.25-mile buffer of the population centroid of each zip code. For that, I used 5 NAICS categories of retail, personal service, education, health, and entertainment for measuring entropy. Table 3.7 shows the NAICS sectors used in this dissertation and their descriptions. Entropy was computed using the following formula:

$$-\sum_j P_j * \ln P_j / \ln \mathrm{J}$$

Where:

Pj = the proportion of land in the jth land use category
J = the total number of land use categories.

The variable equals 1 for block groups with equal numbers of jobs in each sector within the buffer; 0 for block groups with all jobs in a single sector within the buffer; and intermediate values for intermediate cases.

Categories	Variable Name	Description
Retail	cns07	Number of jobs in NAICS sector 44-45 (Retail Trade)
Personal Service	cns10	Number of jobs in NAICS sector 52 (Finance and Insurance)
	cns11	Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)
	cns19	Number of jobs in NAICS sector 81 (Other Services [except Public Administration])
Education	cns15	Number of jobs in NAICS sector 61 (Educational Services)
Health Care	cns16	Number of jobs in NAICS sector 62 (Health Care and Social Assistance)
Entertainment	cns17	Number of jobs in NAICS sector 71 (Arts, Entertainment, and Recreation)
	cns18	Number of jobs in NAICS sector 72 (Accommodation and Food Services)

Table 3. 7 NAICS codes and categories used for entropy (Source: Moazzeni, 2018)

Population Density

As discussed in the literature review, population density is a determinant in higher accessibility to on-demand ride services (Wang & Mu, 2018). Population density, the density of housing units, and employment density shorten travels, enables taking public transit, and lessens dependency on the private car (Sun et al., 2017). Also, the literature displays that population density, along with other determinates such as land-use mix and regional accessibility by cars, travel time to work, waiting time for the arrival of vehicle, influence the demand for on-demand services and the preferences for this travel mode (Brown, 2018; Wang & Mu, 2018; Chen et al., 2017; Dias et al., 2017; Alemi et al., 2018; Hughes & MacKenzie, 2016; Lavieri & Bhat, 2019). Following Ewing and Hamidi (2014), I used ACS 2018 (2012-2016 ACS Total Population) to derive the gross population density in persons per square mile. I create a 1.25-mile buffer around the pop centroid of each participant’s zip code to measure the population density within each buffer.

Employment Density

The literature has cited employment density (jobs/acre) as an applicable built environment attribute in exploring the geographical distribution of trips made by ridehailing service across neighborhoods (Brown, 2018). Gross employment density (total employment divided by area in U.S. Acre) is selected as the second attribute of the built environment (Hamidi et al., 2015). I followed the method used by Hamidi et al. (2015) to measure this variable. I derived employment data from the Local Employment Dynamics (LED) database. I then aggregated the LED data from census block geography to create total jobs by 2-digit NAICS code for every block group. Then, I divided it by land area to generate a measure for employment density (Hamidi et al., 2015).

Other Explanatory Variables

Household Car Ownership has been examined in the survey through a question asking the numbers of cars available in the household for daily travel regardless of the respondent's access to them. Importance of service time efficiency in mode preference measures the importance of service time efficiency (travel time and waiting time) in selecting the preferred travel mode from the viewpoint of passengers. Also, Importance of service availability in mode preference measures the importance of service availability (on the day, at the time, and in the area) in selecting the preferred travel mode from the viewpoint of passengers (see table 3.5).

3.8 Analytical Method

In the present study, I have used proper statistical methods in proportion to the levels of measurement of variables. The statistical analysis methods in this study consist of two main parts. First, descriptive analysis method. After collecting the data, according to the type of data, I calculated frequency, percentage, minimum, maximum, mean, and standard deviation statistics to describe the nominal, ordinal, and ratio data. Second, I studied the inferential analysis method in several sections. I did Pearson tests for correlation between research variables, which is followed by one-sample t-test to investigate the status of the distribution of research variables among the sample individuals. Next, I did Friedman test to prioritize indicators related to research variables, and finally, I conducted structural equations to draw the final model and statistics related to model goodness of fit (including CMIN / DF, RMSEA, CFI, IFI).

Structural Equation Modeling (SEM)

This study uses Structural Equation Modeling (SEM) as the analytical method. Using this method helps researchers to model the direct, indirect, and total effects of exogenous variables on endogenous variables. SEM is very much applicable in behavioral sciences. The reason for the popularity of this modeling technique often relates to theoretical constructs displayed by latent factors (Hox and Bechger, 1998). A graphical path diagram often visualizes the structural equation models, and a set of matrix equations usually represent the statistical model. SEM has its roots in path analysis (Hox and Bechger, 1998). Researchers utilize path analysis as a methodology for the evaluation of the systems of structural equations. Based on the contemporary applications of this methodology, the three components of path analysis are defined as the path diagram; decomposition of covariances and correlations in terms of model parameters; and the distinctions between direct, indirect, and total effects of one variable on another. A path diagram demonstrates a picture of a system of simultaneous equations and the assumed relationships. This pictorial representation looks more apparent to many researchers than the equations (Bollen, 1989).

SEM differentiates three types of effects, including direct, indirect, and total effects. The direct effect represents that impact of one variable on another, that has not been mediated by any other variables in a path model. At least one intervening variable intervenes the indirect effects of a variable are mediated . Total effects are the outcomes of the aggregation of direct and indirect effects. A specific model always determines the decomposition of effects. Estimation of total, direct, and indirect effects might vary according to the modification of the system of equations by the inclusion and exclusion of variables (Bollen, 1989).

SEM utilizes various types of models to demonstrate the association between observed variables. A researcher can test various theoretical models in SEM that hypothesize the circumstances under which constructs are defined by sets of variables and the relationships between these constructs. The purpose of conducting the SEM analysis is figuring out the extent to which the sample data supports the theoretical model. If the sample data supports the existing theoretical model, this can result in hypothesizing more complex models, but if the sample data does not support the theoretical model, then it either needs to be modified to test the original model, or the researcher needs to develop and test other theoretical models. Hypothesis testing is the scientific method through which SEM tests theoretical models to explore the complex relationships between constructs (Lomax & Schumacker, 2004).

Understanding the mechanism of structured equation models requires introducing two essential types of variables including latent variables and observed variables. The latent variable which represents constructs or factors include the variables that are not directly observable or measured and are derived from a set of variables that a researcher measures based on various techniques such as a survey. A researcher uses the observed, measured, or indicator variables to define or infer the latent variable or construct. Each of these variables represents one definition of the latent variable (Lomax & Schumacker, 2004). Observed variables and latent variables, whether independent or dependent, form structural equation models and a researcher measures, defines, or infers the influence of independent latent variable(s) on the latent dependent variable(s) by multiple observed or measured indicator variables (Lomax & Schumacker, 2004).

Structural equations are equivalent to the use of analysis based on covariance and variance, which, in addition to showing the effects of independent and dependent variables as done in regression, also show how indirect effects can be calculated. In other words, in SEM, it is possible for the researcher to identify the indirect effects of independent variables by the placement of multiple dependent variables. Because our research data is covariance-based, and we also have various dependent variables, in this research, I use SEM to analyze data and generate the model. Considering these explanations about the analytical method, the results of the study are presented in the next chapter.

4 CHAPTER FOUR: RESULTS

In this chapter, I analyze the research data obtained as a result of following the previous steps. Data analysis is a multi-step process in which data collected by a questionnaire as a research tool are summarized, categorized and finally processed to provide a variety of links between this data to test the hypotheses. In this process, data are refined both conceptually and empirically, and various statistical techniques play an important role in inference and generalization. In this regard, to explain some of the relationships between the research variables that were problematic in the SE models, I have investigated a combination of research variables in the descriptive statistics section to identify and explain the patterns of individuals' response pathways that change or modify the results or effects of the data.

This study surveyed 385 people from 48 cities in 27 states across the United States. 31 cases were excluded from the final analysis for various reasons such as contradictory answers in the questionnaire, misspelling, less than standard response time, answers like geometric shapes as explained in previous chapter. Thus, the sample size was 354 individuals which contributed to the final analysis. Selected cities differ in location, size, access to transportation systems and other urban features, so a wide range of behavioral traits of individuals residing in these cities can be observed in the sample responses, although the entire sample is low income. It should be noted that the most frequent respondents are in New York City (16%) and the least frequent participants are in El Paso, Kansas City, Milwaukee, Oakland, Saint Paul, St Louis, Tempe and Wichita.

The research findings are classified and explained into the descriptive and analytical sections. First, the descriptive statistics of the findings are presented in terms of sex, age, education, income, race, employment, etc., the research hypotheses are answered using inferential statistics. In this regard, I analyzed and explained the effects of each independent variables on the travel behavior of the respondents, and examined how these behaviors were changed by using Pearson correlation test, one sample t-test, and finally, in the form of structural equation models. The objective of the analyst is to describe insights into research issues in large, complex and even incomprehensible collections of data. Therefore, the main purpose of the analysis is to arrange and summarize the data in a clear, readable, and interpretable way so that relationships in research issues can be explored and tested. In this regard, in order to analyze the research findings in detail and to explain the underlying relationships, I have also used descriptive findings in addition to using statistical tests to document the problematic aspects of the data on the basis of descriptive and raw data.

4.1 Summary of the travel behavior of the respondents, their socioeconomic and demographic features and some other characteristics

Travel behavior				
	Minimum	Maximum	Average	Standard deviation
Vehicle Miles Travelled	0	200	32.1	37.8
Overall use of private ride services	0	8	2.8	2.4
Overall use of ridesharing services	0	8	1.9	2.3
Overall use of fixed-route transit services	0	8	4.4	3.2
Social-Economic status				
	Minimum	Maximum	Average	Standard deviation
Household Car Ownership	0	4	0.43	0.8
Income	0	120,000	28,476.2	22,524.3
	Frequency			
Education	6.8% Some grade/high school, 26.8% High school/GED , 33.9% Some college/technical school, 11.6% Associate degree, 16.1% Bachelor’s degree, 4.0% Graduate degree (e.g. MS, PhD, MBA, etc.), 0.6% Professional degree (e.g. JD,			

	MD, DDS, etc.), 0.3% Prefer not to answer. (Median falls into the category of Some college/technical school)			
Studentship	82.8%NO; 8.5%Yes, Part-time; 8.8%Yes, Full-time			
House Ownership	83.9%Rent; 16.1%Own			
Full-/Part-time employed	80.2% Non-Fulltime Worker; 19.8% Fulltime Worker			
Demographic status				
	Minimum	Maximum	Average	Standard deviation
Age	18	70	43.2	15.7
Household size	1	7	2.4	1.5
	Frequency			
Gender	34.7%Male; 64.7%Female; 0.6%Non-binary			
Race/Ethnicity	51.4%NoWhite; 48.6% White			
Other Factors				
	Frequency			
Disability/health status	34.7% Disabled; 65.3% Not disabled			
Possessing Drive License	53.4%No; 46.6%Yes			

Table 4. 1 Summary of the variables included in the analysis

Table 4.1 reports the travel behavior of the respondents, their socioeconomic and demographic features, and some other characteristics. Concerning travel behavior variables, investigating the vehicle miles traveled (VMT) indicates that respondents travel on average about 32 miles per week. As mentioned in the previous chapter, the overall frequency of using traditional public transit services, private ride services and ridesharing services in the survey were rated on a scale including “never”, “less than once per month”, “once or twice a month”, “about once every 2 weeks”, “about once per week”, “two or more times per week”. In order to convert these choices to real numbers to allow statistical analysis, they were recoded using the SPSS software. The first choice (never) was assigned a score of zero, the second choice (Less than once per month) a score of 1, the third (once or twice a month) and the fourth (About once every 2 weeks) choices a score of 2, the fifth choice (about once per week) a score of 4, and the sixth choice (Two or more times per week) a score of 8. Investigating the frequency of the use of traditional public transit services, private ride services, and ridesharing services shows that respondents on average use the private ride services 2.8 times a month, 1.9 times ridesharing services, and 4.4 times traditional transit. It is noted that the frequency of traditional transit usage is higher than the other two modes, which was predictable, given the sample's low-income status. Figure 4.1 shows the frequency of use of the three modes in general.

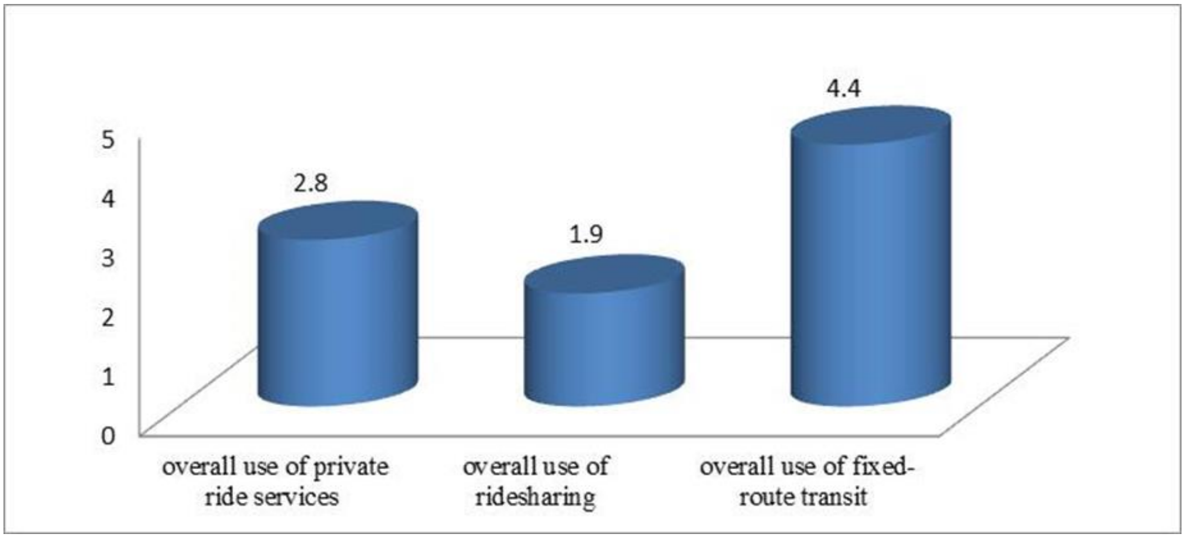

Figure 4. 1 Frequency of use of the three modes

Under the heading of “socio-economic status”, the table 4.1 reports the number of cars in the households. It shows that there are on average 0.43 cars per household, or there is on average one car in two households. Investigating the approximate total annual income of all working adults in the family mate total annual combined income of all the working adults in the household of the respondents shows that on average, the approximate annual income per household is $ 28,476.2.

Responses to the question about education status show that 6.8% of respondents have some grade/high school education, 26.8% high school/GED, 33.9% some college/technical school, 11.6% associate degree, 16.1% bachelor's degree, 4.0% graduate degree, 0.6% professional degree, and 0.3% preferred not to answer to this question. It is noted that the median in this distribution falls into the category of “some college/technical school”. Therefore, the data suggests that the sample is in the lower levels of education. Responses to the studentship status question indicate that 82.8% are not students, 8.5% are part-time students and 8.8% are full-time students. Regarding house ownership, 83.9% of respondents rent property, while 16.1% own their home. Investigating the respondents' employment status resulted in finding that 80.2% of them are non-full-time workers and 19.8% are full-time workers. It seems like the low level of full-time workers, education, home ownership, household car ownership, and income are all related, because our typical population sample is comprised of people who are all low income.

Participants’ demographic status was also assessed by variables such as age, sex, household size, and race/ethnicity. Findings showed that the average age of the respondents was 43.2 and the household size investigation showed that the average number of household members was 2.4. 34.7% of the respondents were male, 64.7% female and 0.6% were non-binary. In response to the question about race, it was found that 51.4% were non-white and 48.6% white.

“Possession of a valid driver license” and the health status in terms of “having/not having any physical or mental disabilities that seriously limit or prevent participants from doing travel activities” are the other variables that were explored in this study and can help in data analysis. Regarding disability, the findings show that 34.7% of our respondents have disabilities, and 65.3% have no disabilities. Also, 53.4% of the sample did not have a valid driver license, while the other 46.6% did. Figure 4.2 through 4.9 display the SES data concerning gender, race, education background, studentship, homeownership, employment status, car ownership, disability/health status, and possession of a valid driver license.

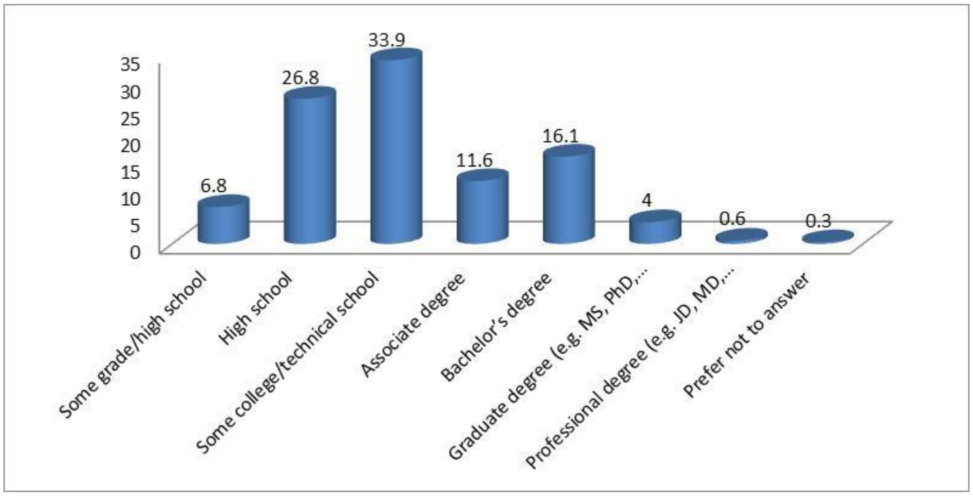

Figure 4. 2 Descriptive Statistics of Educational Background

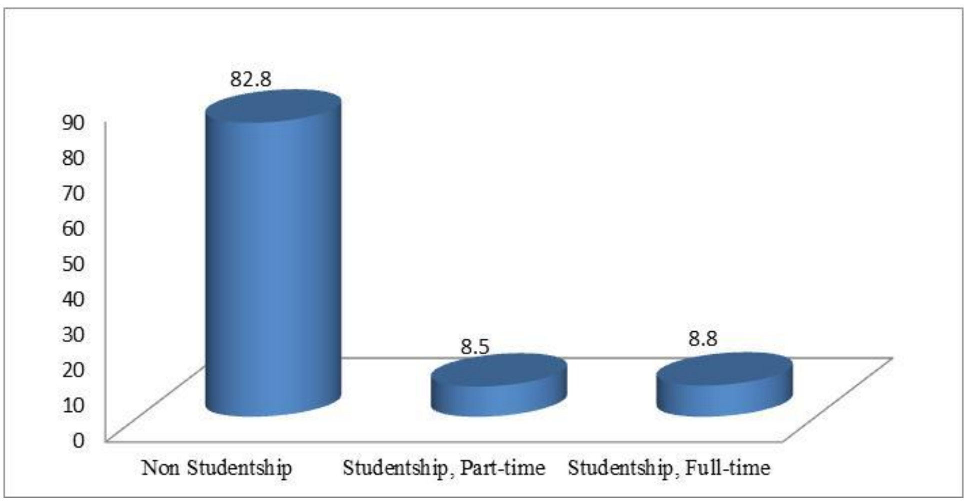

Figure 4. 3 Descriptive Statistics of Studentship

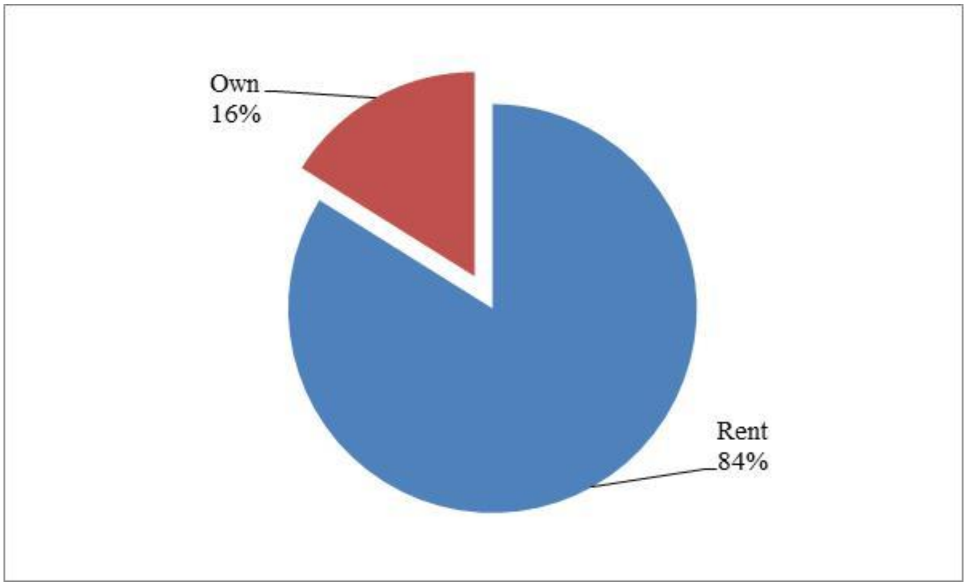

Figure 4. 4 Descriptive Statistics of Homeownership

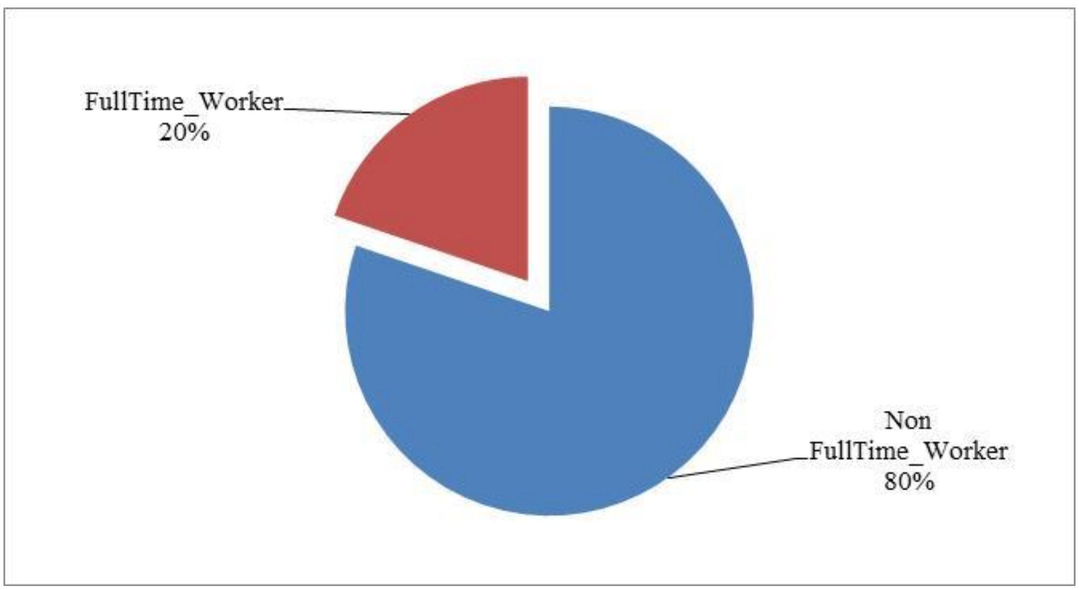

Figure 4. 5 Descriptive Statistics of Employment status

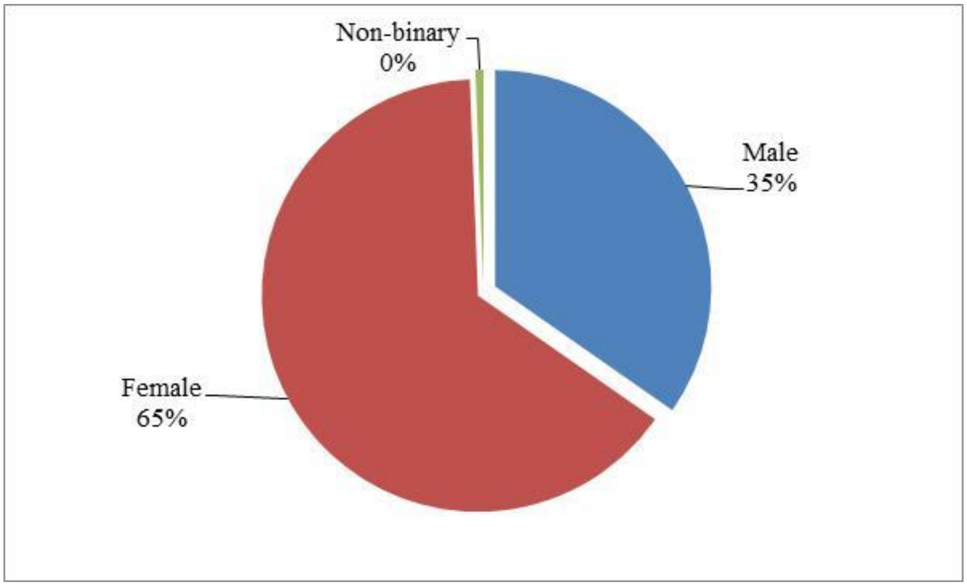

Figure 4. 6 Descriptive Statistics of Gender

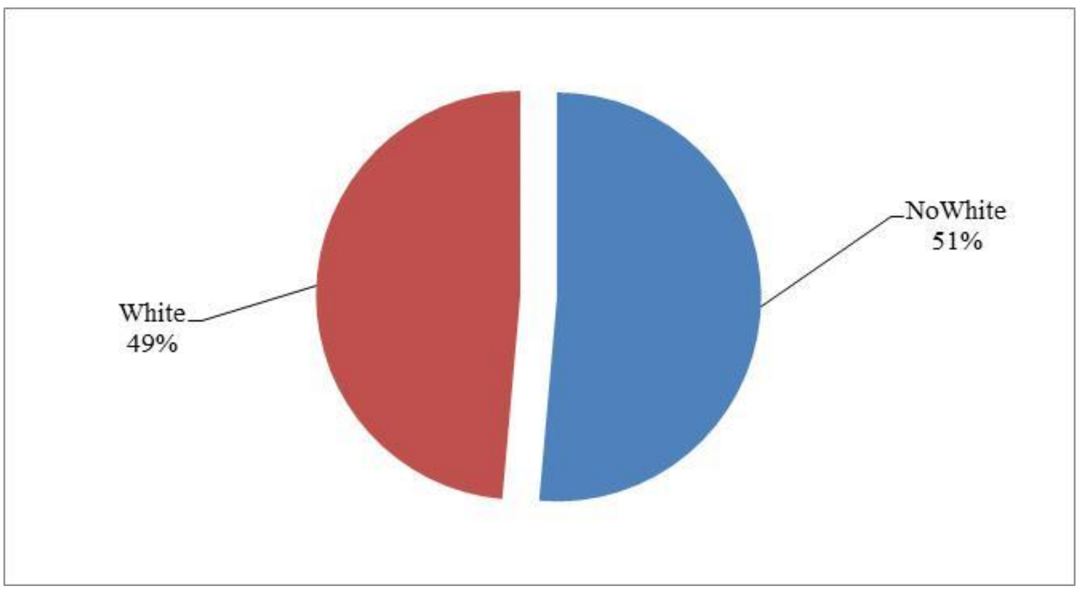

Figure 4. 7 Descriptive Statistics of Race

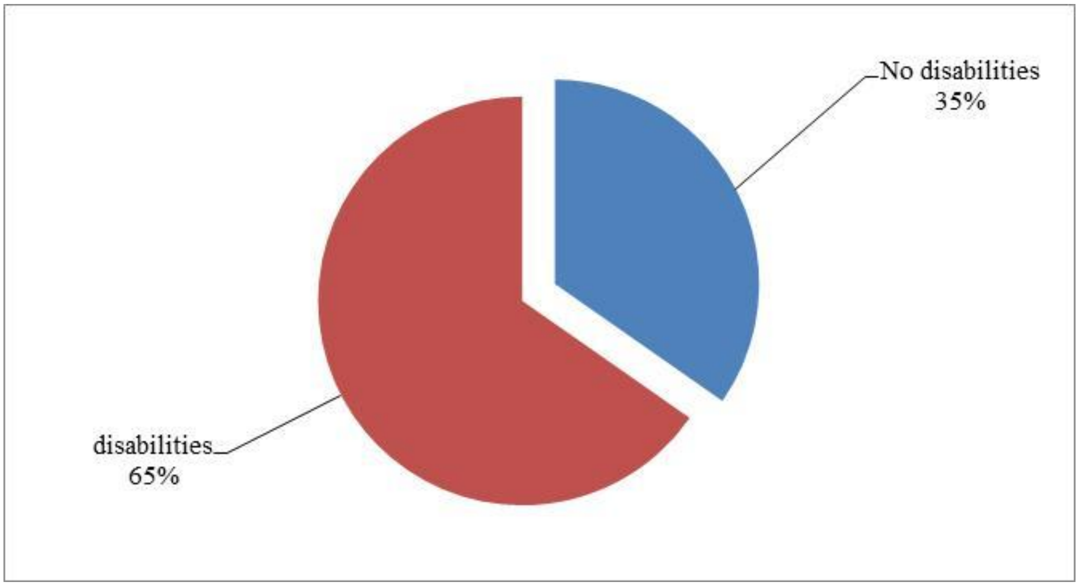

Figure 4. 8 Descriptive Statistics of Disability/Health Status

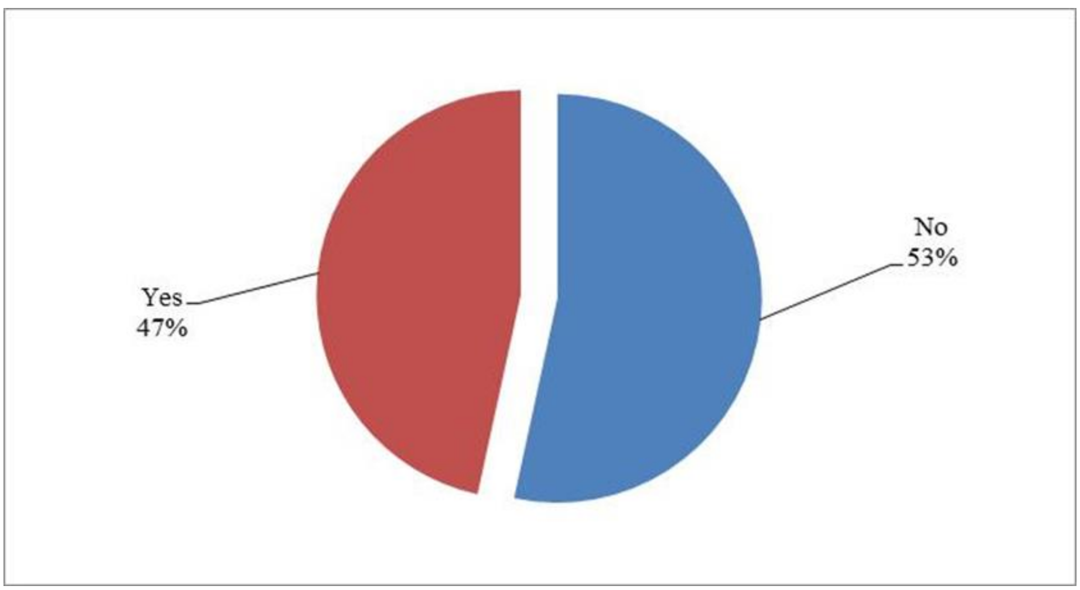

Figure 4. 9 Descriptive Statistics of Possession of a valid driver license

Table 4.2 displays information about the travel activities of participants who are currently employed and/or a student, with respect to the main way they make trips from home to work/school. As the table shows, the mean of trip frequency to work among the users of app-based systems is higher than the mean for those who use non-app-based systems.

Statistics	Question	N	Minimum	Maximum	Mean	Std. Deviation
Trip frequency to work/school per week	App-based	55	0	7	4.53	1.2
	Non-app-based	111	0	7	4.41	1.8
Distance in miles from residence to place of work/school	App-based	55	0	30	8.21	5.8
	Non-app-based	111	0	50	7.99	8.7
How long does it usually take to get to your primary place of work/school (Min)	App-based	55	0	60	23.11	14.8
	Non-app-based	111	0	90	31.07	24.6
How often do you work at home instead of making the trip to work/school? (days per month)	App-based	55	0	30	4.56	7.0
	Non-app-based	111	0	31	4.8	8.5

Table 4. 2 Travel activities of participants who are currently employed and/or a student with respect to the main way they make trips from home to work/school

In terms of distance in miles from residence to place of work/school, the mean of distance among the users of app-based systems is higher than those not using these services. It seems that respondents who have to travel a long distance from their residence to their place of work/school tend to use app-based services to save time and get to work faster, while those who have to travel a shorter distance from their residence to their place of work/school may spend more time to get there, so they use the cheaper options such as bus and rail and thus they save money. But the mean of time taken to get to work/school is lower among those using app-based services than those not using these services. As mentioned, respondents who have to travel a long distance from their residence to their place of work/school tend to use app-based services to save time and get to work/school faster, so it takes less time to get there than those using other modes. Also, the table shows that the mean of the frequency of working at home instead of making the trip to work/school, among those using app-based services, is lower than those not using them.

The distance between the place of residence and the place of work/education is an important factor in the selection and use of ridehailing services by transit-dependent people. That is, the greater the distance from one's home to his/her place of work/education, the more likely it is for that person to use app-based, on-demand ride services. It aligns with findings from Alemi et al. (2018) study about the more significant likelihood of ridehailing use among travelers who have more long-distance business trips. However, it should be noted that the population studied in Alemi et al. (2018) study was millennials (generation Y), who are known with their comfort with using digital interactive technologies for communication (Venter, 2017). The sample population in the present study are transit-dependent people who may feel discomfort using the ridehailing app or even the smartphone due to low digital literacy (Dillahunt et al., 2017). Investigating the Barrier of Digital Literacy in the present study also indicated that the most important digital literacy barrier to the sample population was feeling need assistance initiating rides through the phone, which will be discussed later in this chapter.

Table 4.3 shows the importance of various factors in choosing the preferred option among app-based, on-demand, ride services and traditional public transit, from the participants' viewpoint.

option / Statement	Very unimportant		Somewhat unimportant		Neither		Somewhat important		Very important		Mean
	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	

Access to credit/debit card	19	5.4	22	6.2	66	18.6	96	27.1	151	42.7	3.95
Access to a smart phone	20	5.6	18	5.1	57	16.1	82	23.2	177	50.0	4.07
Have internet access at home	24	6.8	18	5.1	71	20.1	63	17.8	178	50.3	4.00
Have a mobile data plan	20	5.6	15	4.2	66	18.6	99	28.0	154	43.5	3.99
Public support for data access such as public Wi-Fi	38	10.7	34	9.6	80	22.6	91	25.7	111	31.4	3.57
Security of my personal financial information	19	5.4	9	2.5	46	13.0	55	15.5	225	63.6	4.29
Scheduling and route finding though apps	20	5.6	21	5.9	61	17.2	100	28.2	152	42.9	3.97
Identity theft	19	5.4	19	5.4	62	17.5	67	18.9	187	52.8	4.08
Out of pocket costs of the service	17	4.8	17	4.8	61	17.2	86	24.3	173	48.9	4.08
Shorter waiting time when I need to use the service	17	4.8	10	2.8	49	13.8	111	31.4	167	47.2	4.13
Fastest way to get to destination	16	4.5	15	4.2	42	11.9	98	27.7	183	51.7	4.18
Sense of security from potential crimes in the vehicle/station	19	5.4	15	4.2	50	14.1	69	19.5	201	56.8	4.18
Comfort/convenience	16	4.5	14	4.0	44	12.4	108	30.5	172	48.6	4.15
Certainty about wait time, particularly during peak hours	14	4.0	9	2.5	57	16.1	104	29.4	170	48.0	4.15
Availability of the service in the area where I need it	13	3.7	9	2.5	31	8.8	68	19.2	233	65.8	4.41
Availability of the service at the time I need it	17	4.8	8	2.3	36	10.2	76	21.5	217	61.3	4.32
Availability of the service on the day I need it	15	4.2	12	3.4	35	9.9	74	20.9	218	61.6	4.32
Cash fare payment	26	7.3	35	9.9	86	24.3	80	22.6	127	35.9	3.70
Traveling at a safe speed	17	4.8	10	2.8	44	12.4	81	22.9	202	57.1	4.25
Concern about drivers	18	5.1	21	5.9	50	14.1	96	27.1	169	47.7	4.06
Discounts on rides	24	6.8	15	4.2	62	17.5	93	26.3	160	45.2	3.99
Free rides on eligible routes	25	7.1	21	5.9	76	21.5	94	26.6	138	39.0	3.84
Discomfort with sharing personal information	26	7.3	30	8.5	88	24.9	87	24.6	123	34.7	3.71

Familiarity with and use of app-based transportation technologies	17	4.8	18	5.1	71	20.1	105	29.7	143	40.4	3.96
Waiting home for the arrival of vehicle	19	5.4	19	5.4	68	19.2	111	31.4	137	38.7	3.93
Simply waiting for a bus/rail service instead of the need to request for a ride	28	7.9	26	7.3	101	28.5	100	28.2	99	28.0	3.61
Potential malfunction of the internet and the transportation app	21	5.9	26	7.3	83	23.4	92	26.0	132	37.3	3.81

Table 4. 3 Importance of the factors in choosing the preferred travel options among app-based ride services (such as Uber/Lyft, UberPool, Via, GoLink) and traditional public transit services (such as bus, light rail).

Participants' responses to these questions range from very unimportant to very important. In this regard, the mean of the response of the sample to each of these factors was obtained. Comparison of these means indicates that "*Availability of Service* in the Area where I need it" is the most important factor in choosing the preferred option. Also, *"Availability of service at the time I need it"* and *"Availability of the service on the day I need it",* hold equal importance, and are the next most important factors. Therefore, it seems that availability of the service is a very significant factor to the respondents in their choice of preferred transport option between the app-based ride services and traditional transit. By contrast, *"Public support for data access such as public Wi-Fi"* is the least important factor in choosing the preferred option. Also, *"Simply waiting for a bus/rail service instead of having to ask for a ride"* and *"Cash fare payment"* are the next least important factors. It is surprising that the poor may not entirely prefer to pay cash as cash is still an important mean of paying transportation fare due to banking restrictions (Brown, 2018).

Table 4.4 discusses the importance of various factors in choosing the preferred option among private ride services and ridesharing services from the viewpoint of the respondents.

Statement / option	Very unimportant		Somewhat unimportant		Neither		Somewhat important		Very important		Mean
	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	
Out of pocket costs of the service	14	4.0	16	4.5	70	19.8	86	24.3	168	47.5	4.07
Shorter waiting time when I need to use the service	11	3.1	8	2.3	50	14.1	114	32.2	171	48.3	4.20
Privacy when traveling	20	5.6	29	8.2	59	16.7	82	23.2	164	46.3	3.96
Fastest way to get to destination	7	2.0	16	4.5	44	12.4	96	27.1	191	54.0	4.27
Comfort/convenience	9	2.5	12	3.4	44	12.4	98	27.7	191	54.0	4.27
Availability of the service in the area where I need it	10	2.8	8	2.3	42	11.9	68	19.2	226	63.8	4.39
Discounts on rides	17	4.8	16	4.5	67	18.9	105	29.7	149	42.1	4.00
Free rides on eligible routes	22	6.2	21	5.9	83	23.4	93	26.3	135	38.1	3.84
Traveling at a safe speed	12	3.4	17	4.8	48	13.6	76	21.5	201	56.8	4.23
Availability of the service at the time I need it	10	2.8	10	2.8	42	11.9	72	20.3	220	62.1	4.36
Availability of the service on the day I need it	9	2.5	10	2.8	40	11.3	71	20.1	224	63.3	4.39
Discomfort with sitting with strangers in a small-size vehicle	23	6.5	35	9.9	77	21.8	85	24.0	134	37.9	3.77
Ability to split fare	29	8.2	37	10.5	105	29.7	78	22.0	105	29.7	3.55

Table 4. 4 Importance of the factors in choosing the preferred travel options among private ride services (such as Uber/Lyft), ride-sharing services (such as UberPool, Via, GoLink)

Examination of the mean of responses indicates that the following factors are weighed in equal importance: *"Availability of the service in the area where I need it"* and *"Availability of the service on the day I need it."* These two factors were ranked to be of highest importance among the sample population. *"Availability of the service at the time I need it"* is next in important factor. Therefore, it seems that availability is, once again, the most significant factor to the respondents in choosing their preferred option among private ride services and ridesharing services. *"Ability to split fare"*, by contrast, is the least important factor in choosing the preferred option. The next least important factors are: *"Discomfort with sitting with strangers in a small-size vehicle"* and then *"Free rides on eligible routes."*

Table 4.5 contains 12 barriers that seriously limit or prevent participants from using app-based, on-demand ride service. The barriers consist of four categories designed in the form of four barriers, including the Barrier of Technology Requirements (Bar_TechReq), Barrier of Affordability (Bar_Afford), Barrier of Digital Literacy (Bar_DigLit) and Barrier of Technology Security (Bar_TechSec), each of which has three factors, as displayed in the table.

Statement		Frequency	Percent
Barrier of Technology Requirements	Access to a smart phone	53	15.0
	Access to Internet at home	38	10.7
	Have a mobile data plan	39	11.0
Barrier of Affordability	Access to credit/debit card	52	14.7
	Unaffordable fares	112	31.6
	Unable to use these services when phone battery runs out or have no internet access	85	24.0
Barrier of Digital Literacy	Feeling need assistance initiating rides via the phone apps	23	6.5
	Need translation for transportation apps into languages other than English	18	5.1
	Need trainings using online methods	19	5.4
Barrier of Technology Security	Unwilling to connect personal financial information to phone	33	9.3
	Discomfort with sharing personal information	73	20.6
	Concern about identity theft	89	25.1
None of the above		111	31.4

Table 4. 5 Barriers that seriously limit or prevent from using app-based, on-demand ride service

Investigating the percentage of choosing each of these factors to measure these barriers indicates that *"Access to a smart phone"* poses the greatest obstacle to the use of app-based services among the barriers related to "Technology Requirements." As for the Barrier of Affordability, *"Unaffordable fares"* is the biggest obstacle. Investigating the Barrier of Digital Literacy also indicates that the most important digital literacy barrier is "*Feeling need assistance initiating rides through the phone*," and finally, examining the category of "Technology Security" indicates that "*Concern about identity theft"* is the most important security obstacle to using the ridehailing apps. It should be noted that 31.4% of the sample stated that they had no obstacle to using ridehailing services. Finally, a look at the frequency of factor selection across all four dimensions of the barriers indicates that the "Barrier of Affordability" has the most frequency of choice, and this is in line with the economic background of the sample individuals, all of whom are low income. Figure 4.10 shows the percentage of the selection of each of the factors related to the barriers to using ridehailing services.

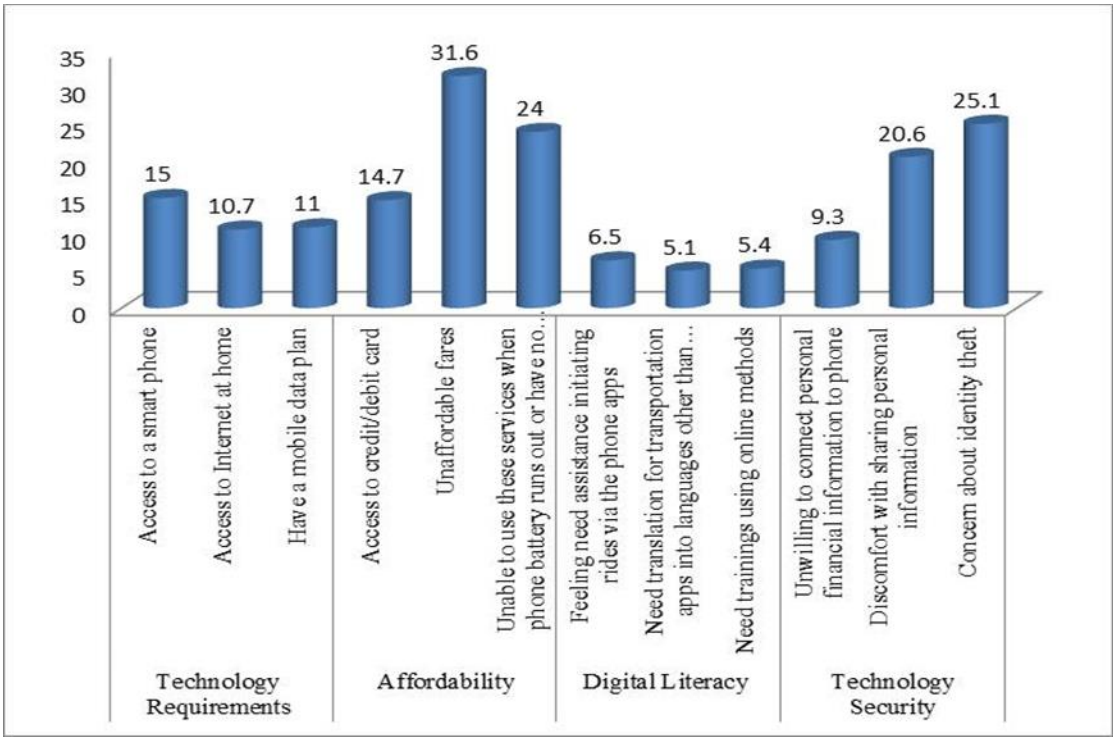

Figure 4. 10 Percentage of the selection of each of the factors related to the barriers to using app-based, on-demand ride services

4.2 Analytical Findings

Before explaining the relationships between the variables in the SE model, I first consider a matrix of the frequency of the modal usage among the respondents. Then, I examine the status of the key research variables in the sample and compare it to the standard mean. Following is an overview of the frequency of the use of three modes, from the perspective of the respondents, as well as prioritization of the barriers to the use of app-based services. Finally, the research models will be presented, and the research hypotheses will be discussed in association with the research models and their results.

4.2.1 Interpreting the Mutual Relationship Between the Dimensions of the Frequency of Use of the Three Modes

The transportation modes in this study were investigated in the form of the overall frequency of using private ride services (Freqtotprivate), ridesharing services (Frqtotrshare) and traditional transit (Freqtottransit). Table 4.7 displays the matrix of the correlation coefficients between the three forms of the transportation modal usage.

	Overall usage frequency of private ride services	Overall usage frequency of ridesharing services	Overall usage frequency of fixed-route transit services
Overall usage frequency of private ride services	1	.617	.066
		.000	.215
	354	354	354
Overall usage frequency of ridesharing services	.617	1	.073
	.000		.172
	354	354	354
Overall usage frequency of fixed-route transit services	.066	.073	1
	.215	.172	
	354	354	354

Table 4. 6 Matrix of the correlation coefficients between the three dimensions of the transportation modal usage

Note: In each cell, the first row is the Pearson coefficient, the second row is the significance level, and the third row is the sample.

In each cell, the first row shows the Pearson correlation coefficient, the second row show the significance level, and the third row shows the sample size. In statistical discussions, Pearson correlation coefficient measures the linear correlation between two random variables. As the table 4.7 shows, there is a positive correlation between the frequency of using private ride services and the frequency of using the ridesharing services, but there is no significant correlation between the frequency of using private ride services and the frequency of using traditional transit. Also, there is no significant correlation between the frequency of using ridesharing and the frequency of using traditional transit. The paired correlation between the three dimensions of the transportation modal usage suggests that the use of the app-base-transportation modes does not have a significant correlation with traditional transit use. That is, the users of each of these transport systems do not necessarily use only one transport system and may use either of these three types of transport depending on the time and space conditions.

4.2.2 Interpretation of the Mutual Relationship Between the Four Dimensions of the Barriers to the Use of App-Based Ride Services

	Barrier of Affordability	Barrier of Technology Requirements	Barrier of Digital Literacy Bar	Barrier of Technology Security
Barrier of Affordability	1	.181	.179	.387
		.001	.001	.000
	354	354	354	354
Barrier of Technology Requirements	.181	1	.371	.255
	.001		.000	.000
	354	354	354	354
Barrier of Digital Literacy	.179	.371	1	.333
	.001	.000		.000
	354	354	354	354
Barrier of Technology Security	.387	.255	.333	1
	.000	.000	.000	
	354	354	354	354

Table 4. 7 Matrix of the correlation coefficients between the four dimensions of the barriers to use of app-based ride services

Note: In each cell, the first row is the Pearson coefficient, the second row is the significance level, and the third row is the sample.

Table 4.8 shows the matrix of the correlation coefficients between the four dimensions of the barriers to use of the app-based ride services. In this study, four categories of barriers that seriously limit or prevent participants from using app-based, on-demand ride service were identified. As mentioned, the barriers consist of four categories, designed in the form of the Barrier of Technology Requirements (Bar_TechReq), Barrier of Affordability (Bar_Afford), Barrier of Digital Literacy (Bar_DigLit) and Barrier of Technology Security (Bar_TechSec). Each of these has three factors, which are displayed in the table 3.5. The paired correlation between these barriers suggests that there is a significant correlation between all dimensions of the barriers to the use of the app-based modes, given the significance level of less than 0.05.

4.2.3 Investigating the Status of the Distribution of Research Variables Among the Sample Individuals

In this section, I examine the status of the ratio variables among the sample individuals, using one sample t-test. Using one sample t-tests for the ratio variables helps one understand the status of the variable among the respondents. In fact, this test compares the scores of the variables with the standard mean, which means that if they are higher than the standard mean, or Test Value, the respondents are at a high level relative to the relevant variable. On the other hand, if they are lower than the Test Value, the respondents are at a lower level, relative to the relevant variable. First, the scores of each variable are standardized[1] as a percentage, and then the score of 50 is considered as the standard or theoretical mean.

Variables	Test Value = 50				
	t	df	Sig	Standard Mean	Mean Difference
Overall usage frequency of private ride services	-9.2	353	.000	35.59	-14.41
Overall usage frequency of ridesharing services	-16.67	353	.000	24.22	-25.78
Overall usage frequency of fixed-route transit services	2.38	353	.018	55.01	5.01
Overall preference for using private ride services	2.98	353	.003	55.76	5.76

[1] - (variable - minimum) / (maximum - minimum) * 100

Overall preference for using ride-sharing services	-5.00	353	.000	39.97	-10.03
Overall preference for using fixed-route transit services	4.61	353	.000	58.69	8.69
Accessibility preference	-17.10	353	.000	29.90	-20.10
Barrier of Affordability	-17.47	353	.000	23.45	-26.55
Barrier of Technology Requirements	-28.73	353	.000	12.24	-37.76
Barrier of Digital Literacy	-50.77	353	.000	5.65	-44.35
Barrier of Technology Security	-21.15	353	.000	18.36	-31.64
Barrier	-39.18	353	.000	15.09	-34.91

Table 4. 8 One-Sample t-test of the Ratio Variables

In the tables 4.9, the results of the one-sample t-test for investigating the ratio variables indicate that the means of three variables, including the overall frequency of traditional transit usage (freqtotTransit), overall preference for using private ride services (Prefprivate_overal), and overall preference for using ridesharing services (Pref_pub_overal), are above the standard mean, and the other variables are below the standard mean. Thus, it can be said that in terms of frequency of use of transport systems, both private ride services and ridesharing services are rarely used by the sample population, but the traditional transit sees a high level of usage by the sample population. Given the low-income status of the sample population, this result is as expected.

Regarding the sample's preferences for each of the three modes, the sample population's preference for using private ride services and traditional transit are at the top level, and the preference for using ridesharing services is below the standard mean. The other key ratio variable in this study is the accessibility preference, in which the results of the one sample t-test show that this variable is below the standard. Thus, it can be argued that sample individuals have little preference for living in compact and accessible places. Barrier and its four dimensions are the other key variables in this study. Examination of these dimensions by one sample t-test shows that these dimensions are lower than the standard mean, which is the result of this study. This result indicates that there are few obstacles for respondents to use app-based ride services, because a low barrier score means less barriers. Given that the level of significance for all variables is less than 0.05, it can be said that the results are statistically acceptable.

4.2.4 Investigating the Status of the Distribution of the Built Environment Variables Among the Sample Individuals

In the table 4.10, the results of the one-sample t-test for the built environment variables (population density, employment density, and entropy) indicate that the means of all three variables are below the standard mean.

Variables	Test Value = 50				
	t	df	Sig	Mean	Mean Difference
Population density	-16.60	353	.000	23.94	-26.06
Employment density	-19.70	353	.000	13.74	-36.26
Entropy	-6682.8	353	.000	.696	-49.30

Table 4. 9 One sample t-test for the Built Environment Variables

Thus, it can be said that our sample population is at a low level in terms of population density, employment density, and land use mix. Given that the level of the significance for all variables is less than .05, the results are statistically acceptable.

After the results of the SEM model, which will be explained in section 4.3.7, show that the built environment variables are not effective on the percentage of ridehailing trips and this is not consistent with the research literature (Cervero & Day, 2008; Sun et al., 2017; TCRP Report 16, 1996; Yu et al. 2019; Porter et al., 2013; Brown, 2018; Wang & Mu, 2018; Hughes & MacKenzie, 2016; Lavieri & Bhat, 2019; Alemi, 2018), I will argue that this ineffectiveness may be related to this fact that the residences of the sample population are at a very low level in terms of the land use mix, population density, and employment density. This issue will be discussed in more detail later.

4.2.5 Prioritizing the Four Dimensions of Barriers to Using App-Based Ride Services

I used the Friedman test to determine the priority of the dimensions of barriers to the use of app-based ride services by transit dependent participants. Friedman is a test to determine priorities among the indicators of a variable or to prioritize between several variables. I used Friedman test to figure out, for example, which dimension of the barriers to using ridehailing services is more important to respondents. The mean rank of this test indicates the importance or priority among the indicators of one variable or prioritization between several variables. The table 4.11 shows the mean rank of each of these dimensions.

Barrier	N	Mean	Std. Deviation	Mean Rank	Min	Max	df	Chi-Square	Sig
Barrier of Affordability	354	.70	.858	2.85	0	3	3	128.98	.000
Barrier of Technology Requirements	354	.37	.742	2.39	0	3			
Barrier of Digital Literacy	354	.17	.493	2.13	0	3			
Barrier of Technology Security	354	.55	.844	2.63	0	3			

Table 4. 10 Comparison of the mean rank of the dimensions of barriers to use app-based ride services

In the rankings obtained through the Friedman test on the comparison and the prioritization of the dimensions of barriers to the use of ridehailing services, the barrier dimensions were ranked as follows (in order of significance): Barrier of Affordability (Bar_Afford), the Barrier of Technology Security (Bar_TechSec), the Barrier of Technology Requirement (Bar_TechReq), the Barrier of Digital Literacy (Bar_DigLit). Their respective means are displayed below in Figure 4.12. It was found that the Barrier of Affordability is the most important obstacle to the use of app-based ride services to the participants, and the Barrier of Digital Literacy is the least important obstacle. Given that the chi-square value (128.98) and significance level (sig = 0.000) less than 0.01, this prioritization can be statistically confirmed.

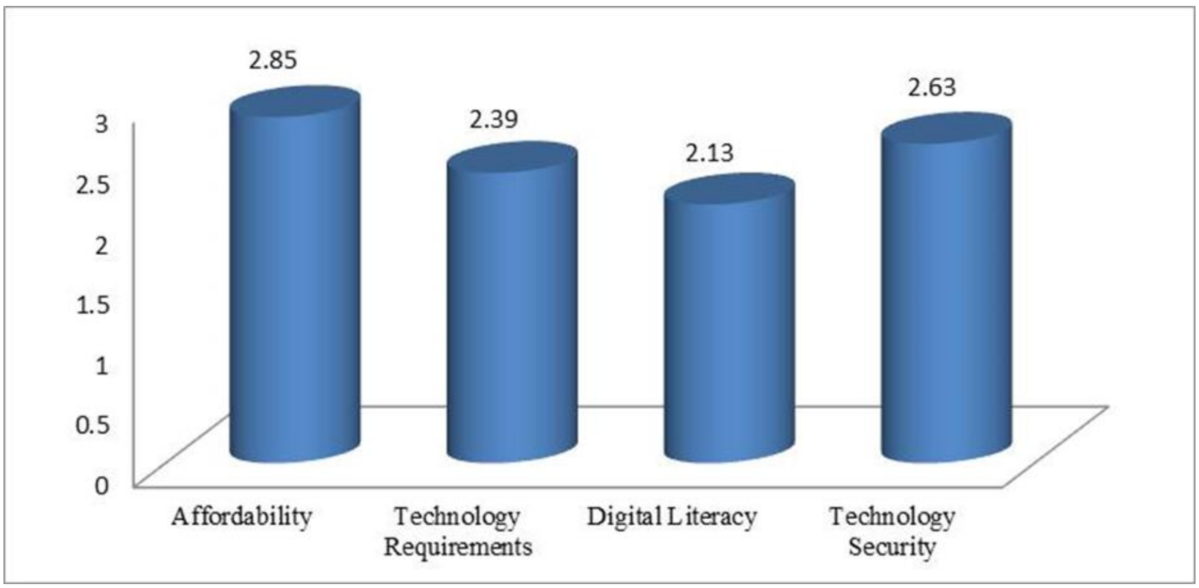

Figure 4. 11 The mean rank of each of the four dimensions of the barriers

4.2.6 Prioritizing the System of Preferences for Using the Three Travel Modes

I used the Friedman test to determine the preference of the sample individuals for the use of the triple transport modes under consideration, private ride services (Prefprivate_overal), ridesharing services (Pref_Ridshar_overal), and traditional transit (Pref_Pub_overal). Table 4.12 shows the mean rank of each of these preferences.

	N	Mean	Std. Deviation	Mean Rank	Min	Max	df	Chi-Square	Sig
Overall preference for using private ride services	354	5.46	2.909	2.15	1	9	2	57.239	.000
Overall preference for using ride-sharing services	354	4.20	3.016	1.73	1	9			
Overall preference for using fixed-route transit services	354	5.69	2.838	2.13	1	9			

Table 4. 11 Comparison of the mean rank of preferences for use of triple transport modes

In the rankings obtained through the Friedman test on the comparison and the prioritization of preferences for the use of transportation modes, the system of preferences were ranked as follows (in order of significance): private ride services, traditional transit, ridesharing services. Their respective means are displayed below in Figure 4.13. Therefore, it was found that most people prefer to use private ride services the most, and ridesharing was found to be least preferred. Given that the chi-square value (57.239) and the significance level (sig = .000) is less than .01, this prioritization can be statistically confirmed.

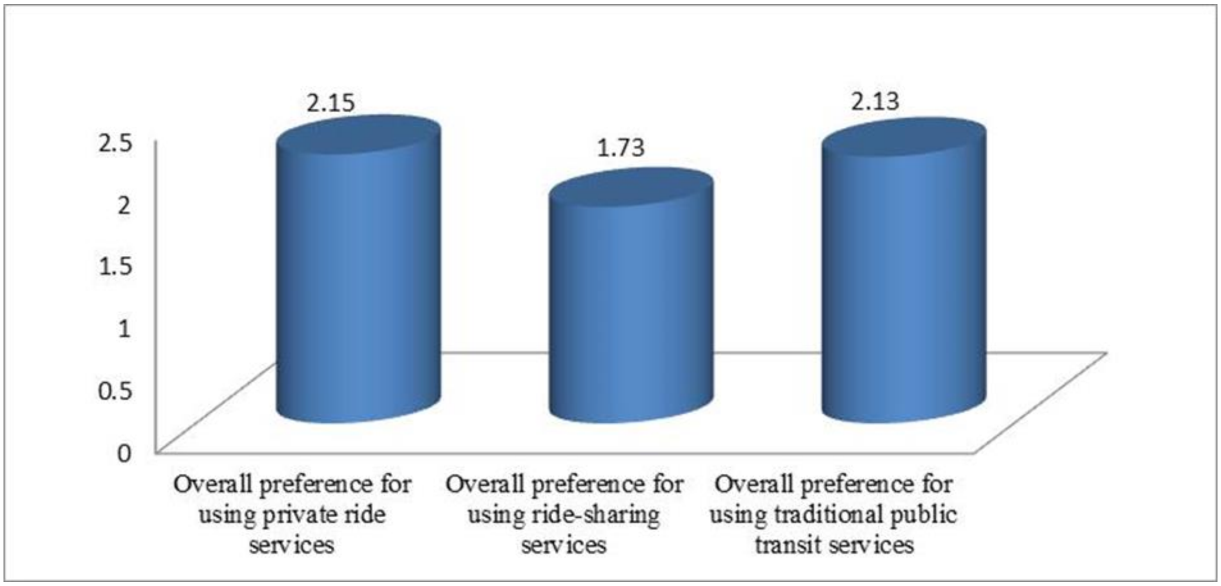

Figure 4. 12 The mean rank of the system of preferences

4.2.7 SE Models

In this section, first, a model was designed by entering 22 variables from the variables examined in the survey, and the effective and meaningful relationships remained in the model so that the overall picture of the effect of all variables in a framework can be observed (see appendix III, figure 6. 1). In this model, the modal preferences and the usage frequency of the three modes of private ride services, ridesharing and traditional transit were present as input variables. The effect of all independent variables was examined directly and indirectly on these variables in the model. But since I wanted to get to the main dependent variable that covers all three modes of transportation systems, I moved this model to the appendices so that the reader could refer to the effects of each of the independent variables on the modal preferences and the usage frequency of the three modes.

Then, based on this model and considering the two types of travel behavior with the app base services and traditional transit, a model was designed based on the analysis of the preference for and frequency of using the private ride services and traditional transit (see appendix III, figure 6. 2). To examine the effect of each of the research variables on these two types of transportation system, I also transferred this model to the appendices in order to achieve the main dependent variable that includes all three modes of transportation system.

Finally, I considered a variable called the percentage of ridehailing trips as the main dependent variable, which indicates the percentage of the sum of the overall use of private ride services and ridesharing services in the sum of the overall use of private ride services, ridesharing services, and traditional transit. Based on the significant effects of the research variables, two models were designed, one without the inclusion of the built environment variables and the other with the inclusion of these variables. In the following, I examine the goodness of fit as well as the effects of the variables in these two models.

In the first step, the acronym for the models' variables, and their description are specified in the following table:

Categories	**Variables**	**Description**
Socio-economic & Demographic	HHSize	Household size
	Dis_No	Any physical or mental disabilities that seriously limit or prevent you from travel activities. Disabled (code 1) or non-disabled/healthy (code 0)
Residential Preference	accessiblityprefenrece	Accessibility preference
Built Environment	PopDensity	Gross population density in persons per square mile.
	EmpDensity	Gross employment density
	Entroy	Land use mix (Entropy)
Service Time Efficiency	Pref_TimeEfficSrv	Importance of service time efficiency in selecting the preferred mode from the viewpoint of passengers
Service Availability	Availability	Importance of service availability in selecting the preferred travel mode from the viewpoint of passengers
Pctridehailtrips	Pctridehailtrips	Percentage of ridehailing trips
Modal Preference	Prefprivate_overal	Overall preference for using private ride services (such as Uber/Lyft)

	Pref_Pub_overal	Overall preference for using traditional public transit services (such as bus, light rail)

Table 4. 12 The models' variables and their definition

4.2.7.1 SE Model Without Built Environment Variables

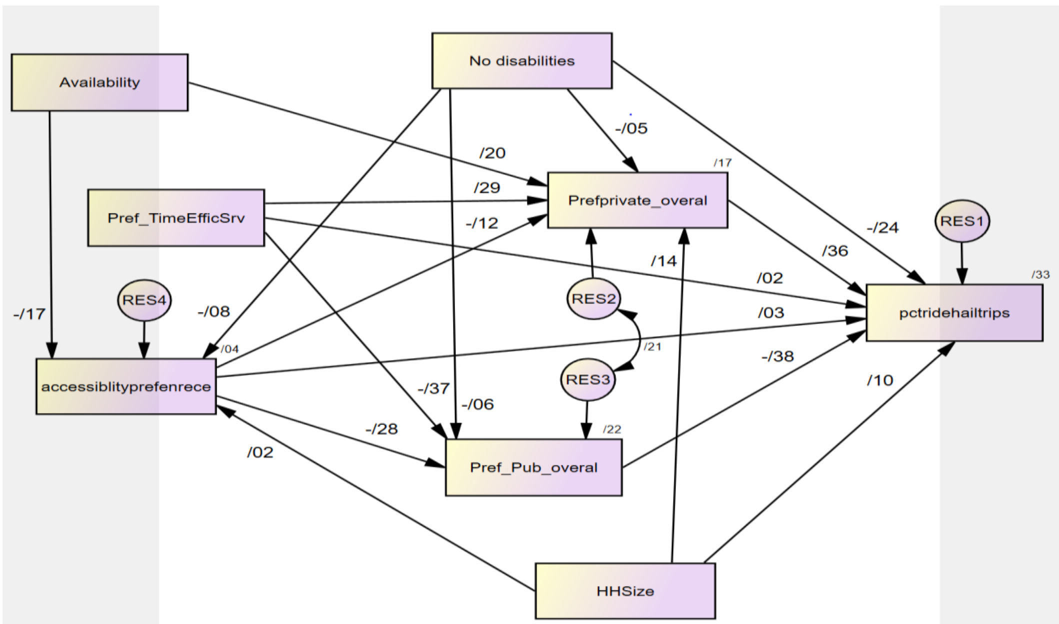

Figure 4. 13 Standardized estimates Model 1st_ Without Built Environment Variables

The model's goodness of fit indices is shown in the following table:

Goodness of fit indices						
IFI	**CFI**	**RMSEA**	**CMIN.DF**	**Chi-square**	**Df**	**p-Value**
.988	.987	.034	1.419	14.185	10	.165

Table 4. 13 Model 1st_ Without Built Environment Variables - goodness of fit indices

One of the indexes of the acceptable fit between the sample and the hypothetical model is the ratio of the CMIN/DF index, which is to be in the range of 2 to 1 or 3 to 1 (Carmines & McIver, 1983). Also, the acceptable threshold level of the RMSEA is to be less than .07 (Steiger, 2007 as cited in Hooper et al., 2008). In a model with a suitable goodness of fit, the lower limit is close to zero, while the upper limit should not exceed 0.08 (Hooper et al., 2008, p.54). The closer the RMSEA index is to zero, the better the fit. In SEM, incremental fit indices are based on comparing "the fit of a substantive model to that of a null model" (Widaman & Thompson, 2003, p.16). IFI values are considered acceptable if they are higher than .90, although these values may be higher than one (Moss, 2009). Also, the Comparative Fit Index (CFI) is a measure of the goodness of fit in relation to other models, which performs well with all sample sizes (Bentler, 1990). CFI values are considered acceptable if they are higher than .90 (Hu and Bentler, 1999 as cited in Hooper et al., 2008). Other indicators of the model's goodness of fit include p-value higher than .05 and low chi-square compared to the degrees of freedom (Ewing et al., 2016).

As can be seen, the result of dividing the value of CMIN/DF is 1.419. The RMSEA value is also 0.034. The CFI value is .987 and the IFI value is 0.988. Given that the values of CFI and IFI are higher than .90 and also according to the value of Chi-square = 14.185 and the p-Value = .165 which is higher than .05, therefore, the null hypothesis that the model does not fit the data is rejected, so the model has an acceptable goodness of fit and the results can be generalized to the statistical community.

Standard Estimation Coefficients of the Model

Dependent variable		**Independent variable**	**Coefficient**	**S.E.**	**C.R.**	**p-Value**
Accessibility preference	<---	Household size	.023	.828	.443	.658
Accessibility preference	<---	Disability/health status	-.082	2.718	-1.566	.117
Accessibility preference	<---	Importance of Service Availability	-.175	.464	-3.352	.000
Overall preference for using fixed-route transit	<---	Accessibility preference	-.283	.005	-5.972	.000

Overall preference for using private ride services	<---	Accessibility preference	-.117	.006	-2.355	.019
Overall preference for using private ride services	<---	Importance of Service time efficiency	.286	.061	5.886	.000
Overall preference for using private ride services	<---	Disability/health status	-.050	.295	-1.021	.307
Overall preference for using fixed-route transit	<---	Importance of Service time efficiency	-.366	.058	-7.771	.000
Overall preference for using private ride services	<---	Importance of Service Availability	.204	.050	4.229	.000
Overall preference for using fixed-route transit	<---	Disability/health status	-.061	.283	-1.283	.199
Overall preference for using private ride services	<---	Household size	.145	.088	3.041	.002
Percentage of ridehailing trips	<---	Overall preference for using fixed-route transit	-.377	.480	-7.502	.000
Percentage of ridehailing trips	<---	Accessibility preference	.032	.051	.704	.481
Percentage of ridehailing trips	<---	Disability/health status	-.238	2.505	-5.425	.000
Percentage of ridehailing trips	<---	Overall preference for using private ride services	.356	.450	7.471	.000
Percentage of ridehailing trips	<---	Service time efficiency	.016	.592	.313	.754
Percentage of ridehailing trips	<---	Household size	.099	.768	2.250	.024

Table 4. 14 Model 1st_ Without Built Environment Variables - Standardized Regression Weights

Table 4.15 shows the effects of each of the independent (exogenous) variables on the dependent (endogenous) variables and the significant level of the effects of these variables entered in the model. I report the effect of independent variables on endogenous variables.

It is essential to consider internal reasons in explaining travel behavior, in addition to paying attention to external causes. Thus, it is possible to explain the endogenous factors in the model that they are the preferences to use the transportation modes. The preferences for the use of private ride services and fixed-route transit were included in the research model, which revealed how these preferences shape people's travel behavior. Travel behavior of individuals is influenced by their preferences for using each of these transport modes, which were expected and supported by the findings of this study. According to table 4.15, the value of the effect of the overall preference for using fixed-route transit services on the percentage of ridehailing trips is -.377, which is in the opposite direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. Also, the value of the effect of the overall preference for using private ride services on the percentage of ridehailing trips is .356, which is in the same direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable.

Examining the status of people's preferences in the use of each mode also showed that preference for using private ride services is the first priority of people's preferences in travel behavior (see table 4. 15). On the other hand, these preferences are affected by various factors, which in the model three variables accessibility preference, importance of service time efficiency and importance of service availability in selecting the preferred travel mode influenced people's preferences in using transportation modes. According to Rayle et al. (2016), private ride services such as Uber offer a faster alternative to trips that could have otherwise been made by the traditional public transit services. Ridehailing sometimes serves a niche demand that traditional public transit services does not serve properly, such as traveling to or from low-density neighborhoods. As the table 4.15 shows, the value of the effect of the “importance of service time efficiency in selecting the preferred mode” on the overall preference for using private ride services is .286, which is in the same direction. Given its significance level (p-Value = .000), this effect is also statistically significant and acceptable. Also, the value of the effect of the "importance of service time efficiency in selecting the preferred mode" on the overall preference for using fixed-route transit services is -.366, which is in the opposite direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. These relationships were expected and could align with the results of Rayle et al. (2016), because time efficiency, as a principal factor that facilitates the travel process, is considered in the intention and preference of individuals to use a particular transportation mode and therefore the use of that mode.

The value of the effect of the "importance of service availability in selecting the preferred mode" on the accessibility preference is -.175, which is in the opposite direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. Also, the value of the effect of the accessibility preference on the overall preference for using fixed-route transit services is -.283, which is in the opposite direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. Moreover, the value of the effect of the accessibility preference on the overall preference for using private ride services is -.117, which is in the opposite direction. Given its significance level (p-Value = .019), this effect is also statistically significant and acceptable. The accessibility preference is the variable that affects the individuals' preferences using private ride services and traditional transit. Given that the model shows that the preference for living in compact areas or accessibility preference reduces the preference for using both private ride services and traditional transit, the need for transportation due to living in accessible areas is likely to decrease. According to the table 4. 15, accessibility preference does not have a significant effect on the percentage of ridehailing trips made by these populations (p-Value = .481). Also, as the importance of service availability in selecting the preferred travel mode increases, preference for living in compact areas (accessibility preference) decreases. This means that transit-dependent people who care about service availability in their modal preferences prefer to live in sprawled areas. This mentality justifies travel distances if access to transportation systems is possible, and thus makes it more preferable to live in sprawled areas. It could align with the results of a survey-based study by Rayle et al. (2016), which displays exploratory evidence of how private ride services such as Uber and Lyft, as the most available transportation service, are used in San Francisco. They argued that there are several neighborhoods with inadequate transit access, inadequate taxi availability, or scarce parking in this city. Passengers who refrained these neighborhoods in the past may now find them accessible, without understanding of the influence of the availability of private ride services (Rayle et al., 2016). The results also indicate that the value of the effect of the "importance of service availability in selecting the preferred mode" on the overall preference for using private ride services is .204, which is in the same direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. The importance of service availability in modal preference from the viewpoint of passengers significantly increases the overall preference for using private ride services as an app-based transport mode. The importance of service availability appears to affect the individuals' preference for using private ride services such as Uber as a type of transport system that is more available than any other mode by facilitating travel behavior. Overall, the timeliness, speed, and availability are all attractive factors for transportation by private ride services, and they are critical in increasing the preference for using this mode. It could serve as a possible justification for the expected and significant positive effect of the "importance of service availability in selecting the preferred mode” on the overall preference for using private ride services. It could also align with the results of Rayle et al. (2016), which argued that travelers who have not previously had the preference for choosing the neighborhoods with inadequate transit access as trip destination or have forgone the activity altogether might now find them accessible due to the influence of the availability of private ride services.

The value of the effect of the “importance of service time efficiency in selecting the preferred mode” on the percentage of ridehailing trips is .016, which is in the same direction. Given its significance level (p-Value = .754), this effect is not statistically significant and thus the effect is rejected. Travel behavior of individuals is influenced by their preferences for using each of these transport modes, which is supported by the findings of this study. Examination of the research model shows three variables accessibility preference, the importance of service time efficiency in modal preference, and the importance of service availability in modal preference as variables affecting the preferences for using different transportation modes that indirectly affect people's use of different transportation modes. It was suggested that the importance of service time efficiency in modal preference affects the preference for the use of private ride services and traditional transit. It raises the preference for using private ride services as an app-base mode and reduces the preference for using traditional transit such as bus, and ultimately indirectly increases the percentage of ridehailing trips. Therefore, time efficiency, as a principal factor that facilitates the travel process, is considered in the intention and preference of individuals to use a particular transportation mode and therefore the use of that mode. It could serve as a possible justification for the unexpected insignificant effect of the “importance of service time efficiency in selecting the preferred mode" on the percentage of ridehailing trips, which does not seem to be aligned with the results of Rayle et al. (2016).

The value of the effect of the household size variable on the overall preference for using private ride services is .145, which is in the same direction. Given its significance level (p-Value = .002), this effect is statistically significant and acceptable. Also, the value of the effect of the household size variable on the percentage of ridehailing trips is .099, which is in the same direction. Given its significance level (p-Value = .024), this effect is statistically significant and acceptable. These relationship does not align with the results of Etminani-Ghasrodashti and Hamidi (2019) indicating that household size is significantly and negatively associated with the frequencies of the trips made by ridehailing services. A possible justification for these unexpected relationships is that the income status of individuals is associated with the income level of their households, especially in low income families with large household sizes. In these households, all family members earn money and spend it together. Therefore, personal income is not a good criterion for survey-based studies that aim to focus on low-income populations to investigate mode choice, mode preference and usage. As mentioned in chapter two it was an area of disagreement in the results of studies applying socio-economic and demographic characteristics of riders in the works of Dias et al. (2017) and Alemi et al. (2018) concerning the usage frequency and the adoption of ridehailing services. According to Dias et al. (2017), ridehailing users tend to be high-income individuals, but the results of Alemi et al. (2018) study on the frequency and the adoption of ridehailing in California showed that about half of the frequent ridehailing users are more likely to reside in low-/medium-income households. It was mentioned that the income status of individuals is associated with the income level of their households, especially in low income families with large household sizes.

The value of the effect of the disability variable on the on the percentage of ridehailing trips is -.238, which is in the opposite direction. Given its significance level (p-Value = .000), this effect is statistically significant and acceptable. This relationship and its direction were expected because ridehailing companies such as Uber provide the service to the travelers through drivers who use their personal cars and do not necessarily have the essential facilities to serve the disabled travelers. These drivers also do not consider themselves obliged to being equipped with these facilities. This relationship could align with the results of a report by an advocacy group in New York which says that people with disabilities cannot use ridehailing services virtually due to "the relative lack of vehicles equipped to handle wheelchairs and motorized scooters" (Kunkle, 2018).

Variables	**Percentage of ridehailing trips**		
	direct	indirect	total
Importance of Service Availability	0	-.069	-.069
Overall preference for using fixed-route transit	-.377	0	-.377
Accessibility preference	.032	.148	.18
Disability/health status	-.238	-.0069	.2449
Overall preference for using private ride services	.356	0	.356
Importance of Service time efficiency	.016	.240	.256
Household size	.099	.054	.153

Table 4. 16 Model 1st_ Without Built Environment Variables - Direct, indirect, and total effects

An examination of the direct and indirect effects of the independent variables on the percentage of ridehailing trips shows that the overall preference for using fixed-route transit with a value of -.377 has the strongest direct effect, and importance of service time efficiency in selecting the preferred mode with a value of .016 has the weakest direct effect on the percentage of ridehailing trips. An examination of the indirect effects also shows that importance of service time efficiency in selecting the preferred mode with a value of .240 has the strongest effect, and the disability variable with a value of .0069 has the weakest indirect effect on the percentage of ridehailing trips made by transit-dependent people.

4.2.7.2 SE Model with Built Environment Variables

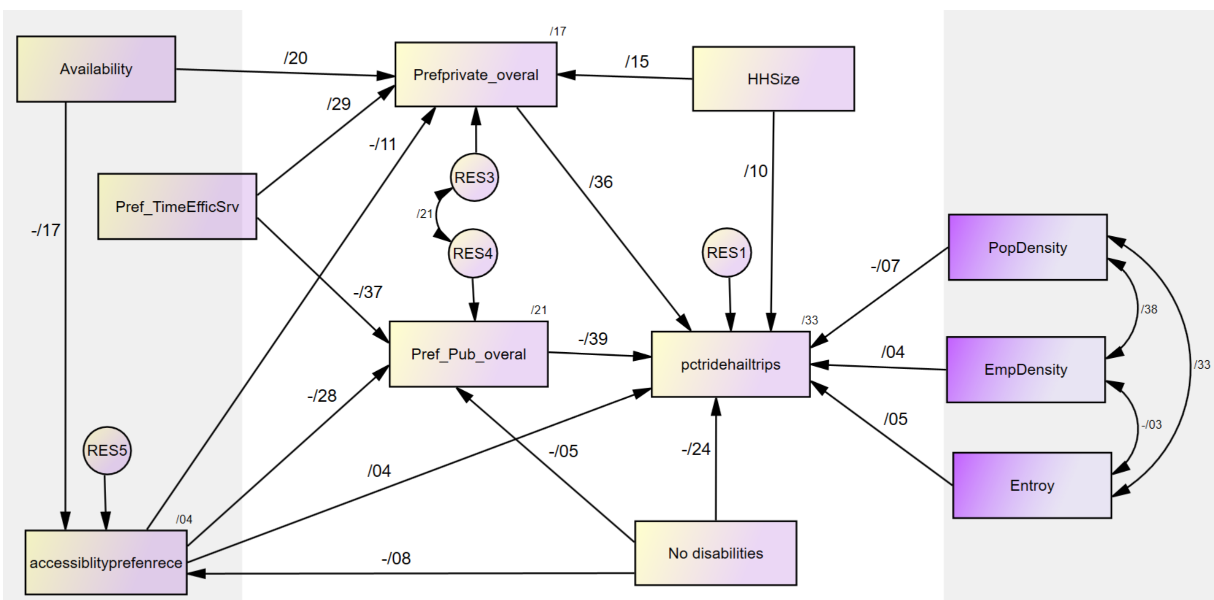

Figure 4. 14 Standardized estimates- Model with Built Environment Variables

The model’s goodness of fit indices is shown in the following table:

Goodness of fit indices						
IFI	**CFI**	**RMSEA**	**CMIN.DF**	**Chi-square**	**Df**	**p-Value**

.969	.968	.034	1.414	48.087	34	.055

Table 4. 17 The goodness of fit indices for the model with built environment variables

As can be seen, the result of dividing the value of CMIN by the degree of freedom is 1.414. The RMSEA value is also .034, the CFI value is .968 and the IFI value is .969 which is higher than the cutoff point of .90. Therefore, the model has a good fit. Also, considering the value of Chi-square = 48.087 and the p-Value = .055 which is higher than .05. Therefore, the null hypothesis that the model does not fit the data is rejected, and the model has an acceptable goodness of fit and the results can be generalized to the statistical community..

Standard Estimation Coefficients of the Model

Dependent variable		Independent variable	Coefficient	S.E.	C.R.	P
Accessibility preference	<---	Importance of Service Availability	-.174	.464	-3.341	.000
Accessibility preference	<---	Disability/health status	-.083	2.718	-1.583	.114
Overall preference for using fixed-route transit	<---	Accessibility preference	-.282	.005	-5.951	.000
Overall preference for using private ride services	<---	Accessibility preference	-.112	.006	-2.275	.023
Overall preference for using private ride services	<---	Importance of Service time efficiency	.292	.061	6.006	.000
Overall preference for using fixed-route transit	<---	Importance of Service time efficiency	-.366	.058	-7.743	.000
Overall preference for using private ride services	<---	Household size	.145	.088	3.058	.002
Overall preference for using fixed-route transit	<---	Disability/health status	-.051	.276	-1.096	.273
Overall preference for using private ride services	<---	Importance of Service Availability	.200	.050	4.144	.000
Percentage of ridehailing trips	<---	Overall preference for using private ride services	.360	.420	8.071	.000
Percentage of ridehailing trips	<---	Employment Density	.042	.038	.874	.382
Percentage of ridehailing trips	<---	Population Density	-.066	.047	-1.300	.194
Percentage of ridehailing trips	<---	Entropy	.046	9.175	.981	.327
Percentage of ridehailing trips	<---	Household size	.101	.765	2.305	.021

Percentage of ridehailing trips	<---	Disability/health status	-.239	2.494	-5.478	.000
Percentage of ridehailing trips	<---	Accessibility preference	.036	.050	.787	.431
Percentage of ridehailing trips	<---	Overall preference for using fixed-route transit	-.386	.435	-8.502	.000

Table 4. 18 Model with Built Environment Variables - Standardized Regression Weights

The table 4.21 shows the effects of each of the independent (exogenous) variables on the dependent (endogenous) variables and the significance level obtained from the effect of these variables entered in the model, in which the built environmental variables are considered. In this model, research hypotheses are tested.

Testing the Research Hypotheses

The first hypothesis: *Population density, employment density, and land use mix (entropy) are determinant factors in identifying the percentage of ridehailing trips made by these populations.* The value of the direct effect of the employment density variable on the percentage of ridehailing trips is .042, which indicates that for one unit standard deviation of change in the employment density variable, .042standard deviation unit is created in the same direction in the percentage of ridehailing trips variable. But this value is very small, and given the significant level obtained that is greater than 0.05 (p = .382), (P> .05), this hypothesis is not confirmed, and that employment density does not have a significant effect on the percentage of ridehailing trips. Also, the direct effect of land use mix variable on the percentage of ridehailing trips is .046, which indicates that for one unit standard deviation unit of change in the entropy variable, .046 standard deviation unit is created in the same direction in the identifying the percentage of ridehailing trips variable. But this effect is negligible and given the significance level of more than .05 (p = .327) (P> .05), this hypothesis is not confirmed, and that entropy has no significant effect on identifying the percentage of ridehailing trips. Moreover, the direct effect of the population density variable on the percentage of ridehailing trips is -.066, indicating that for one unit standard deviation of change in population density, -.066 standard deviation unit in the opposite direction occurs on the percentage of ridehailing trips variable. But this effect is also very small, and given the significant level obtained that is more than .05 (p = .194), (P>.05), it is also very insignificant to consider the effect of this variable, and this effect is not acceptable and we cannot accept this hypothesis. Therefore, population density does not have a significant effect on the percentage of ridehailing trips made by these populations.

Examination of the last hypothesis of the research shows that the built environment variables are not effective on the percentage of ridehailing trips. This is not consistent with the research literature concering the relationship between the built envornment and travel behaviour (Cervero & Day, 2008; Sun et al., 2017; TCRP Report 16, 1996; Yu et al., 2019; Porter et al., 2013; Brown, 2018; Wang & Mu, 2018; Hughes & MacKenzie, 2016; Lavieri & Bhat, 2019; Alemi, 2018). Also, with respect to the relationshsip between population density, employment density, and land use mix (entropy) and the identification of the percentage of ridehailing trips, as the literature cites, employment density as a built environment attribute is applicable in exploring the geographical distribution of trips made by ridehailing service across neighborhoods (Brown, 2018). Also, higher accessibility to Uber is correlated with population density (Wang & Mu, 2018). Ridehailing services offer more significant performance in dense urban areas, and higher population and employment densities, presumably attributes to more frequent trip requests (Hughes & MacKenzie, 2016). Also, there is an association between more significant land-use mix and the higher likelihood of the adoption of on-demand ride services (Alemi, 2018). Given that the residences of the sample population are at a very low level in terms of population density, employment density, and land use mix (see table 4.10, one-sample t-test for the built environment variables), arguably this ineffectiveness may be related to the very low level of these three variables in these residences.

Explaining this contradiction with literature leads us to examine the variables of the built environment in the sample under study. In the table 4.10, the results of the one-sample t-test for the built environment variables indicated that the mean of land use mix was .696, employment density was 13.74, and population density was 23.94, which are all below the standard mean. Comparing these means shows that there is a kind of heterogeneity in these three variables, which raises the premise in the researcher's mind that the contradiction between the results and the literature arises from this heterogeneity, and the low level of these three built environment variables in the residences of the transit dependent subjects. In fact, an examination of the status of the built variables in our sample shows that these three variables, in addition to the significant difference in their percentage, are also at a low level in terms of density and land use diversity. My conclusion from the above result is that while transit-dependent people, on the one hand, reside in very low density and land use mix areas, on the other hand, there is a big difference between the three built environment variables examined in the sample, these two factors, given that people are low-income, lead to different behaviors between them in the use of transportation modes. In fact, transit-dependent people's behavior in these situations is influenced by very low status of density and land use diversity in the residence and big differences in the status of these three built environment attributes, which may be followed by contradictory behaviors due to being affected by different situations.

A review of the preferences system has previously shown that participants have a high preference for using private ride services, but this preference is influenced by important variables, such as the importance of service time efficiency and service availability in selecting the preferred travel mode. Therefore, the discussion is about these two influential factors in the system of preferences of individuals, which can be linked to the discussion of the effect of built environment variables on the frequency of use of transportation modes. In fact, very low status of density and land use diversity of the surveyed areas has led to an increase in the cost of using private ride services, and due to the fact that people are low-income, their ability to pay for travel expenses has been weakened. But this is not always the case, and a person behaves differently under the influence of circumstances. For example, when people do not have enough time to reach their destination, they may use app-base modes, and when they have enough time to reach their destination, they may use traditional public services, such as buses to reduce travel costs. Discussing the effects of the importance of service time efficiency and service availability in selecting the preferred travel mode on the system of preferences reinforces this claim.

Finally, it can be concluded that for the poor, choices or patterns of behavior arise from the choice of necessities. This means their choices are driven by what is technically necessary to get things done, and no more. It also calls for an examination of the environmental, economic, and social determinism factors that forces them to act in a certain way. Therefore, here are two types of choices that are made, according to the time and situation in which the person is placed, which in most cases, is accompanied by forced choice. But in some cases, such as the lack of time to reach the destination, the poor must break this rule in choosing a transportation mode and act differently. It seems that the contrast between the results of this study and the research literature is caused by this breaking of the norm.

The second hypothesis: *Preference for living in compact places (accessibility preference) is a determinant factor in identifying the percentage of ridehailing trips made by these populations.* The direct effect value of the accessibility preference variable on the percentage of ridehailing trips is .036, which indicates that for one unit standard deviation of change in the accessibility preference variable, .036 standard deviation units is created in the same direction in the percentage of ridehailing trips variable. But this value is very small, and given the significant level obtained that is greater than .05 ($p = .431$), ($P > .05$), this hypothesis is not confirmed, and accessibility preference does not have a significant effect on the percentage of ridehailing trips made by these populations.

The third hypothesis: *Importance of service availability in selecting the preferred travel mode from the viewpoint of passengers is a determinant factor in identifying the preference for using private ride services by these populations.*

The direct effect value of the importance of service availability in selecting the preferred travel mode from the viewpoint of passengers on the preference for using private ride services is .200, which indicates that for one unit standard deviation of change in the importance of service availability in modal preference, .200 standard deviation units is created in the same direction in the preference for using private ride services. This means that people giving more importance to service availability in selecting their preferred travel mode have higher preference for using private ride services. This hypothesis is confirmed by a significant level of less than .05 (p = .000) (P <.05).

The fourth hypothesis: *Importance of service time efficiency in selecting the preferred mode from the viewpoint of passengers is a determinant factor in identifying the preference for using private ride services and fixed-route transit services by these populations.*

The direct effect value of the importance of service time efficiency in selecting the preferred travel mode from the viewpoint of passengers on the preference for using private ride services is .292, which indicates that for one unit standard deviation of change in the importance of service time efficiency in modal preference, .292 standard deviation units is created in the same direction in the preference for using private ride services. This means that people giving more importance to service time efficiency in selecting their preferred travel mode have higher preference for using private ride services. This hypothesis is confirmed by a significant level of less than .05 (p = .000) (P < .05). Also, the direct effect value of the importance of service time efficiency in selecting the preferred travel mode from the viewpoint of passengers on the preference for using fixed-route transit is - .366, which indicates that for one unit standard deviation of change in the importance of service time efficiency in modal preference, .366 standard deviation units is created in the opposit direction in the preference for using fixed-route transit services. This means that people giving more importance to service time efficiency in selecting their preferred travel mode have lower preference for using fixed-route transit services. This hypothesis is confirmed by a significant level of less than .05 (p = .000) (P < .05).

The fifth hypothesis: *Preference for living in compact places (accessibility preference) is a determinant factor in identifying the preference for using private ride services and fixed-route transit services by these populations.*

The direct effect value of the accessibility preference variable on the preference for using private ride services is - .112, which indicates that for one unit standard deviation of change in the accessibility preference variable, .112 standard deviation units is created in the opposit direction in the preference for using private ride services. This means that people with more preference for living in compact places have lower preference for using private ride services. This hypothesis is confirmed by a significant level of less than .05 ($p = .023$) ($P < .05$). Also, the direct effect value of the accessibility preference variable on the preference for using fixed-route transit services is - .282, which indicates that for one unit standard deviation of change in the accessibility preference variable, .282 standard deviation units is created in the opposit direction in the preference for using private ride services. This means that people with more preference for living in compact places have lower preference for using fixed-route transit services. This hypothesis is confirmed by a significant level of less than .05 ($p = .000$) ($P < .05$).

Variables	Percentage of ridehailing trips		
	direct	indirect	total
Importance of Service Availability	0	.064	.064
Importance of Service time efficiency	0	.246	.246
Overall preference for using private ride services	.0360	0	.0360
Employment Density	.0042	0	.0042
Population Density	-.066	0	-.066
Entropy	.0046	0	.0046
Household size	.0101	.145	.246
Disability/health status	-.239	.011	-.228

Accessibility preference	.0036	.068	.104
Overall preference for using fixed-route transit	-.386	0	-.386

Table 4. 19 Model with Built Environment Variables - Direct, indirect, and total effects

An examination of the direct and indirect effects on the percentage of ridehailing trips with the presence of the built environmental variables show that the overall preference for using fixed-route transit, with a value of - .386, has the strongest direct effect and accessibility preference, with an effect of .036, has the weakest direct effect on the percentage of ridehailing trips. An examination of the indirect effects also shows that the importance of service time efficiency in selecting the preferred mode, with a value of .246 has the strongest effect and the disability variable, with a value of .011, has the weakest indirect effect on the percentage of ridehailing trips made by transit-dependent people.

4.3 Summary

This chapter dealt with the two parts of the descriptive and analytical findings of data needed to test the research hypotheses. In this regard, two SEM models were presented: one model constitutes the built environment variables and the other one does not constitute these variables. The statistical response to the research hypotheses was reported in this chapter, but the theoretical and empirical discussion of these hypotheses is postponed to Chapter 5, where I explain the results of the research findings by referring to the results of statistical tests and following unknown paths in the effects of the research variables on the model, which sometimes appear to be contradictory.

5 CHAPTER FIVE: DISCUSSION AND CONCLUSIONS

5.1 Discussion

Understanding riders' attitudes is important for planners and policymakers in transit agencies, local governments as well as ridehailing companies. It would enable transportation agencies in public and private sector to better aligns their service with people's needs and preferences. For the private sector it could lead to more economic productivity and for the public sector it results in more efficiency and the increase in ridership. Therefore, the other side of the coin implies that the preference for the use of each of the transportation modes, both ridehailing and fixed-route transit, can be affected by numerous factors. Based on what has been mentioned, I discuss the direct and indirect effects of the independent variables on the dependent variables in the model, as well as the research hypotheses.

In this study, I tested two models. The first model included the most important variables that could influence dependent variables. In this model, I considered a principal dependent variable called the percentage of ridehailing trips, which is the result of the percentage of the use of app-based modes of the total use of private ride services, ridesharing, and traditional transit. In the second model, I tested the model one with the presence of the built environmental variables. I discuss the hypotheses based on the second model, which is the final research model.

Although travel planning can be considered an individual decision, in the broader perspective, travel planning is influenced by individual constraints and, potentially, psychological elements, such as the preference for using different transport systems. Therefore, one of the most important variables determining the use of both the app-based and traditional transit services, is the system of preferences for each of mode. The importance of preferences can be examined from two dimensions. First, it is possible to predict people's behavior by recognizing the preferences of individuals that result from their attitudes towards the use of each transportation mode. Second, it can be argued that by reinforcing the system of preferences among individuals over various issues, their need to make decisions about choosing a behavior is reduced, and their attitudes toward things become habitual.

Beliefs, attitudes, and conscious intentions only play a role in the preliminary stages when a behavior is recent, but when behavior is repeated many times, there is usually no need to consider beliefs, attitudes, and intentions (Ajzen & Fishbein, 2000). In this case, intentions and attitudes stored in memory do not require significant cognitive effort to be retrieved directly (Ajzen & Fishbein, 2000). Thus, it can be argued that behavioral intentions and preferences for performing a behavior overtime becomes a habit through repetition (Wood, & Neal, 2016). Therefore, a variety of factors can influence the preference for using each of the transport modes, whether ridehailing or fixed-route transit. In this section, I discuss these factors in the form of relationships between model variables. Testing research hypotheses that examine the transit-dependent people's system of preferences showed that the overall preference for using private ride services has a positive effect and the overall preference for using fixed-route transit services has a negative or inverse effect on the percentage of ridehailing trips.

5.1.1 Planned Behavior Theory and the Discussion of the Sample’s Modal Preferences

I discuss the status of the system of preferences for the use of transportation modes based on the theory of planned behavior. The main mechanism of the theory of planned behavior assumes that one's actual accomplishment of the behavior is influenced by one's intention towards adopting a specified course of action (Haugtvedt et al., 2018). Therefore, according to the theory of planned behavior, it can be argued that travel behavior of individuals is influenced by their preferences for using each of these transport modes, which is supported by the findings of this study. On the other hands, in the theory of planned behavior the factors that influence the intentions of individuals are also discussed. Examination of the research model shows three variables accessibility preference, the importance of service time efficiency in modal preference, and the importance of service availability in modal preference as variables affecting the preferences for using different transportation modes that indirectly affect people's travel behavior.

In planned behavior theory, control beliefs are the factors that influence people's behavior (Ajzen, 1991). Considering control beliefs is effective in analyzing the preferences for using transportation modes in the discussion of our model. Under these factors, the three variables accessibility preference, the importance of service time efficiency, and the importance of service availability in modal preference, as the variables affecting people's preferences, indirectly affected people's use of different transportation modes.

According to the result of this study, the importance of service time efficiency in modal preference is a determinant factor in identifying the preference for the use of private ride services and traditional transit. The importance of service time efficiency in modal preference increases the preference for the use of private ride services and decreases the preference for the use of traditional transit. The ultimate and indirect impact of the importance of service time efficiency in modal preference is increasing the percentage of ridehailing trips made by transit-dependent respondents. As such, time efficiency is a determinant factor that eases the travel process, and transit-dependent people consider this factor in their intention and preferences to use a particular travel mode and ultimately using that mode. Also, the impact of the importance of services availability on the overall preference for the use of private ride services is positive and significant. It can be argued that the importance of service availability affects transit-dependent respondents' preference for using private ride services such as Uber as a type of transport system that is more available than any other mode by easing travel process. Therefore, this effect can also be explained under the theory of planned behavior. Overall, the timeliness, speed, and availability are all attractive factors for transportation by private ride services, and they are critical in increasing the preference for using this mode.

People turn the pattern of using certain transportation modes into internalized mental patterns following the repeated use of these modes. Thus, in different situations, they choose their desired transportation modes without the need to think, and subconsciously. Researchers can identify these preferences, and urban transport policy makers can implement their transportation plans according to these known preferences. In fact, according to these preferences, a series of policies should be developed based on how they can take measures such as improving routes and bus service stations, especially for transit-dependent populations. Given the significance of the preferences for using transportation modes, by re-formulating transportation management policies based on the modal preferences, it will be possible for the users to turn the pattern of using certain transportation modes into internalized mental patterns of using the optimal transportation modes.

5.1.2 Accessibility Preference and the Discussion of the Sample's Modal Preferences and Travel Behavior

Research shows that the variation in transit travel is significantly associated with residential preferences and travel attitudes (Cao et al., 2006). Schwanen and Mokhtarian (2005) examined the interconnectedness between residential location choice and travel choices by studying the variation in the commute mode choice by residential neighborhood and by the inconformity between the existing neighborhood type of commuters and their preferences for physical characteristics of the residential neighborhood (Schwanen & Mokhtarian 2005). They found that although mismatched suburban residents may prefer more to use transit compared to their matched neighbors, for many, it may feel like they have no choice but to commute by private vehicle, due to noncompliance between the level of transit available to them and, for instance, their workplace. The present study also showed that residential preference is the variable that affects the individuals' preferences for using private ride services and traditional transit, but this study examined the travel behavior and the modal preferences of low-income individuals who do not own personal car. The results also showed that 70.3% of these individuals have no vehicles available in their household for daily travel (see Appendix II, table 6. 21). Given that the model indicated that the preference for living in compact areas or accessibility preference reduces the preference for using both private ride services and traditional transit, the need for transportation due to living in accessible areas is likely to decrease.

This led me to testing the second hypothesis: preference for living in compact places (accessibility preference) is a determinant factor in identifying the percentage of ridehailing trips made by these populations. Testing this hypothesis suggested that accessibility preference does not have a significant effect on the percentage of ridehailing trips made by these populations. More interestingly, as the importance of service availability in selecting the preferred travel mode increases, preference for living in compact areas (accessibility preference) decreased. This means that transit-dependent people who care about service availability in their modal preferences prefer to live in sprawled areas. This mentality justifies travel distances if access to transportation systems is possible, and thus makes it more preferable to live in sprawled areas. Thus, the preference for living in compact areas appears to reduce the dependence of individuals on transport systems among the sample population. Given that our sample individuals are all low-income, it is possible that high compactness may cause these people to reduce living costs in a variety of ways, such as using a bicycle or walking instead of using paid transport systems, which requires closer scrutiny, in the form of another future scientific research.

5.2 Recommendations and the Directions for Future Studies

To recognize and study the phenomena related to human beings and the issues related to human behavior, it is essential to study its various dimensions and look at issues from different angles. Different studies can only examine the limited dimensions of an issue, while human behavior has many different dimensions and is influenced by different factors. Also, in line with this study, executive instructions should be developed to improve and supply services, and as a result, policymakers should make more proper decisions. The following are some examples in the form of recommendation for the future studies and practical recommendations for policymakers.

5.2.1 Practical Recommendations for Policy Makers

Understanding the patterns of travel behavior and the process of selecting the modes of transportation system yields several benefits. These benefits include assisting policymakers to make decisions, providing a cognitive basis, by analyzing the travel behavior, and choosing the mode of transportation system by passengers, assisting legislators and regulators to provide rules for providing transportation services for better decision making. In addition, studying the behavior and patterns of transportation use and preferences on daily trips can help us understand the factors that affect human behavior.

Investigating the Barrier of Digital Literacy in the result chapter indicated that the most important digital literacy barrier is "*feeling need assistance initiating rides through the phone*". There are third party platforms that may provide feasible resolutions for transit-dependent riders like seniors who are deterred from using ridehailing due to technological barriers. GoGoGrandparent is one of these services that allow seniors to access Uber or Lyft without access to smartphone. Seniors can call to a phone number to request for a ride by Uber or Lyft and they can also "speak with an operator about scheduling requests in advance or anything else" (GoGoGrandparent, 2018). These types of third-party platforms can be modeled by organizations such as health care providers and municipalities (Brown, 2018).

The findings concerning the frequency of factor selection across all four dimensions of the barriers showed that the "Barrier of Affordability" had the most frequency of choice, and this was in line with the economic background of the sample individuals, all of whom are low income. There are programs developed by transportation and non-profit organizations that promote the support of low-income populations and address the unaffordable costs of transportation to them. For example, the Pinellas County Transportation Disadvantaged (TD) Program is the partnership between Uber and Pinellas County, Florida, which works towards supporting low-income populations through subsidizing transportation for individuals earning income lower than the 150% of the federal poverty guidelines. Low-income riders who meet the eligibility criteria may request to hail at most 23 free late-night rides (between 9 p.m. and 6 a.m.) every month. Another pilot is the partnership between the county government in Tarrant County, Texas with the nonprofit Catholic Charities, in which they work towards engaging app-based, on-demand ride services to supply transportation service to low-income people, as a part of an employment program (Moran, 2016a). Although ridehailing has introduced a new choice for transportation, all populations, especially transit dependents and low-income individuals, may be the beneficiaries of these services in terms of equal access. There are examples concerning the partnership between app-base, on-demand ride services, with transit agencies and organizations, such as health care providers towards helping seniors. For instance, the pilot program between Uber and the Laguna Beach (California) City Council help older adult riders to hail the ride with Uber for medical appointments at medical centers by calling Uber directly rather than booking the ride through the smartphone app.

According to the results, *"concern about identity theft"* was the most important security obstacle to using the ridehailing apps by the sample individuals. It is essential to start policies that secure ways of using cash for unbanked riders. The significance of information security relates to the vulnerable financial status of low-income household. It is not likely that many of these household are protected by insurance to protect them from identity theft or losing money from online or smartphone accounts (Golub et al., 2018).

The findings showed that *"access to a smart phone"* poses the greatest obstacle to the use of app-based services among the barriers related to "Technology Requirements." Also, "*have a mobile data plan*" and "*access to internet at home*" are the second and third barriers related to "Technology Requirements" to using ridehailing serices, respectively.. The results also showed that the most important digital literacy barrier to the use of ridehailing services by the sample was "*feeling need assistance initiating rides through the phone*". Cities should consider mobility hubs that allow riders without access to smartphone to hail a ride with shared mobility systems, such as the linkNYC—Wi-Fi kiosks in New York City providing free Wi-Fi and phone service to neighborhoods (Mcgeehan, 2016). Feasible recommendations for resolving the challenge of transit dependent people with the lack access to internet at home or having a mobile data plan who cannot afford buying internet and data plan would be the installation of public Wi-Fi access hotspots in key cites, or providing subsidies to disadvantaged populations for purchasing mobile data plans (Yan et al., 2019). The Federal Communications Commission offers Americans using welfare programs the choice to use subsidy to help some of the Americans for whom Internet access at home is unaffordable (Risen, 2016). Installing public kiosks in intermediate locations which accept various means of payment such as cash and credit/debit cards and riders with low digital literacy can use them. Riders without access to smartphone can call ridehailing services by these public kiosks (Dillahunt et al., 2017).

It is obvious that achieving all the above-mentioned recommendations requires providing cultural, social, political and urban models to the transit-dependent people, and only in this way can we increase their satisfaction and the proper and optimal use of transportation systems in our cities.

5.2.2 Directions for the Future Studies

Research must be conducted in which the statistical population, in addition to the low-income, includes members of the other economic classes to examine and compare the class preferences and tastes, as well as the exhibitive consumption of travel among different classes. Also, researchers are recommended to conduct a comparative study of the travel behavior of transit dependent individuals, especially their modal use and preferences in a larger number of different urban communities in one country, or different urban communities in different countries. Moreover, repeating this study could provide further evidence to support the findings. Therefore, it is suggested that research be conducted on the travel behavior in larger samples from different classes. In addition, to achieve more precise results, it is recommended that the relationship between the variables studied in this study be examined in a longitudinal study, to be able to detect changes in transit-dependent people's travel behavior over time.

It is recommended that a meta-analysis of the research conducted on the travel behavior of transit dependent citizens' be done to clarify conflicting results in a series of experimental works, in order to provide the groundwork for the accurate and scientific application of the findings in society. In addition to summarizing and describing the results of studies in the background of this topic, this meta-analysis also follows the actual relationship or difference in society of different studies, and estimates the effect of methodological features of studies on the estimated differences or relationships in different studies in certain areas.

One of the findings of this study was the detection of the non-significant effect of the built environment variables on the percentage of ridehailing trips made by transit-dependent subjects, which is not in harmony with the findings of previous studies. Also, the results of this study showed that the residential areas of the sample population are at a very low level in terms of population and employment densities and the diversity of land use (table 4.10). Therefore, it is recommended that future researchers, while targeting transit-dependent subjects, examine study areas with this level of built environment characteristics and compare the results with the findings of the present study and challenge the previous theoretical literature to verify the results of this study.

5.3 Limitations

It is important to recognize the problems and limitations of the research. Paying attention to these problems and limitations provides the researcher with a more comprehensive understanding of the subject. Of course, some of the problems and limitations are not in the control of the researcher, and some problems can only be discovered and observed if the researcher completes his work and is determined in the process of conducting research. Pointing out research limitations can pave the way for future researchers, to facilitate their work.

The sample size in this study was small compared to the number of selected cities as the study area. The question may be, how can 385 people represent the statistical population at 48 cities across the United States? It is about eight people for each city. It is why choosing a small size for sampling was a big limitation in this study. Given that hiring more people in the sample was costly and unaffordable, I had to opt out of the larger sample. Also I cannot recommend future researcher to use more variables to test the results of this study because such recommendation depends on the sample size.

The other limitation of this research pertained to the data collection method. My initial plan was to conduct both paper-based and online surveys, but due to the limitation of the financial resources, and time constraints, in addition to the selection of 48 cities across the U.S., which made it impossible to travel and distribute the paper-based questionnaires in person, I changed the method of data collection to the online survey.

I intended to explore the determinants behind the modal preferences and the usage frequency of the ridehailing services and fixed-route transit by transit-dependent populations in transit desert areas across the study area. Transit deserts refer to “geographic areas with high transit demand but low transit service” (Jiao, 2017, p. 529). Transit deserts are characterized as areas with lower density, limited diversity of uses, limited sidewalks, and very car-oriented design. In transit deserts, stops are often located on arterials, and it takes a lot of time to access transit; plus there is long travel distance to access stops (Allen, 2014; Allen 2018).There has been recent research that has recognized and mapped transit deserts in 52 major U.S. cities (ranked by population), including the cities defined as the study area of this dissertation. That research has located transit deserts within cities, through the identification of transit-dependent populations as a measure of transit demand, assessing the transit supply, and then subtracting the supply from the demand to figure out the gap.

Using the results of that research, I needed the information of the nearest intersection to their place of residence, which shows the approximate place of residence of the respondents—which would help me to determine if the respondents lived in transit deserts. Right before launching the survey, the Qualtrics company informed me that based on their policy, requesting such information is a violation of personal privacy, and the company would not include these questions in the survey. Therefore, I decided to consider the most specific information about the residence of respondents, which was their zip codes. The most accurate feature of a zip code concerning the residence of individuals living there is the zip code population centroid. I described the measurement of the pop-centroid of zip codes in chapter three. But it is not exactly clear if that place of residence of a respondent overlaps the pop-centroid or a place near there, to truly determine if he/she is living in a transit desert. Therefore, I had no other option but to disregard the investigation of transit deserts in my study. It was a big limitation for my work.

5.4 Conclusion

The models depicted in this study were examined in the analysis of transit-dependent people's travel behavior in two ways with the presence of the built environment variables and without these variables. The models were well-fitted and the goodness of fit showed that we can generalize the results to the statistical community. In general, the study of the preferences and use of transportation modes indicated that transit-dependent people prefer to use private ride services as the main mode of transportation (in the absence of private vehicle and for destinations that are not within a walkable distance). But in practice, they mostly use fixed-route transit services. Of course, the preference for use of fixed-route transit as the main mode of transportation is also high among these people, which seems to be due to the importance of travel cost in the use of app-based transportation systems more because these people are generally low-income, and this behavior has been influenced by the financial reality of their lives.

The sample people were expected to behave similarly, given that they are all on the low-income class. But it is not always possible for people to reflect their preferences in their behavior and choices (Weininger, 2005). Rather, these preferences, as mentioned earlier, may change under the influence of other factors, most of which are deterministic, and make people's behavior more problematic. Therefore, the behavior of the sample people who use another type of transportation system for travel despite the preference for one type is a kind of strategy influenced by the factors, examples of which were described in the model. It can be argued that the transit-dependent people's modal usage and preferences do not derive only from the structures that enclose the individual within themselves, that is, belonging to a low-income class, or the result of logical and rational choices, but it can be derived as the result of these two. Because of this, there are dilemmas in people's behavior that sometimes go against the structure in which they are located (for example, despite their low income level, they use a more expensive transportation mode like Uber), and sometimes they act against their logical choice (for example, when they have little time to reach a destination, contrary to their logical choice, which comes from their income level, they choose to fill the time gap via a faster transportation mode, despite the expenses). In fact, there is a kind of objective and subjective space here that dominates transit-dependent people's travel behavior. As the results showed, the importance of service availability and service time efficiency in selecting the preferred mode are very significant variable in shaping the respondents' modal preferences. What is needed to explain the findings of this study is to place a dynamic spatial and temporal framework in explaining travel behavior, because the influence of variables—the "importance of service availability and service time efficiency"—in modal preferences showed that in different spatial and temporal frameworks, travel behavior can be affected differently.

To sum up, it can be said that transit-dependent people do not necessarily have the opportunity to present their preferences in choosing transportation modes, both app-based, on-demand rides services or fixed-route transit services, because these preferences are in a relationship with various factor that can influence the preference for using each of the transport modes. As such, it depicts an axiomatic system, in which these individulas fit the different preferences and different situations in which they have the power to behave.

6 APPENDICES

6.1 Appendix I: Survey Questionnaire

Consent

Q1.1

Dear participant,

My name is Farokh Bagheri, and I am a researcher at the University of Texas at Arlington. I am requesting your participation in a study about app-based ride services (Uber/Lyft, Golink, Via, UberPool, etc.). This survey will take about 15 minutes. You will be compensated the amount you agreed upon before you entered into the survey. There are no perceived risks for participating in the survey and you can quit the survey at any time you want. The data collected will be anonymous and personal information will not be collected or accessed. If you have any questions about the study, please contact me at farokh.bagheri@mavs.uta.edu or regulatoryservices@uta.edu. By clicking on the bottom below, you indicate your voluntary agreement to participate in this online survey.

- Agree
- Disagree

Condition: Disagree Is Selected. Skip To: End of Block. Options

Screening Questions

Q2.1

Are you 18 years old and over?

- Yes
- No

Condition: No Is Selected. Skip To: End of Block. Options

Page Break

Q2.2

Do you own a car(s)?

- Yes
- No

Condition: Yes Is Selected. Skip To: End of Block. Options

Page Break

Q2.3

Do you currently belong to one of the following categories of households?

- One or two persons with less than $14,999 annual income
- One, or two persons with $15,000 to $24,999 annual income
- One, or two persons with $25,000 to $34,999 annual income
- Two, three or four persons with $35,000 to $49,999 annual income
- Three or four persons with $50,000 to $64,999 annual income
- More than four persons with less than $65,000 annual income
- I do not belong to the above categories

Condition: I do not belong to the abov... Is Selected. Skip To: End of Block. Options

Q2.4

Have you ever used an app-based ride service (such as Uber/Lyft, Golink, Via, UberPool, etc.)?

- Yes
- No

Condition: No Is Selected. Skip To: End of Block. Options

Page Break

Q2.5

Have you ever used traditional public transit services (such as bus and rail), even if they are not available in your current residence?

- Yes
- No

Condition: No Is Selected. Skip To: End of Block. Options

Page Break

Q2.6

Are you responding to this survey from your place of residence?

- Yes
- No

Condition: No Is Selected. Skip To: End of Block. Options

Q117

What city do you reside in?

Albuquerque

Condition: None of the Above Is Selected. Skip To: End of Block. Options

Q2.7

Please provide the zip code of your current home.

Import Questions From... Create a New Question

Transportation

Q3.1

The questions in this section ask about your daily travel – for example, trips from home to work or to the store. We are interested in ***your trips*** only, not those of other members of your household.

Are you currently employed and/or a student?

- Yes
- No

Condition: No Is Selected. Skip To: In a typical month with good weather,.... Options

Page Break

Q3.2

Please tell us about your work/school trip.

How often do you make the trip to work/school? Please enter in days per week.

Page Break

Q3.3

How far is it in miles from your residence to your primary place of work/school?

Page Break

Q3.4

How long does it usually take to get to your primary place of work/school? Please enter in minutes.

Page Break

Q3.5

How often do you work at home *instead* of making the trip to work/school? Please enter in days per month.

Page Break

Q3.7

Think about your typical trip from home to work/school. What is the main way you make this trip?

- Bus
- Rail
- Private ride services (such as Uber/Lyft)
- Ride-sharing services (such as UberPool, Via, GoLink)
- Walking/biking
- Other (Please specify)

Page Break

Q3.8

In a ***typical month with good weather,*** how often do you take ***private ride services (such as Uber/Lyft)*** from your home to each of the following places?

A work place or school location

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.9

A church or civic building (ex. library)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.10

A service provider (ex. bank, post-office)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.11

A restaurant or coffee place

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.12

A store or place to shop

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.13

A place to exercise (ex. a gym or a park)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.14

Other places?

Yes (please specify):

No

Condition: No Is Selected. Skip To: Please specify your overall use of pr....

Options

Q3.15

In a ***typical month with good weather***, how often do you take ***private ride services (such as Uber/Lyft)*** from your home to this place?

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.16

Please specify your overall use of private ride services (such as Uber/Lyft).

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Page Break

Q3.17

In a ***typical month with good weather***, how often do you take ***ride-sharing services (such as UberPool, Via, GoLink)*** from your home to each of the following places?

A work place or school location

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.18

A church or civic building (ex. library)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.19

A service provider (ex. bank, post-office)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.20

A restaurant or coffee place

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.21

A store or place to shop

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.22

A place to exercise (ex. a gym or a park)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week

Q3.23

Other places?

Yes (please specify):

No

Q3.24

In a ***typical month with good weather***, how often do you take ***ride-sharing services (such as UberPool, Via, GoLink)*** from your home to this place?

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.25

Please specify your overall use of ride-sharing services (such as UberPool, Via, GoLink).

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Page Break

Q3.26

In a ***typical month with good weather***, how often do you take ***traditional public transit services (such as bus or light rail)*** from your home to each of the following places?

A work place or school location

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.27

A church or civic building (ex. library)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.28

A service provider (ex. bank, post-office)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.29

A restaurant or coffee place

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.30

A store or place to shop

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.31

A place to exercise (ex. a gym or a park)

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.32

Other places?

Yes (please specify):	No
○	○

Condition: No Is Selected. Skip To: Please specify your overall use of tr....

Options

Q3.33

In a ***typical month with good weather***, how often do you take ***traditional public transit services (such as bus or light rail)*** from your home to this place?

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Q3.34

Please specify your overall use of traditional public transit services (such as bus or light rail).

Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
○	○	○	○	○	○

Page Break

Active Transportation

Q4.1

How many times in the last 30 days did you take a walk or a stroll around your neighborhood - for example to get exercise or to walk the dog?

Page Break

Q4.2

How many times in the last 30 days did you walk from your residence to a local store or shopping area?

Page Break

Q4.3

How many days in the last 30 days did you exercise somewhere in the neighborhood hard enough to breathe somewhat harder than normal for at least 10 minutes?

Page Break

Q4.4

Can you please tell me approximately what your height is?

Q4.4.1

Feet

Q4.4.1

Inches

Page Break

Q4.4

Can you please tell me approximately what your weight is?

Q4.4.2

Pounds

Page Break

Q4.5

In a typical week, how many days do you eat at least some green vegetables or fruit?

Page Break

Q4.6

In a typical week, how many days do you engage in exercise that lasts 30 minutes or more?

Page Break

Q4.7

In a typical week, on those weekdays, about how much time did you spend per day watching TV?

Q113

Hours

Q115

Minutes

Page Break

Transportation (Preferred)

Q5.1

We'd like to ask about your preferences with using the following transit services. Please indicate the extent to which you prefer to use each of the following services as your main mode of transportation (in the absence of private vehicle and for destinations that are not within a walkable distance) from ***1 "not prefer at all" to 9 "strongly prefer"*** to the following destinations.

Using private ride services (such as Uber/Lyft) to go to my workplace/school

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.2

Using private ride services (such as Uber/Lyft) to go to a store or place to shop

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.3

Using private ride services (such as Uber/Lyft) to go to a restaurant or coffee place

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.4

Please indicate your overall preference for using private ride services (such as Uber/Lyft) as your main mode of transportation (in absence of private vehicle and for destinations that are not within a walkable distance).

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.5

Using ride-sharing services (such as UberPool, Via, GoLink) to go to my workplace/school

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.6

Using ride-sharing services (such as UberPool, Via, GoLink) to go to a store or place to shop

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.7

Using ride-sharing services (such as UberPool, Via, GoLink) to go to a restaurant or coffee place

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Q5.8

Please indicate your overall preference for using ride-sharing services (such as UberPool, Via, GoLink) as your main mode of transportation (in absence of private vehicle and for destinations that are not within a walkable distance).

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.9

Using traditional public transit services (such as bus, light rail) to go to my workplace/school

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.10

Using traditional public transit services (such as bus, light rail) to go to a store or place to shop

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.11

Using traditional public transit services (such as bus, light rail) to go to a restaurant or coffee place

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Q5.12

Please indicate your overall preference for using traditional public transit services (such as bus, light rail) as your main mode of transportation (in absence of private vehicle and for destinations that are not within a walkable distance).

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.13

Is there a transit service other than private ride services (such as Uber/Lyft), ride-sharing services (such as UberPool, Via, GoLink), and traditional public transit services (such as bus, light rail) that you prefer to use as your main mode of transportation?

Yes (please specify):	No
○	○

Condition: No Is Selected. Skip To: Please think about your preferred tra....

Options

Q5.14

Please indicate the extent to which you prefer to use this transit service (in the absence of private vehicle and for destinations that are not within a walkable distance) from ***1 "not prefer at all" to 9 "strongly prefer"*** to the following destinations.

Using this transit service to go to my workplace/school

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.15

Using this transit service to go to a store or place to shop

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Page Break

Q5.16

Using this transit service to go to a restaurant or coffee place

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Q5.17

Please indicate your overall preference for using this transit service

1 - Not prefer at all	2	3	4	5	6	7	8	9 - Strongly prefer
○	○	○	○	○	○	○	○	○

Q5.18

Please think about your preferred transit option among app-based ride services (such as Uber/Lyft, UberPool, Via, GoLink) and traditional public transit services (such as bus, light rail). How important is each of the following factors in choosing the preferred option?

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Access to credit/debit card					
Access to a smart phone					
Have internet access at home					
Have a mobile data plan					
Public support for data access such as public Wi-Fi					
Security of my personal financial information					
Scheduling and route finding through apps					

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Identity theft					
Out of pocket costs of the service					
Shorter waiting time when I need to use the service					
Fastest way to get to destination					
Sense of security from potential crimes in the vehicle/station					
Comfort/convenience					
Certainty about wait time, particularly during peak hours					

	unimportant	unimportant	Neither	important	Very important
Availability of the service in the area where I need it					
Availability of the service at the time I need it					
Availability of the service on the day I need it					
Cash fare payment					
Traveling at a safe speed					
Concern about drivers					
Discounts on rides					

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Free rides on eligible routes					
Discomfort with sharing personal information					
Familiarity with and use of app-based transportation technologies					
Waiting home for the arrival of vehicle					
Simply waiting for a bus/rail service instead of the need to request for a ride					
Potential malfunction of the internet and the transportation app					

Page Break

Q5.19

Please continue to think about your preferred transit option among private ride services (such as Uber/Lyft), and ride-sharing services (such as UberPool, Via, GoLink). How important is each of the following factors in choosing the preferred option?

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Out of pocket costs of the service					
Shorter waiting time when I need to use the service					
Privacy when traveling					
Fastest way to get to destination					
Comfort/convenience					

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Availability of the service in the area where I need it					
Discounts on rides					
Free rides on eligible routes					
Traveling at a safe speed					
Availability of the service at the time I need it					

	Very unimportant	Somewhat unimportant	Neither	Somewhat important	Very important
Availability of the service on the day I need it					
Discomfort with sitting with strangers in a small-size vehicle					
Ability to split fare					

Page Break

Q5.20

Please indicate the extent to which you agree or disagree with each of the following statements on a scale *from 1 "strongly disagree" to 7 "strongly agree"*

If I were to move, I would like to find a neighborhood where...

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
...there is plenty of distance between my neighbors and me, even if this means that I have to drive just about everywhere.	○	○	○	○	○	○	○
...I can walk to stores, restaurants, and other important destinations, even if this means that commercial areas are within a few blocks (1/3 mile) of my house	○	○	○	○	○	○	○
...I can walk, bicycle, or take public transit for some of my trips, even if this means that homes are smaller	○	○	○	○	○	○	○
...it is a lively and active place, even if this means it has a mixture of single-family houses, townhouses, and small apartment buildings that are close together on various sized lots.	○	○	○	○	○	○	○

Page Break

Burden/Access

Q6.1

Do you have any of the following barrier(s) that seriously limit or prevent you from using app-based ride service (such as Uber/Lyft, UberPool, Via, GoLink)? Please check all that apply.

- ☐ Access to credit/debit card
- ☐ Access to a smart phone
- ☐ Access to Internet at home
- ☐ Have a mobile data plan
- ☐ Unaffordable fares
- ☐ Feeling need assistance initiating rides via the phone apps
- ☐ Unable to use these services when phone battery runs out or have no internet access
- ☐ Unwilling to connect personal financial information to phone
- ☐ Need translation for transportation apps into languages other than English
- ☐ Discomfort with sharing personal information
- ☐ Concern about identity theft
- ☐ Need trainings using online methods
- ☐ None of the above
- ☐ Other (please specify)

Page Break

Q6.2

Which statement describes your level of familiarity with and use of modern technologies?

- ○ I am a tech-savvy person.
- ○ I complete errands such as shopping, paying bills and registrations using online technology.
- ○ I can do basic Internet tasks like checking emails.
- ○ I need someone to help me navigate the internet.

Page Break

Residential Neighborhood

Q7.1

How would you describe the type of housing unit in which you currently live?

- ○ Duplex
- ○ Apartment/Condo
- ○ Townhouse
- ○ Single-family detached house
- ○ Other (please specify)

Page Break

Q7.2

When did you move to your current residence?

- ○ Less than six months ago
- ○ One year ago
- ○ About two to three years ago
- ○ About four to five years ago
- ○ More than six years ago

Page Break

Attitudes

Q8.1

Please indicate the extent to which you agree or disagree with each of the following statements on a scale from "strongly disagree" to "strongly agree".

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I feel carefree to travel using app-based ride services any time of the days.	○	○	○	○	○
I usually feel nervous when using app-based ride services because I think the driver may have unreported criminal records.	○	○	○	○	○
Getting around is easier than ever with my smartphone.	○	○	○	○	○
Learning how to use new technologies is often frustrating.	○	○	○	○	○
Technology creates as least as many problems as it does solutions.	○	○	○	○	○

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I feel uncomfortable when I travel with others using ride-sharing services (such as UberPool, Via, GoLink).	○	○	○	○	○
I believe that ride-sharing services (such as UberPool, Via, GoLink) offer me affordable fares.	○	○	○	○	○
I believe that using private ride services (such as Uber/Lyft) is an economic burden to me because of their unaffordable fares.	○	○	○	○	○
Owning a private car can reduce my travel burden.	○	○	○	○	○
We need more traditional public transit services (such as bus/rail) because it is the most affordable option.	○	○	○	○	○

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I prefer to use app-based ride services (such as Uber/Lyft), even if it is likely to need to reduce data use because of cost.	○	○	○	○	○
I prefer to use traditional public transit services (such as bus/rail) even if I have to have a longer waiting time.	○	○	○	○	○
I think I waste my time when a rideshare vehicle is strolling to pick up or drop off other passengers.	○	○	○	○	○
Although using app-based ride services are more expensive than using traditional public transit services (such as bus/rail), I prefer to use app-based ride services to avoid the low speed of bus and rail.	○	○	○	○	○
Access to traditional public transit services (such as bus/rail) can reduce my travel burden.	○	○	○	○	○

Background

Q9.1

What gender do you identify with?

- ○ Male
- ○ Female
- ○ A gender that is not listed here. ______

Page Break

Q9.2

Please place a check on the scale below which indicates your age.

70 or more

18 23 28 34 39 44 49 54 60 65 70

Page Break

Q9.3

Please specify the number of persons, including yourself, in the following age categories in your household.

Q9.3.1

Under 18 years old

Q9.3.2

18-24

Q9.3.3

25-34

Q9.3.4

35-44

Q9.3.5

45-54

Q9.3.6

55 or older

Page Break

Q9.4

With which racial or ethnic group do you most identify?

- American Indian or Alaska Native
- Asian
- African American
- Hispanic
- Native Hawaiian or Pacific Islander
- White (Non-Hispanic)
- A racial or ethnic group that is not listed here.

Page Break

Q9.5

What is your educational background? Please check the highest level attained.

- Prefer not to answer
- Some grade/high school
- High school/GED
- Some college/technical school
- Associate degree
- Bachelor's degree
- Graduate degree (e.g. MS, PhD, MBA, etc.)
- Professional degree (e.g. JD, MD, DDS, etc.)

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Q9.6

Are you currently a student?

- Yes, full time
- Yes, part time
- No

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Q9.7

Which statement best describes your current employment situation? Please check all that apply.

- I work full-time.
- I work part-time.
- I am a homemaker/unpaid caregiver.
- I currently do not work/I am retired.

Page Break

Q9.8

To understand travel choices, and for statistical purposes, we need an idea of your total household income. Please place a check on the scale below so that it indicates the ***approximate total annual combined income*** of all the working adults in your household.

120,000 or more

0 20000 40000 60000 80000 100000 120000

Page Break

Q9.9

Do you rent or own your current residence?

- Rent
- Own

Page Break

Q9.10

Do you have a valid driver's license?

- Yes
- No

Q9.11

Please specify the numbers of vehicles available in your household for daily travel regardless of your access to them.

Page Break

Q9.12

Approximately how many miles do you travel in a typical week (including weekends)?

Page Break

Q9.13

Do you have any physical or mental disabilities that seriously limit or prevent you from doing any of the following? Please check all that apply.

- Driving a vehicle
- Driving a vehicle on the freeway
- Walking outside the home
- Riding a bicycle
- Using public transit
- Using shared app-based ride services
- No disabilities

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6.2 Appendix II: Additional Statistical Output Tables

	Frequency	Percent	Valid Percent	Cumulative Percent
One or two persons with less than $14,999 annual income	115	32.5	32.5	32.5
One, or two persons with $15,000 to $24,999 annual income	102	28.8	28.8	61.3
One, or two persons with $25,000 to $34,999 annual income	63	17.8	17.8	79.1
Two, three or four persons with $35,000 to $49,999 annual income	38	10.7	10.7	89.8
Three or four persons with $50,000 to $64,999 annual income	20	5.6	5.6	95.5
More than four persons with less than $65,000 annual income	16	4.5	4.5	100.0
Total	354	100.0	100.0	

Table 6. 1 Categories of households

	Frequency	Percent	Valid Percent	Cumulative Percent
No	188	53.1	53.1	53.1
Yes	166	46.9	46.9	100.0
Total	354	100.0	100.0	

Table 6. 2 Are you currently employed and/or a student?

	Frequency	Percent	Valid Percent	Cumulative Percent
Bus	64	38.6	38.6	38.6
Rail	19	11.4	11.4	50.0
Private ride services (such as Uber/Lyft)	34	20.5	20.5	70.5
Ride-sharing services (such as UberPool, Via, GoLink)	21	12.7	12.7	83.1
Walking/biking	14	8.4	8.4	91.6

Other (Please specify)	14	8.4	8.4	100.0
Total	354	100.0	100.0	

Table 6. 3 Think about your typical trip from home to work/school. what is the main way you make this trip?

		Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
A work place or school location	Frequency	161	71	41	18	19	44
	Percent	45.5	20.1	11.6	5.1	5.4	12.4
A church or civic building (ex. library)	Frequency	196	74	34	11	25	14
	Percent	55.4	20.9	9.6	3.1	7.1	4.0
A service provider (ex. bank, post-office)	Frequency	183	72	45	23	16	15
	Percent	51.7	20.3	12.7	6.5	4.5	4.2
A restaurant or coffee place	Frequency	131	85	59	27	29	23
	Percent	37.0	24.0	16.7	7.6	8.2	6.5
A store or place to shop	Frequency	93	97	74	38	28	24
	Percent	26.3	27.4	20.9	10.7	7.9	6.8
A place to exercise (ex. a gym or a park)	Frequency	247	47	22	9	15	14
	Percent	69.8	13.3	6.2	2.5	4.2	4.0

Table 6. 4 In a typical month with good weather, how often do you take private ride services (such as Uber/Lyft) from your home to each of the following places?

		Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
A work place or school location	Frequency	211	45	41	9	15	33
	Percent	59.6	12.7	11.6	2.5	4.2	9.3
A church or civic building (ex. library)	Frequency	236	42	39	6	17	14
	Percent	66.7	11.9	11.0	1.7	4.8	4.0
A service provider (ex. bank, post-office)	Frequency	223	49	40	12	15	15
	Percent	63.0	13.8	11.3	3.4	4.2	4.2
A restaurant or coffee place	Frequency	192	58	44	18	25	17
	Percent	54.2	16.4	12.4	5.1	7.1	4.8
A store or place to shop	Frequency	161	64	61	22	28	18
	Percent	45.5	18.1	17.2	6.2	7.9	5.1
	Frequency	265	29	29	7	14	10

A place to exercise (ex. a gym or a park)	Percent	74.9	8.2	8.2	2.0	4.0	2.8

Table 6. 5 In a typical month with good weather, how often do you take ride-sharing services (such as UberPool, Via, GoLink) from your home to each of the following places?

		Never	Less than once per month	Once or twice a month	About once every 2 weeks	About once per week	Two or more times per week
A work place or school location	Frequency	145	29	34	9	20	117
	Percent	41.0	8.2	9.6	2.5	5.6	33.1
A church or civic building (ex. library))	Frequency	177	47	45	17	34	34
	Percent	50.0	13.3	12.7	4.8	9.6	9.6
A service provider (ex. bank, post-office)	Frequency	144	57	66	21	31	35
	Percent	40.7	16.1	18.6	5.9	8.8	9.9
A restaurant or coffee place	Frequency	125	64	58	27	36	44
	Percent	35.3	18.1	16.4	7.6	10.2	12.4
A store or place to shop	Frequency	86	58	81	34	39	56
	Percent	24.3	16.4	22.9	9.6	11.0	15.8
A place to exercise (ex. a gym or a park)	Frequency	232	40	26	14	11	31
	Percent	65.5	11.3	7.3	4.0	3.1	8.8

Table 6. 6 In a typical month with good weather, how often do you take traditional public transit services (such as bus or light rail) from your home to each of the following places?

Question / **option**	Please specify your overall use of private ride services (such as Uber/Lyft)		Please specify your overall use of ride-sharing services (such as UberPool, Via, GoLink)		Please specify your overall use of traditional public transit services (such as bus or light rail).	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Never	21	5.9	123	34.7	40	11.3
Less than once per month	99	28.0	73	20.6	42	11.9
Once or twice a month	88	24.9	57	16.1	64	18.1
About once every 2 weeks	51	14.4	37	10.5	24	6.8
About once per week	45	12.7	31	8.8	39	11.0
Two or more times per week	50	14.1	33	9.3	145	41.0

Total	354	100.0	354	100.0	354	100.0

Table 6. 7 Overall use of private ride services, ride-sharing services, and traditional public transit services

Question **option**	go to my workplace/school		go to a store or place to shop		go to a restaurant or coffee place	
	Frequency	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
1 - Not prefer at all	87	24.6	68	19.2	82	23.2
2	30	8.5	35	9.9	46	13.0
3	33	9.3	37	10.5	35	9.9
4	28	7.9	31	8.8	22	6.2
5	45	12.7	39	11.0	45	12.7
6	12	3.4	26	7.3	25	7.1
7	30	8.5	37	10.5	28	7.9
8	19	5.4	16	4.5	19	5.4
9 - Strongly prefer	70	19.8	65	18.4	52	14.7
Total	354	100.0	354	100.0	354	100.0

Table 6. 8 Using private ride services (such as Uber/Lyft) to go to the following places

Question **option**	*go to my workplace/school*		*go to a store or place to shop*		*go to a restaurant or coffee place*	
	Frequency	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
1 - Not prefer at all	139	39.3	117	33.1	128	36.2
2	44	12.4	39	11.0	36	10.2
3	28	7.9	26	7.3	35	9.9
4	18	5.1	27	7.6	20	5.6
5	32	9.0	32	9.0	34	9.6
6	17	4.8	20	5.6	28	7.9
7	18	5.1	29	8.2	22	6.2
8	15	4.2	19	5.4	12	3.4
9 - Strongly prefer	43	12.1	45	12.7	39	11.0
Total	354	100.0	354	100.0	354	100.0

Table 6. 9 Using ride-sharing services (such as UberPool, Via, GoLink) to go to the following places

Question **option**	*go to my workplace/school*		*go to a store or place to shop*		*go to a restaurant or coffee place*	
	Frequency	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
1 - Not prefer at all	82	23.2	62	17.5	70	19.8

2	18	5.1	13	3.7	23	6.5
3	30	8.5	31	8.8	32	9.0
4	21	5.9	22	6.2	25	7.1
5	35	9.9	48	13.6	48	13.6
6	21	5.9	24	6.8	25	7.1
7	35	9.9	43	12.1	42	11.9
8	30	8.5	31	8.8	22	6.2
9 - Strongly prefer	82	23.2	80	22.6	67	18.9
Total	354	100.0	354	100.0	354	100.0

Table 6. 10 Using traditional public transit services (such as bus, light rail) to go to the following places

Question / **option**	Prefprivate_overal		Pref_Ridshar_overal		Pref_Pub_overal	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
1 - Not prefer at all	52	14.7	110	31.1	45	12.7
2	26	7.3	38	10.7	22	6.2
3	33	9.3	31	8.8	30	8.5
4	25	7.1	18	5.1	19	5.4
5	37	10.5	40	11.3	48	13.6
6	26	7.3	18	5.1	30	8.5
7	38	10.7	20	5.6	30	8.5
8	30	8.5	24	6.8	39	11.0
9 - Strongly prefer	87	24.6	55	15.5	91	25.7
Total	354	100.0	354	100.0	354	100.0

Table 6. 11 Please indicate the extent to which you prefer to use each of the following services as your main mode of transportation (in the absence of private vehicle and for destinations that are not within a walkable distance).

Statement / **option**	there is plenty of distance between my neighbors and me, even if this means that I have to drive just about everywhere	I can walk to stores, restaurants, and other important destinations, even if this means that commercial areas are within a few blocks (1/3 mile) of my house	I can walk, bicycle, or take public transit for some of my trips, even if this means that homes are smaller	it is a lively and active place, even if this means it has a mixture of single-family houses, townhouses, and small apartment buildings that are close together on various sized lots

	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
1 – Strongly disagree	97	27.4	19	5.4	28	7.9	27	7.6
2	44	12.4	6	1.7	7	2.0	14	4.0
3	28	7.9	16	4.5	16	4.5	26	7.3
4	46	13.0	41	11.6	44	12.4	73	20.6
5	39	11.0	45	12.7	66	18.6	63	17.8
6	40	11.3	68	19.2	56	15.8	55	15.5
7 - Strongly agree	60	16.9	159	44.9	137	38.7	96	27.1
Total	354	100.0	354	100.0	354	100.0	354	100.0

Table 6. 12 Please indicate the extent to which you agree or disagree with each of the following statements on a scale from 1 "strongly disagree" to 7 "strongly agree". If I were to move, I would like to find a neighborhood where …

option / Statement	**No**		**Yes**	
	Frequency	**Percent**	**Frequency**	**Percent**
I am a tech-savvy person	202	57.1	152	42.9
I complete errands such as shopping, paying bills and registrations using online technology.	208	58.8	146	41.2
I can do basic Internet tasks like checking emails	306	86.4	48	13.6
I need someone to help me navigate the internet	346	97.7	8	2.3

Table 6. 13 Which statement describes your level of familiarity with and use of modern technologies?

	Frequency	Percent	Valid Percent	Cumulative Percent
Duplex	24	6.8	6.8	6.8
Apartment/Condo	205	57.9	57.9	64.7
Townhouse	20	5.6	5.6	70.3
Single-family detached house	95	26.8	26.8	97.2
Other (please specify)	10	2.8	2.8	100.0
Total	354	100.0	100.0	

Table 6. 14 How would you describe the type of housing unit in which you currently live?

	Frequency	Percent	Valid Percent	Cumulative Percent
Less than six months ago	66	18.6	18.6	18.6
One year ago	60	16.9	16.9	35.6
About two to three years ago	67	18.9	18.9	54.5
About four to five years ago	59	16.7	16.7	71.2
More than six years ago	102	28.8	28.8	100.0
Total	354	100.0	100.0	

Table 6. 15 When did you move to your current residence?

Statement / option	Strongly disagree		Disagree		Neither agree nor disagree		Agree		Strongly agree	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
I feel carefree to travel using app-based ride services any time of the days	24	6.8	59	16.7	99	28.0	108	30.5	64	18.1
I usually feel nervous when using app-based ride services because I think the driver may have unreported criminal records	54	15.3	72	20.3	103	29.1	80	22.6	45	12.7
Getting around is easier than ever with my smartphone	13	3.7	22	6.2	70	19.8	123	34.7	126	35.6
Learning how to use new technologies is often frustrating	73	20.6	93	26.3	79	22.3	78	22.0	31	8.8
Technology creates as least as many problems as it does solutions	33	9.3	58	16.4	107	30.2	103	29.1	53	15.0
Owning a private car can reduce my travel burden	35	9.9	34	9.6	72	20.3	96	27.1	117	33.1
We need more traditional public transit services (such as bus/rail) because it is the most affordable option	11	3.1	22	6.2	74	20.9	112	31.6	135	38.1
I prefer to use app-based ride services (such as Uber/Lyft), even if it is likely to need to reduce data use because of cost	35	9.9	49	13.8	131	37.0	87	24.6	52	14.7
I prefer to use traditional public transit services (such as bus/rail) even if I have to have a longer waiting time	37	10.5	50	14.1	102	28.8	94	26.6	71	20.1
Although using app-based	40	11.3	61	17.2	94	26.6	99	28.0	60	16.9

ride services are more expensive than using traditional public transit services (such as bus/rail), I prefer to use app-based ride services to avoid the low speed of bus and rail										
Access to traditional public transit services (such as bus/rail) can reduce my travel burden	12	3.4	28	7.9	86	24.3	123	34.7	105	29.7
I feel uncomfortable when I travel with others using ride-sharing services (such as UberPool, Via, GoLink)	43	12.1	55	15.5	104	29.4	90	25.4	62	17.5
I believe that ride-sharing services (such as UberPool, Via, GoLink) offer me affordable fares	16	4.5	41	11.6	133	37.6	118	33.3	46	13.0
I believe that using private ride services (such as Uber/Lyft) is an economic burden to me because of their unaffordable fares	43	12.1	63	17.8	100	28.2	91	25.7	57	16.1
I think I waste my time when a rideshare vehicle is strolling to pick up or drop off other passengers	41	11.6	56	15.8	121	34.2	89	25.1	47	13.3

Table 6. 16 Please indicate the extent to which you agree or disagree with each of the following statements on a scale from "strongly disagree" to "strongly agree."

Question option	Under 18 years old		18-24		25-34		35-44		45-54		55 or older	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
0	270	76.3	276	78.0	222	62.7	259	73.2	265	74.9	208	58.8
1	38	10.7	54	15.3	92	26.0	72	20.3	73	20.6	98	27.7
2	26	7.3	14	4.0	33	9.3	20	5.6	10	2.8	43	12.1
3	8	2.3	5	1.4	5	1.4	1	.3	0	00.0	2	.6
4	4	1.1	3	.8	0	00.0	0	00.0	1	.3	0	00.0
4+	8	2.3	2	.6	2	.6	2	.6	5	1.4	3	.8
Total	354	100.0	354	100.0	354	100.0	354	100.0	354	100.0	354	100.0

Table 6. 17 Please specify the number of persons, including yourself, in the following age categories in your household.

	Frequency	Percent	Valid Percent	Cumulative Percent
American Indian or Alaska Native	4	1.1	1.1	1.1
Asian	17	4.8	4.8	5.9
African American	122	34.5	34.5	40.4
Hispanic	33	9.3	9.3	49.7
Native Hawaiian or Pacific Islander	1	.3	.3	50.0
White (Non-Hispanic)	172	48.6	48.6	98.6
A racial or ethnic group that is not listed here.	5	1.4	1.4	100.0
Total	354	100.0	100.0	

Table 6. 18 With which racial or ethnic group do you most identify?

	Frequency	Percent	Valid Percent	Cumulative Percent
Some grade/high school	24	6.8	6.8	6.8
High school/GED	95	26.8	26.8	33.6
Some college/technical school	120	33.9	33.9	67.5
Associate degree	41	11.6	11.6	79.1
Bachelor's degree	57	16.1	16.1	95.2
Graduate degree (e.g. MS, PhD, MBA, etc.)	14	4.0	4.0	99.2
Professional degree (e.g. JD, MD, DDS, etc.)	2	.6	.6	99.7
Prefer not to answer	1	.3	.3	100.0
Total	354	100.0	100.0	

Table 6. 19 What is your educational background?

	option	Frequency	Percent
Driving a vehicle	No	296	83.6
	Yes	58	16.4
Driving a vehicle on the freeway	No	312	88.1
	Yes	42	11.9
Walking outside the home	No	305	86.2
	Yes	49	13.8

Riding a bicycle	No	306	86.4
	Yes	48	13.6
Using public transit	No	297	83.9
	Yes	57	16.1
Using shared app-based ride services	No	323	91.2
	Yes	31	8.8
No disabilities	No	123	34.7
	Yes	231	65.3

Table 6. 20 Do you have any physical or mental disabilities that seriously limit or prevent you from doing any of the following?

HHcar	Frequency	Percent	Valid Percent	Cumulative Percent
0	249	70.3	70.3	70.3
1	71	20.1	20.1	90.4
2	24	6.8	6.8	97.2
3	8	2.3	2.3	99.4
4	2	.6	.6	100.0
Total	354	100.0	100.0	

Table 6. 21 Please specify the numbers of vehicles available in your household for daily travel regardless of your access to them.

		Age	Income
N	Valid	354	354
	Missing	0	0
Mean		43.18	28476.17
Median		41.00	22524.27
Mode		70	0
Std. Deviation		15.716	22524.27
Minimum		18	0
Maximum		70	120000

Table 6. 22 Table of age and annual household income distribution indicators

	Studentship	N	Mean	Std. Deviation	Std. Error Mean
freqtotprivate	Non Student	293	2.6826	2.26610	.13239
	Student	61	3.6393	2.62699	.33635
frqtotRshare	Non Student	293	1.7782	2.26239	.13217
	Student	61	2.7049	2.49896	.31996
freqtotTransit	Non Student	293	4.2116	3.18649	.18616
	Student	61	5.3115	2.98631	.38236

Table 6. 23 Comparison of the average frequency of use of all three modes of transportation among students and non-students

	white	N	Mean	Std. Deviation	Std. Error Mean
freqtotprivate	Non white	182	3.0989	2.51649	.18653
	white	172	2.5814	2.14920	.16388
frqtotRshare	Non white	182	2.2692	2.46053	.18239
	white	172	1.5872	2.12984	.16240
freqtotTransit	Non white	182	4.1154	3.14351	.23301
	white	172	4.7035	3.19162	.24336

Table 6. 24 Comparison of the average use of all three types of transport system among white and non-white people

	No disabilities	N	Mean	Std. Deviation	Std. Error Mean
freqtotprivate	DIS	231	2.7403	2.27502	.14969
	DIS-NO	123	3.0488	2.49870	.22530
frqtotRshare	DIS	231	1.7100	2.10957	.13880
	DIS-NO	123	2.3659	2.64658	.23863
freqtotTransit	DIS	231	5.0173	3.12906	.20588
	DIS-NO	123	3.2439	2.94301	.26536

Table 6. 25 Comparison of the average use of all three types of transportation system among disabled and disabled people

	Edubachler	N	Mean	Std. Deviation	Std. Error Mean
freqtotprivate	Non Edubachler	240	2.8250	2.37548	.15334
	Edubachler	114	2.8947	2.32481	.21774
frqtotRshare	Non Edubachler	240	1.9458	2.39796	.15479
	Edubachler	114	1.9211	2.18257	.20442
freqtotTransit	Non Edubachler	240	4.1250	3.23956	.20911
	Edubachler	114	4.9825	2.96881	.27805

Table 6. 26 Comparison of the average use of all three modes of transportation between respondents who have undergraduate education or over (Edubachler) and respondents with education lower than undergraduate (Non Edubachler)

	Gender	N	Mean	Std. Deviation	Std. Error
freqtotprivate	Male	123	2.9024	2.44082	.22008
	Female	229	2.8122	2.32353	.15354
	Non-binary	2	3.5000	.70711	.50000
frqtotRshare	Male	123	2.0894	2.49921	.22535
	Female	229	1.8428	2.23640	.14779
	Non-binary	2	3.5000	.70711	.50000
freqtotTransit	Male	123	4.7236	3.03342	.27351
	Female	229	4.2227	3.24419	.21438
	Non-binary	2	5.0000	4.24264	3.00000

Table 6. 27 Comparison of the average use of all three modes of transportation systems by gender

	Gender	N	Mean	Std. Deviation	Std. Error
Prefprivate_overal	Male	123	5.46	2.909	.262
	Female	229	5.45	2.917	.193
	Non-binary	2	6.50	3.536	2.500
Pref_Ridshar_overal	Male	123	4.22	3.001	.271
	Female	229	4.16	3.025	.200
	Non-binary	2	7.00	2.828	2.000
Pref_Pub_overal	Male	123	6.31	2.539	.229
	Female	229	5.40	2.928	.194
	Non-binary	2	1.50	.707	.500

Table 6. 28 Comparison of the average preference for the use of all three modes of transportation systems by gender

	Studentship	N	Mean	Std. Deviation	Std. Error Mean
Prefprivate_overal	Non Student	293	5.40	2.937	.172
	Student	61	5.75	2.779	.356
Pref_Ridshar_overal	Non Student	293	4.08	3.025	.177
	Student	61	4.79	2.922	.374
Pref_Pub_overal	Non Student	293	5.60	2.841	.166
	Student	61	6.13	2.808	.359

Table 6. 29 Comparison of the average preference for the use of all three modes of transportation among students and non-students

	white	N	Mean	Std. Deviation	Std. Error Mean
Prefprivate_overal	Non white	182	5.96	2.795	.207
	white	172	4.94	2.944	.224
Pref_Ridshar_overal	Non white	182	4.74	3.047	.226
	white	172	3.62	2.880	.220
Pref_Pub_overal	Non white	182	5.42	2.813	.209
	white	172	5.99	2.843	.217

Table 6. 30 Comparison of the average preference for all three types of transport system among white and non-white people

	No disabilities	N	Mean	Std. Deviation	Std. Error Mean
Prefprivate_overal	DIS	123	5.70	2.908	.262
	DIS-NO	231	5.33	2.908	.191
Pref_Ridshar_overal	DIS	123	4.91	3.057	.276
	DIS-NO	231	3.82	2.930	.193
Pref_Pub_overal	DIS	123	5.64	2.858	.258
	DIS-NO	231	5.72	2.833	.186

Table 6. 31 Comparison of the average preference for the use of all three modes of transportation among disabled and non-disabled people

	Edubachler	N	Mean	Std. Deviation	Std. Error Mean
Prefprivate_overal	Non Edubachler	240	5.58	2.913	.188
	Edubachler	114	5.22	2.899	.271
Pref_Ridshar_overal	Non Edubachler	240	4.19	2.990	.193
	Edubachler	114	4.21	3.081	.289
Pref_Pub_overal	Non Edubachler	240	5.49	2.901	.187
	Edubachler	114	6.12	2.661	.249

Table 6. 32 Comparison of the average preference for all three types of transportation systems between respondents who have undergraduate education or over (Edubachler) and respondents with education lower than undergraduate (Non Edubachler)

Profile	Freqtotprivate	Frqtotrshare	Freqtottransit	Prefprivate_overal	Pref_ridshar_overal	Pref_pub_overal	Accessiblityprefenrece	Barriar	Preferenceforprivate	Preferencefortraditional	Pctridehailtrips	Vehicle_Miles_travel	N
DL.HC.TF.EB	3.8	2.8	4.7	5.4	4.9	5.5	92.3	1.9	93.0	93.0	54.4	46.5	22
DL.HC.TF.NEB	4.2	3.0	3.5	6.7	5.1	5.0	105.1	1.6	101.1	106.9	65.7	43.4	29

DL.HC.NTF.EB	4.0	4.0	8.0	5.0	8.0	8.0	157.3	8.0	104.0	107.8	50.0	200.0	1
DL.HC.NTF.NEB	2.5	1.8	2.8	3.5	3.8	4.2	115.6	3.2	90.2	91.5	44.8	32.7	6
DL.NHC.TF.EB	2.8	1.7	5.1	5.1	4.1	6.4	97.0	1.5	101.1	96.6	46.3	30.8	46
DL.NHC.TF.NEB	3.0	2.0	4.6	5.6	4.2	6.1	97.2	1.9	97.8	101.7	53.7	23.3	51
DL.NHC.NTF.EB	1.7	1.7	5.0	4.7	5.2	4.0	84.0	1.0	93.3	97.8	46.7	62.5	4
DL.NHC.NTF.NEB	1.8	1.3	6.2	4.3	3.0	6.2	105.1	3.3	97.8	87.9	36.0	23.3	6
NDL.HC.TF.EB	3.1	1.8	2.3	5.9	4.0	5.3	113.1	2.1	90.5	91.2	71.6	22.4	9
NDL.HC.TF.NEB	3.3	2.1	3.7	6.8	5.0	6.0	96.2	2.0	95.7	100.1	60.3	38.1	28
NDL.HC.NTF.EB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
NDL.HC.NTF.NEB	1.7	1.5	3.0	4.8	3.5	5.3	108.4	3.5	102.1	91.0	44.1	12.1	10
NDL.NHC.TF.EB	2.6	1.8	5.8	5.4	4.0	6.7	99.1	1.6	97.6	95.8	41.7	35.0	27
NDL.NHC.TF.NEB	2.5	1.7	4.3	5.3	3.8	5.2	99.8	1.4	104.0	106.8	52.2	30.9	86
NDL.NHC.NTF.EB	1.2	0.6	4.6	3.2	0.0	5.8	90.5	2.2	101.3	88.4	26.1	55.0	5
NDL.NHC.NTF.NEB	2.3	1.7	3.7	5.0	4.1	5.4	102.4	2.2	104.9	93.0	45.9	18.2	24

Table 6. 33 Reporting the Research Variables Among the Sample Individuals in Proportion to Sociodemographic VariablesCharacteristics (Possessing Valid Driver's License, Household Car Ownership, Technology Familiarity, Education Status)

Note: The initialization of each profile is as follows; the first letter (1) indicates Possessing Valid Driver's License (DL= Possessing Valid Driver's License, NDL= Not Possessing Valid Driver's License), (2) Household Car Ownership (HC = Having Car(s) in the Household, NHC = Not Having Car(s) in the Household), (3) Technology Familiarity (TF= Tech Familiar, NTF=Non Tech Familiar) and (4) Education Status (EB = Having Bachelor's Degree or Higher Degrees, NEB = Education Lower Than Bachelor's Degree).

Profile	Freqtotprivate	Frqtotrshare	Freqtottransit	Prefprivate_overal	Pref_ridshar_overal	Pref_pub_overal	Accessiblityprefenrece	Barriar	Preferenceforprivate	Preferencefortraditional	Pctridehailtrips	Mile_travel	N
HO.FW.SF	6.2	4.1	4.4	6.6	5.4	5.1	103.0	0.78	97.4	103.7	69.3	41.4	9
HO.FW.NSF	4.6	4.2	5.8	5.0	5.0	4.6	96.1	3.6	74.9	92.1	58.7	55.0	5
HO.NFW.SF	2.8	1.7	3.3	5.6	4.1	4.8	105.2	1.8	100.5	98.1	55.4	37.3	30
HO.NFW.NSF	3.3	1.7	3.1	5.6	3.4	6.5	103.2	2.1	118.0	119.6	64.4	21.8	13
NHO.FW.SF	3.6	3.5	5.2	6.9	5.9	4.5	106.0	1.4	99.9	106.7	59.4	58.0	10

NHO.FW.NSF	4.0	2.5	5.8	5.6	4.4	5.7	97.5	1.7	101.2	101.0	50.0	41.5	46
NHO.NFW.SF	2.9	1.5	3.3	5.9	4.5	5.7	104.4	1.4	104.7	99.4	56.0	26.2	46
NHO.NFW.NSF	2.3	1.7	4.5	5.2	4.0	5.9	97.6	1.9	97.8	98.2	48.3	28.9	195

Table 6. 34 Reporting the Research Variables Among the Sample Individuals in Proportion to Sociodemographic VariablesCharacteristics (House Ownership, Full Time Worker, Living in the Single-Family Detached Houses)

Note: The initialization of each profile is as follows; the first letter (1) indicates House Ownership (HO= House Owner, NHO= Not House Owner), (2) Full Time Worker (FW = Full Time Worker, NFW = Not Full Time Worker), and (3) Living in the Single Family Detached Houses (SF= Living in the Single Family Detached Houses, NSF=Non Living in the Single Family Detached Houses).

6.3 Appendix II: Early Models Tested to Achieve the Model with the Acceptable Goodness of Fit

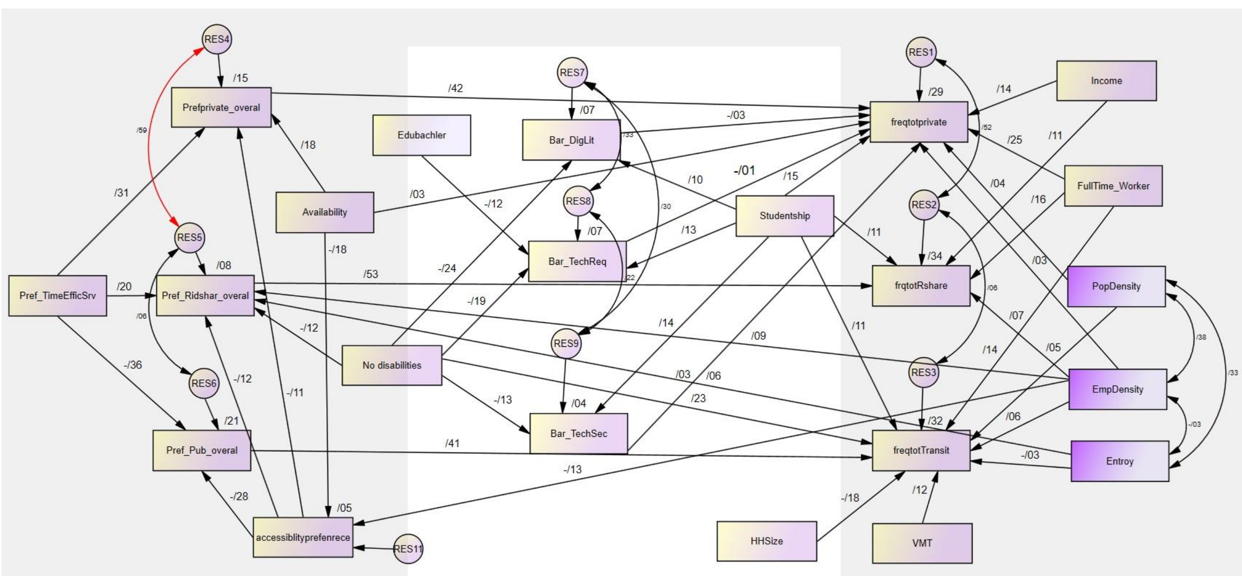

Figure 6. 1 Model 1st Tested to Achieve the Model with the Acceptable Goodness of Fit

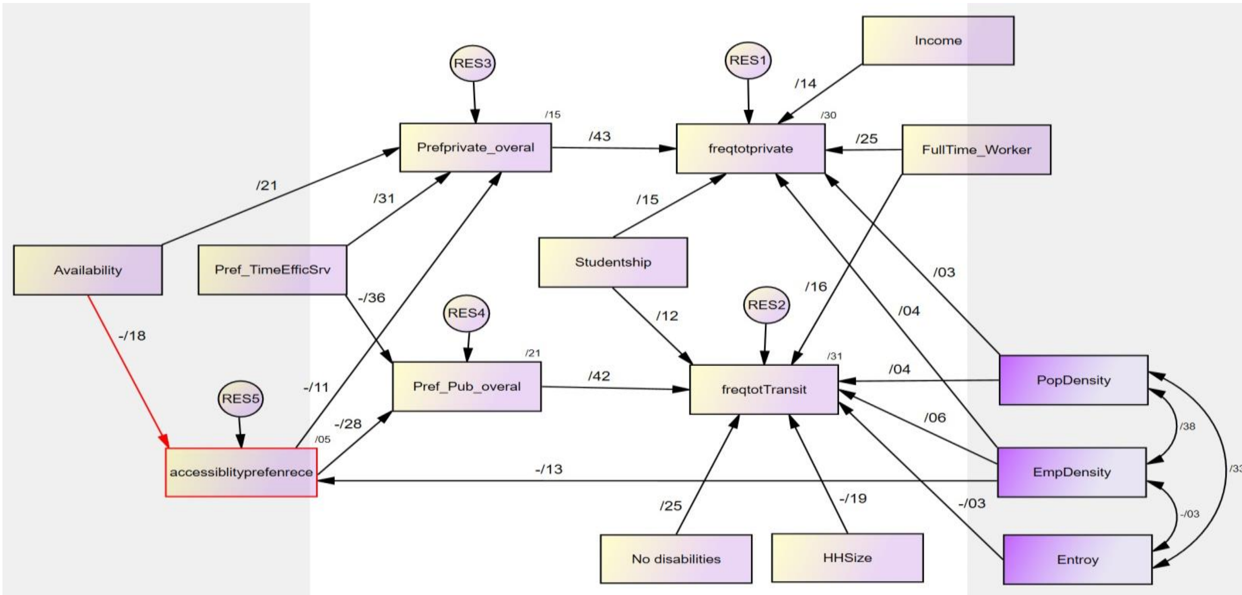

Figure 6. 2 Model 2nd Tested to Achieve the Model with the Acceptable Goodness of Fit

7 REFERENCES

Aarhaug, J., & Olsen, S. (2018). Implications of ride-sourcing and self-driving vehicles on the need for regulation in unscheduled passenger transport. *Research in Transportation Economics, 69*, 573–582. https://doi.org/10.1016/j.retrec.2018.07.026

Ajzen, I. (2008). Consumer attitudes and behavior. *Handbook of consumer psychology, 1*, 525-548.

Ajzen, I., & Fishbein, M. (2000). Attitudes and the attitude-behavior relation: Reasoned and automatic processes. *European review of social psychology, 11*(1), 1-33.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Albert, D., Aschenbrenner, K. M., & Schmalhofer, F. (1989). Cognitive choice processes and the attitude-behavior relation. In *Attitudes and behavioral decisions* (pp. 61-99). Springer, New York, NY.

Alemi, F. (2018). *What Makes Travelers Use Ridehailing? Exploring the Latent Constructs behind the Adoption and Frequency of Use of Ridehailing Services, and Their Impacts on the Use of Other Travel Modes*. University of California, Davis.

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2018). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society, 13,* 88–104. https://doi.org/10.1016/j.tbs.2018.06.002

Allen, D. J. (2014). *Operating within" transit deserts": The application of just, open and equitable circulator systems within outer urban residential neighborhoods*. Morgan State University.

Allen, D. J. (2017). *Lost in the Transit Desert*. Routledge. https://doi.org/10.4324/9781315667027

Allen, D. J. (2018). *Allen Diane Jones_TexasA&M_Transit Deserts*. NC State College of Design. https://design.ncsu.edu/urban/wp-content/uploads/2018/03/Allen-Diane-Jones_TexasAM_Transit-Deserts_UDC2018.pdf

Associates, K. &, Administration, U. S. F. T., Program, T. C. R., & Corporation, T. D. (2003). *Transit capacity and quality of service manual* (Issue 100). Transportation Research Board.

Astroza, S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Lavieri, P. S., & Dias, F. F. (2017). Analysis of the Impact of Technology Use on Multimodality and Activity Travel Characteristics. *Transportation Research Record: Journal of the Transportation Research Board*, *2666*(1), 19–28. https://doi.org/10.3141/2666-03

Attoh, K. A. (2013). Rights in Transit: Public Transportation and the" Right to the City" in California's East Bay.

Baida, A. H. (2003). Civil rights in transportation projects. *NCHRP Legal Research Digest*, (48).

Ben-Akiva, M., & Atherton, T. J. (1977). Methodology for short-range travel demand predictions: Analysis of carpooling incentives. *Journal of Transport Economics and Policy*, 224–261.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin*, *107*(2), 238.

Bernetti, G., Longo, G., Tomasella, L., & Violin, A. (2008). Sociodemographic Groups and Mode Choice in a Middle-Sized European City. *Transportation Research Record: Journal of the Transportation Research Board*, *2067*(1), 17–25. https://doi.org/10.3141/2067-03

Bollen, K. A. (1989). Structural Equation Models with Observed Variables. In *Structural Equations with Latent Variables* (pp. 80–150). https://doi.org/doi:10.1002/9781118619179.ch4

Bordoloi, R., Mote, A., Sarkar, P. P., & Mallikarjuna, C. (2013). Quantification of Land Use Diversity in The Context of Mixed Land Use. *Procedia - Social and Behavioral Sciences*, *104*, 563–572. https://doi.org/10.1016/j.sbspro.2013.11.150

Brinckerhoff, P. (2013). *Transit Capacity and Quality of Service Manual, Third Edition*. Transportation Research Board. https://doi.org/10.17226/24766

Brown, A. E. (2018). *Ridehail revolution: Ridehail travel and equity in Los Angeles*. UCLA.

Brownson, R. C., Chang, J. J., Eyler, A. A., Ainsworth, B. E., Kirtland, K. A., Saelens, B. E., & Sallis, J. F. (2004). Measuring the environment for friendliness toward physical activity: a comparison of the reliability of 3 questionnaires. *American Journal of Public Health*, *94*(3), 473-483.

Bullard, R. D., Johnson, G. S., & Torres, A. O. Highway robbery: transportation racism and new routes to equity. 2004.

Cao, X, Handy, S., & Mokhtarian, P. (2008). Neighborhood Design as a Strategy for Improving Air Quality: Evidence from Northern California. In *Transportation Land Use, Planning, and Air Quality*. American Society of Civil Engineers. https://doi.org/10.1061/40960(320)1

Cao, Xinyu, Mokhtarian, P. L., & Handy, S. L. (2008). Differentiating the Influence of Accessibility, Attitudes, and Demographics on Stop Participation and Frequency during the Evening Commute. *Environment and Planning B: Planning and Design*, *35*(3), 431–442. https://doi.org/10.1068/b32056

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2006). *Impacts of the built environment and residential self-selection on nonwork travel: seemingly unrelated regression approach* (No. 06-1595).

Carmines, E. G., & McIver, J. P. (1983). An introduction to the analysis of models with unobserved variables. *Political Methodology*, 51-102.

Cervero, R. (2002). Built environments and mode choice: toward a normative framework. *Transportation Research Part D: Transport and Environment*, *7*(4), 265–284.

https://doi.org/10.1016/s1361-9209(01)00024-4

Cervero, R., & Day, J. (2008). Suburbanization and transit-oriented development in China. *Transport Policy*, *15*(5), 315–323. https://doi.org/10.1016/j.tranpol.2008.12.011

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199–219. https://doi.org/10.1016/s1361-9209(97)00009-6

Chen, J. Y. (2017). Thrown under the bus and outrunning it! The logic of Didi and taxi drivers' labour and activism in the on-demand economy. *New Media & Society*, *20*(8), 2691–2711. https://doi.org/10.1177/1461444817729149

Chen, X. (Michael), Zahiri, M., & Zhang, S. (2017). Understanding ridesplitting behavior of on-demand ride services: An ensemble learning approach. *Transportation Research Part C: Emerging Technologies*, *76*, 51–70. https://doi.org/10.1016/j.trc.2016.12.018

Choo, S., & Mokhtarian, P. L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A: Policy and Practice*, *38*(3), 201–222. https://doi.org/10.1016/j.tra.2003.10.005

Circella, G. (2017). ICT-Dependent Life and Its Impacts on Mobility. In *Life-Oriented Behavioral Research for Urban Policy* (pp. 149–173). Springer Japan. https://doi.org/10.1007/978-4-431-56472-0_6

Circella, G., Alemi, F., Tiedeman, K., Berliner, R. M., Lee, Y., Fulton, L., Mokhtarian, P. L., & Handy, S. (2017). *What affects millennials' mobility? Part II: the impact of residential location, individual preferences and lifestyles on young adults' travel behavior in California*.

Circella, G., Mokhtarian, P. L., & Handy, S. L. (2008). *Land use, attitudes, and travel behavior relationships: A cross-sectional structural equations model for Northern California*.

Circella, G., Tiedeman, K., Handy, S., Alemi, F., & Mokhtarian, P. (2016). *What Affects Millennials' Mobility? PART I: Investigating the Environmental Concerns, Lifestyles, Mobility-Related Attitudes and Adoption of Technology of Young Adults in California*.

Clewlow, R. R., & Mishra, G. S. (2017). Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States. In *University of California, Davis, Institute of Transportation Studies, Davis, CA, Research Report UCD-ITS-RR-17-07*.

Clifton, K. J., & Handy, S. L. (2003). Qualitative Methods in Travel Behaviour Research. In *Transport Survey Quality and Innovation* (pp. 283–302). Emerald Group Publishing Limited. https://doi.org/10.1108/9781786359551-016

Clifton, K., & Lucas, K. (2004). Examining the empirical evidence of transport inequality in the US and UK. *Running on empty: transport, social exclusion and environmental justice*, 15-38.

Daniel WW (1999). Biostatistics: A Foundation for Analysis in the Health Sciences. 7th edition. New York: John Wiley & Sons.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

de Souza Silva, L. A., de Andrade, M. O., & Alves Maia, M. L. (2018). How does the ride-hailing systems demand affect individual transport regulation? *Research in Transportation Economics*, *69*, 600–606. https://doi.org/10.1016/j.retrec.2018.06.010

Diana, M., & Mokhtarian, P. L. (2008). *Travelers' segmentation based on multimodality behaviors and attitudes*.

Dias, F. F., Lavieri, P. S., Garikapati, V. M., Astroza, S., Pendyala, R. M., & Bhat, C. R. (2017). A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation*, *44*(6), 1307–1323. https://doi.org/10.1007/s11116-017-9797-8

Dillahunt, T. R., Kameswaran, V., Li, L., & Rosenblat, T. (2017). Uncovering the Values and Constraints of Real-time Ridesharing for Low-resource Populations. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*. ACM Press. https://doi.org/10.1145/3025453.3025470

Dillahunt, T. R., & Veinot, T. C. (2018). Getting There: Barriers and facilitators to transportation access in underserved communities. *ACM Transactions on Computer-Human Interaction*, *25*(5), 1–39. https://doi.org/10.1145/3233985

Dyer, E. L. (2016). Need a Ride: Uber: The Trendy Choice That Could Turn Threatening. *Nev. LJ*, *17*, 239.

EDR Group. (2017). *Uber's Economic Impacts in the United States*. https://drive.google.com/file/d/1P6HMbPc8T91Y8NlYyFGv8NQS9g4ckAq9/view?usp=sharing

Etezady, A., Shaw, F. A., Mokhtarian, P. L., & Circella, G. (2019). *What Drives the Gap? Decomposing Differences between Millennials and Generation X in Transportation-Related Attitudes*.

Etminani-Ghasrodashti, R., & Hamidi, S. (2019). Individuals' Demand for Ride-hailing Services: Investigating the Combined Effects of Attitudinal Factors, Land Use, and Travel Attributes on Demand for App-based Taxis in Tehran, Iran. *Sustainability*, 11(20), 5755.

Euchner, C. (n.d.). *MAKING IT HERE: The Future of Manufacturing in New York City*. Center for an Urban Future. https://books.google.com/books?id=UJFCzQEACAAJ

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, *1780*(1), 87–114. https://doi.org/10.3141/1780-10

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment: a meta-analysis. *Journal of the American Planning Association*, *76*(3), 265–294. https://doi.org/10.1080/01944361003766766

Ewing, R., & Hamidi, S. (2014). Measuring urban sprawl and validating sprawl measures. *Washington, DC: National Institutes of Health and Smart Growth America*.

Ewing, R., Hamidi, S., Grace, J. B., & Wei, Y. D. (2016). Does urban sprawl hold down upward mobility?. *Landscape and Urban Planning*, *148*, 80-88.

Flannelly, K. J., & McLeod, M. S. (1989). A multivariate analysis of socioeconomic and attitudinal factors predicting commuters' mode of travel. *Bulletin of the Psychonomic Society*, *27*(1), 64–66. https://doi.org/10.3758/bf03329899

Flater, D. (n.d.). Understanding Geodesic Buffering. *Esri Geoprocessing Development Team*.

Florida, R. (2012). What Is the World's Most Economically Powerful City?. *The Atlantic*, *5*(08).

Fujii, S., & Gärling, T. (2003). Development of script-based travel mode choice after forced change. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*(2), 117–124. https://doi.org/10.1016/s1369-8478(03)00019-6

Garrett, M., & Taylor, B. (1999). Reconsidering social equity in public transit. *Berkeley Planning Journal*, *13*(1).

Gaudry, M., Domencich, T. A., & McFadden, D. (1977). Urban Travel Demand: A Behavioral Analysis. *The Canadian Journal of Economics*, *10*(4), 724. https://doi.org/10.2307/134305

Ge, Y., Knittel, C., MacKenzie, D., & Zoepf, S. (2016). *Racial and Gender Discrimination in Transportation Network Companies*. National Bureau of Economic Research. https://doi.org/10.3386/w22776

Getis, A., & Aldstadt, J. (2004). Constructing the Spatial Weights Matrix Using a Local Statistic. *Geographical Analysis*, *36*(2), 90–104. https://doi.org/10.1111/j.1538-4632.2004.tb01127.x

GoGoGrandparent. (2018). *GoGoGrandparent | Call to Order a Ride*. https://gogograndparent.com/

Golub, A. (2018). *Community-Based Assessment of Smart Transportation Needs in the City of Portland*. Transportation Research and Education Center. https://doi.org/10.15760/trec.204

Gonzales, E. J., Yang, C., Morgul, E. F., Ozbay, K., & Consortium, M. N. T. R. (2014). *Modeling taxi demand with GPS data from taxis and transit.* Mineta National Transit Research Consortium.

Gordon, C. (2010). Varieties of Transportation Justice: US Transportation Equity Policy and the Civil Rights Movement. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2388554

Gutiérrez, C. C. L. V. (2014). *America's Growing Inequality: The Impact of Poverty and Race*. Lexington Books.

Hamidi, S. (2017). *A Comprehensive Study on the State of Transportation Equity in Dallas*.

Hamidi, S., Ewing, R., Preuss, I., & Dodds, A. (2015). Measuring Sprawl and Its Impacts. *Journal of Planning Education and Research*, *35*(1), 35–50. https://doi.org/10.1177/0739456x14565247

Hampshire, R., Simek, C., Fabusuyi, T., Di, X., & Chen, X. (2017). Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX. *Lyft in Austin, TX (May 31, 2017)*.

Hands, D. W. (2009). Economics, psychology and the history of consumer choice theory. *Cambridge Journal of Economics*, *34*(4), 633–648. https://doi.org/10.1093/cje/bep045

Handy, S. (1993). *Regional versus local accessibility: Implications for nonwork travel*.

Handy, S., Cao, X., & Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), 427–444. https://doi.org/10.1016/j.trd.2005.05.002

Handy, S. L., Mokhtarian, P. L., & Kwong, K. (2006). *The Role of Attitudes and Neighborhood Characteristics in Explaining Transit Use: A Study of Eight Northern California Neighborhoods*.

Handy, S., & Mokhtarian, P. (2004). *RESIDENTIAL LOCATION CHOICE AND TRAVEL BEHAVIOR*. UCD-ITS-RR-04-48. Institute of Transportation Studies, University of ….

Handy, S., Mokhtarian, P., Buehler, T., & Cao, X. (2004). Residential location choice and travel behavior: Implications for air quality. *Prepared for the California Department of Transportation, Davis, CA*.

Hanson, S. (1982). THE DETERMINANTS OF DAILY TRAVEL-ACTIVITY PATTERNS: RELATIVE LOCATION AND SOCIODEMOGRAPHIC FACTORS. *Urban Geography*, *3*(3), 179–202. https://doi.org/10.2747/0272-3638.3.3.179

Harvey, D. (2013). The political economy of public space. In *The politics of public space* (pp. 23-188). Routledge.

Haugtvedt, C. P., Herr, P. M., & Kardes, F. R. (Eds.). (2018). *Handbook of consumer psychology*. Routledge.

Heath, Y., & Gifford, R. (2002). Extending the theory of planned behavior: Predicting the use of public transportation 1. *Journal of Applied Social Psychology*, 32(10), 2154-2189.

Henao, A. (2017). *Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior*. University of Colorado at Denver.

Henry, L., & Litman, T. (2006). *Evaluating new start transit program performance: comparing rail and bus*. Victoria Transport Policy Institute.

Holloway, C. (2015). Uber unsettled: how existing taxicab regulations fail to address transportation network companies and why local regulators should embrace Uber, Lyft, and comparable innovators. *Wake Forest J. Bus. & Intell. Prop. L.*, *16*, 20.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic journal of business research methods, 6*(1), 53-60.

Hox, J. J., & Bechger, T. M. (1998). *An introduction to structural equation modeling*.

Hughes, R., & MacKenzie, D. (2016). Transportation network company wait times in Greater Seattle, and relationship to socioeconomic indicators. *Journal of Transport Geography*, *56*, 36–44. https://doi.org/10.1016/j.jtrangeo.2016.08.014

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal, 6*(1), 1-55.

Hu, W. (2018). When Calling an Uber Can Pay Off for Cities and States. *The New York Times.*

Inwood, J. F., Alderman, D., & Williams, J. (2015). "Where Do We Go From Here?" Transportation Justice and the Struggle for Equal Access. *southeastern geographer, 55(4), 417-433.*

Jiao, J. (2017). Identifying transit deserts in major Texas cities where the supplies missed the demands. *Journal of Transport and Land Use*, 10(1), 529-540.

Jiao, J. (2018). *Transit Desert Research*. http://www.transitdeserts.org/

Jiao, J., & Bischak, C. (2018). *Transit Deserts USA*. UTexas. https://soa.utexas.edu/events/transit-deserts-usa

Kamruzzaman, M., Baker, D., Washington, S., & Turrell, G. (2013). Residential dissonance and mode choice. *Journal of Transport Geography*, *33*, 12–28. https://doi.org/10.1016/j.jtrangeo.2013.09.004

Kanter, R. M. (2015). *Move: How to Rebuild and Reinvent America's Infrastructure: Putting America's Infrastructure Back in the Lead*. WW Norton & Company.

Kaufman, S., Moss, M. L., Tyndall, J., & Hernandez, J. (2014). Mobility, Economic Opportunity and New York City Neighborhoods. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2598566

KFH Group. (2013). *Transit capacity and quality of service manual*.

Koppelman, F. S., & Lyon, P. K. (1981). *Dynamic Analysis of Attitude-behavior Response to Transportation Service Innovation: Executive Summary*.

KORNAI*, J. (1986). The Soft Budget Constraint. *Kyklos*, *39*(1), 3–30. https://doi.org/10.1111/j.1467-6435.1986.tb01252.x

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190–202. https://doi.org/10.1016/j.tra.2017.05.013

Kunkle, F. (2018). Uber, Lyft and other ride-hailing apps are 'useless' for disabled riders, NYC advocates say. *The Washington Post. Available at:* https://www.washingtonpost.com/news/tripping/wp/2018/05/26/uber-lyft-and-other-ride-hailing-apps-are-useless-for-disabled-riders-nyc-advocates-say/

Kuppam, A. R., Pendyala, R. M., & Rahman, S. (1999). Analysis of the Role of Traveler Attitudes and Perceptions in Explaining Mode-Choice Behavior. *Transportation Research*

Record: Journal of the Transportation Research Board, *1676*(1), 68–76. https://doi.org/10.3141/1676-09

Lavieri, P. S., & Bhat, C. R. (2019). Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C: Emerging Technologies*, *105*, 100–125. https://doi.org/10.1016/j.trc.2019.05.037

Lavieri, P. S., Dias, F. F., Juri, N. R., Kuhr, J., & Bhat, C. R. (2018). A Model of Ridesourcing Demand Generation and Distribution. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(46), 31–40. https://doi.org/10.1177/0361198118756628

Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. *Transportation Research Record: Journal of the Transportation Research Board*, *2665*(1), 1–10. https://doi.org/10.3141/2665-01

Lee, Y., Circella, G., Mokhtarian, P. L., & Guhathakurta, S. (2019). Are millennials more multimodal? A latent-class cluster analysis with attitudes and preferences among millennial and Generation X commuters in California. *Transportation*. https://doi.org/10.1007/s11116-019-10026-6

Lewis, E. O., & MacKenzie, D. (2017). UberHOP in Seattle: Who, Why, and How? *Transportation Research Record: Journal of the Transportation Research Board*, *2650*(1), 101–111. https://doi.org/10.3141/2650-12

Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology adoption behavior life cycle: Toward a Technology Continuance Theory (TCT). *International Journal of Information Management*, *29*(4), 309–320. https://doi.org/10.1016/j.ijinfomgt.2009.03.004

Limtanakool, N., Dijst, M., & Schwanen, T. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. *Journal of Transport Geography*, *14*(5), 327–341. https://doi.org/10.1016/j.jtrangeo.2005.06.004

Litman, T. (1999). *Evaluating transportation equity*. Victoria Transport Policy Institute Victoria, BC, Canada.

Litman, T. (2015). *Evaluating public transit benefits and costs*. Victoria Transport Policy Institute Victoria, BC, Canada.

Lyft. (2017). *Economic Impact Report 2017*. https://take.lyft.com/economic-impact/2017/Lyft-Drives-Economy-pre.pdf

Lyon, P. K. (1982). *Time-dependent structural equations modelling of the relationship between attitudes and discrete choice behavior of transportation consumers.*

Lyon, P. K. (1984). Time-Dependent Structural Equations Modeling: A Methodology for Analyzing the Dynamic Attitude-Behavior Relationship. *Transportation Science*, *18*(4), 395–414. https://doi.org/10.1287/trsc.18.4.395

Mallett, W. (2013). *Federal Public Transportation Program: In Brief*.

McGeehan, P. (2016). Free Wi-Fi kiosks were to aid New Yorkers: an unsavory side has spurred a retreat. *The New York Times. Available at: https://www. nytimes. com/2016/09/15/nyregion/internet-browsers-to-be-disabled-on-new-yorks-free-wi-fi-kiosks. html.*

McKenzie, B. S. (2013). Neighborhood Access to Transit by Race, Ethnicity, and Poverty in Portland, OR. *City & Community*, *12*(2), 134–155. https://doi.org/10.1111/cico.12022

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice*, *83*, 14–29. https://doi.org/10.1016/j.tra.2015.11.001

Moran, M. (2016a). *Policy Implications of Transportation Network Companies*.

Moran, M. (2016b). *Transportation network companies*. Denver, CO, USA: Colorado Legislative Council.

Moss, S. (2009). Fit indices for structural equation modeling. *Website: http://www. psych-it. com. au/Psychlopedia/article. asp.*

Naing, L., Winn, T., & Rusli, B. N. (2006). *Practical issues in calculating the sample size for prevalence studies.* Archives of orofacial Sciences, 1, 9-14.

Pike, S., Rodier, C., & Martinez, J. (2017). *The Potential for Shared Use Mobility in Affordable Housing Complexes in Rural California*.

Polzin, S. E., Chu, X., & Rey, J. R. (2000). Density and Captivity in Public Transit Success: Observations from the 1995 Nationwide Personal Transportation Study. *Transportation Research Record: Journal of the Transportation Research Board*, *1735*(1), 10–18. https://doi.org/10.3141/1735-02

Porter, C. D., Brown, A., Dunphy, R. T., & Vimmerstedt, L. (2013). *Transportation Energy Futures Series. Effects of the Built Environment on Transportation. Energy Use, Greenhouse Gas Emissions, and Other Factors*. Office of Scientific and Technical Information (OSTI). https://doi.org/10.2172/1219931

Qualtrics. (2014). *esomar 28 - School of Communication*. Illinois State University.

Qualtrics. (2019a). *For How Long Should Your Survey Be Open?* https://www.qualtrics.com/blog/long-survey-field/

Qualtrics. (2019b). *Qualtrics XM // The Leading Experience Management Software*. from: https://www.qualtrics.com/

Qualtrics. (2019c). *Survey Data Cleaning: Getting Accurate Survey?* from: https://www.qualtrics.com/uk/experience-management/research/survey-data-cleaning/%0A%0A

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy*, *45*, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Rayle, L., Shaheen, S. A., Chan, N., Dai, D., & Cervero, R. (2014). *App-based, on-demand ride services: comparing taxi and ridesourcing trips and user characteristics in San Francisco*. Citeseer.

Raziul Hasan, M., Arif I. Mahmood, M., Raheel Khanzada, R., Mansur, N., Adnan, A., & M. Iqbal, S. (2016). Molecular Dynamics Study of Protein Deformation through Solid-State Nanopore. *Functional Nanostructures*. https://doi.org/10.24274/fn.2016.a14

Regional Plan Association. (2019). *Fourth Regional Plan: Making the Region Work for All of Us*. Regional Plan Association.

Risen, T. (2016). *FCC Expands Obamaphone Program to Include Internet*. https://www.usnews.com/news/articles/2016-03-31/fcc-expands-obamaphone-program-to-include-internet

Sallis, J. F., Frank, L. D., Saelens, B. E., & Kraft, M. K. (2004). Active transportation and physical activity: opportunities for collaboration on transportation and public health research. *Transportation Research Part A: Policy and Practice, 38*(4), 249-268.

Sánchez, J. M., Espino, E., & Cirelli, F. (2018). *Designing Unemployment Insurance for Developing Countries*. Federal Reserve Bank of St. Louis. https://doi.org/10.20955/wp.2018.006

Sanchez, T. W., & Brenman, M. (2010). Transportation and civil rights. *Poverty & Race*, *19*(4), 1–9.

Sanchez, T. W., Stolz, R., & Ma, J. S. (2004). Inequitable effects of transportation policies on minorities. *Transportation research record*, *1885*(1), 104-110.

Sanchez, T. W., Stolz, R., & Ma, J. S. (2003). *Moving to equity: Addressing inequitable effects of transportation policies on minorities*.

Schaller, B. (2005). A Regression Model of the Number of Taxicabs in U.S. Cities. *Journal of Public Transportation*, *8*(5), 63–78. https://doi.org/10.5038/2375-0901.8.5.4

Schaller, B. (2018). *The new automobility: Lyft, Uber and the future of American cities*.

Schumacker, R. E. (2004). *A Beginner's Guide to Structural Equation Modeling*. Psychology Press. https://doi.org/10.4324/9781410610904

Schwanen, T., & Mokhtarian, P. L. (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods? *Journal of Transport Geography*, *13*(1), 83–99. https://doi.org/10.1016/j.jtrangeo.2004.11.001

Shaheen, S., Bell, C., Cohen, A., & Yelchuru, B. (2017). *Travel behavior: Shared mobility and transportation equity*.

Shaheen, S., & Cohen, A. (2018). Is It Time for a Public Transit Renaissance?: Navigating

Travel Behavior, Technology, and Business Model Shifts in a Brave New World. *Journal of Public Transportation*, *21*(1), 67–81. https://doi.org/10.5038/2375-0901.21.1.8

Shirgaokar, M. (2018). Expanding Seniors' Mobility through Phone Apps: Potential Responses from the Private and Public Sectors. *Journal of Planning Education and Research*, 0739456X1876913. https://doi.org/10.1177/0739456x18769133

Spears, S., Houston, D., & Boarnet, M. G. (2013). Illuminating the unseen in transit use: A framework for examining the effect of attitudes and perceptions on travel behavior. *Transportation Research Part A: Policy and Practice, 58*, 40–53. https://doi.org/10.1016/j.tra.2013.10.011

Starkey, P., & Hine, J. (2014). Poverty and sustainable transport, how transport affects poor people with policy implications for poverty reduction, a literature review. *UN-Habitat, and the Overseas Development Institute (ODI)*.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual differences, 42*(5), 893-898.

Sun, B., Ermagun, A., & Dan, B. (2017). Built environmental impacts on commuting mode choice and distance: Evidence from Shanghai. *Transportation Research Part D: Transport and Environment*, *52*, 441–453. https://doi.org/10.1016/j.trd.2016.06.001

TCRP Report16. (1996). *TCRP Report 16: Transit and Urban Form (Volume 1, Part A)*. http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_16-1.pdf

Treasure, M. W. (2018). *Vehicle Utilization Rates Optimization in the Transport Network Company (TNC) Model*. The George Washington University.

U.S. Census Bureau. (2016). *New Census Data Show Differences Between Urban and Rural Populations*. https://www.census.gov/newsroom/press-releases/2016/cb16-210.html

U.S. Census Bureau. (2018). *2010 Census Urban and Rural Classification and Urban Area Criteria*. https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html

U.S. Census Bureau. (2019a). *American FactFinder - Results*. https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk

U.S. Census Bureau. (2019b). *American FactFinder - Search - American FactFinder*. https://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t

U.S. Census Bureau. (2019c). *Census Glossary*. https://www.census.gov/glossary/#term_Employed

U.S. Census Bureau. (2019d). *Geography Program - Census Bureau*. https://www.census.gov/programs-surveys/geography.html

U.S. Census Bureau. (2020). *U.S. Census Bureau QuickFacts*. https://www.census.gov/quickfacts/fact/table/US/PST045219

U.S. Department of Transportation. (2013). *Transit Dependent Population*. https://collaboration.fhwa.dot.gov/dot/fhwa/renepa/lists/adiscussions/dispform.aspx?id=8891

U.S. Trade Representative. (2020). *Economy & Trade*. https://ustr.gov/issue-areas/economy-trade

Uber. (2019). *Find a City | Start Here to Plan Your Trip*. https://www.uber.com/global/en/cities/

Van Acker, V. (2010). *Spatial and social variations in travel behaviour: incorporating lifestyles and attitudes into travel behaviour-land use interaction research*. Ghent University.

Van Wee, B., Holwerda, H., & Van Baren, R. (2002). Preferences for modes, residential location and travel behaviour. *European Journal of Transport and Infrastructure Research*, *2*(4).

Via. (2019). *Via for Cities*. https://platform.ridewithvia.com/cities/

Vij, A., Gorripaty, S., & Walker, J. L. (2017). From trend spotting to trend 'splaining: Understanding modal preference shifts in the San Francisco Bay Area. *Transportation Research Part A: Policy and Practice, 95*, 238–258. https://doi.org/10.1016/j.tra.2016.11.014

Vinayak, P., Dias, F. F., Astroza, S., Bhat, C. R., Pendyala, R. M., & Garikapati, V. M. (2018). Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. *Transport Policy, 72*, 129–137. https://doi.org/10.1016/j.tranpol.2018.09.013

Wang, M., & Mu, L. (2018). Spatial disparities of Uber accessibility: An exploratory analysis in Atlanta, USA. *Computers, Environment and Urban Systems, 67*, 169–175. https://doi.org/10.1016/j.compenvurbsys.2017.09.003

Weinreich, D., Skuzinski, T., Hamidi, S., & Reeves, S. M. TRANSIT IN FLEX: EXAMINING SERVICE FRAGMENTATION OF APP-BASED, ON-DEMAND PUBLIC TRANSIT SERVICES.

Welch, T. F., & Mishra, S. (2013). A measure of equity for public transit connectivity. *Journal of Transport Geography*, *33*, 29-41.

Weng, G. S., Zailani, S., Iranmanesh, M., & Hyun, S. S. (2017). Mobile taxi booking application service's continuance usage intention by users. *Transportation Research Part D: Transport and Environment*, *57*, 207–216. https://doi.org/10.1016/j.trd.2017.07.023

Widaman, K. F., & Thompson, J. S. (2003). On specifying the null model for incremental fit indices in structural equation modeling. *Psychological methods*, *8*(1), 16.

Wood, W., & Neal, D. T. (2016). Healthy through habit: Interventions for initiating & maintaining health behavior change. *Behavioral Science & Policy*, *2*(1), 71-83.

Yan, X., Levine, J., & Zhao, X. (2019). Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data. *Transportation Research Part C: Emerging Technologies, 105*, 683–696.

https://doi.org/10.1016/j.trc.2018.07.029

Yan, X., Zhao, X., Han, Y., Van Hentenryck, P., & Dillahunt, T. (2019). Mobility-on-demand versus fixed-route transit systems: an evaluation of traveler preferences in low-income communities. *ArXiv Preprint ArXiv:1901.07607*.

Yang, Z., Franz, M. L., Zhu, S., Mahmoudi, J., Nasri, A., & Zhang, L. (2018). Analysis of Washington, DC taxi demand using GPS and land-use data. *Journal of Transport Geography*, *66*, 35–44. https://doi.org/10.1016/j.jtrangeo.2017.10.021

Yu, H., & Peng, Z.-R. (2019). Exploring the spatial variation of ridesourcing demand and its relationship to built environment and socioeconomic factors with the geographically weighted Poisson regression. *Journal of Transport Geography*, *75*, 147–163. https://doi.org/10.1016/j.jtrangeo.2019.01.004

Yu, L., Xie, B., & Chan, E. (2018). How does the Built Environment Influence Public Transit Choice in Urban Villages in China? *Sustainability*, *11*(1), 148. https://doi.org/10.3390/su11010148

Zhao, F., & Gustafson, T. (2013). *Transportation needs of disadvantaged populations: where, when, and how?* United States. Federal Transit Administration.