Opportunities and Challenges for Urban Public Transportation in the Era of App-based Shared Mobility

Yiyuan Wang

A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2022

Reading Committee:

Qing Shen, Chair

Anne Vernez Moudon

Xuegang (Jeff) Ban

Program Authorized to Offer Degree:

URBAN DESIGN & PLANNING

Abstract

Opportunities and Challenges for Urban Public Transportation in the Era of App-based Shared Mobility

Yiyuan Wang

Chair of the Supervisory Committee:
Qing Shen
Urban Design and Planning

This dissertation is a collection of research on urban public transportation planning and policymaking in the era of app-based shared mobility. The dissertation has an emphasis on how public transit agencies can better incorporate shared mobility modes into public transportation service provision. It consists of three studies. The first study uses longitudinal data to examine the impacts of app-based ride-hailing, the most commonly used form of shared mobility, on individual travel behavior. The second study employs latent class analysis to analyze riders' adoption of a pilot mobility service, where an on-demand shared mode is incorporated to supplement fixed-route transit. The third study introduces an effective approach for transit agencies to compare the costs of incorporating new on-demand modes and expanding traditional fixed-route transit. The approach in this study consists of an economic-theory-based conceptual framework and a transportation simulation model.

This dissertation is among the earliest efforts in the academic literature that rigorously studies the impacts of shared mobility modes and more importantly, investigates transit agencies' recent innovations of incorporating app-based shared mobility. The three studies utilize economic theories, statistical models, and transportation modeling techniques. Jointly, they

provide evidence-based policy insights that are urgently needed by transportation researchers and practitioners.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the help of many people. First of all, my deepest thanks go to my advisor Professor Qing Shen, who has always been a supportive, kind, patient, and insightful mentor throughout my entire doctoral study. His passion and wisdom inspired me and motivated me to be a better researcher, and what I've learned from him will be forever cherished.

Professor Anne Vernez Moudon and Professor Xuegang (Jeff) Ban have served on my dissertation committee and have advised me on multiple research projects. I am grateful for their valuable advice on the research. I would like to thank Professor Joaquín Herranz for serving as my graduate school representative. In addition, I have been fortunate to work with Professor Andy Dannenberg and Professor Jan Whittington during my study.

I want to thank my parents, for unambiguously and consistently supporting whatever I decided to do, including pursuing this PhD. I want to give a special thanks to my partner, Yifan, whom I met at the University of Washington, for all the love and support. I also wish to thank our dog, Mika, for letting me cuddle her whenever I want. Many thanks to my colleagues and friends in the Interdisciplinary PhD in Urban Design and Planning Program, who have accompanied me through this memorable experience.

Studies in this dissertation were partially funded by grants from Pacific Northwest Transportation Consortium (PacTrans) and the College of Built Environments at the University of Washington.

Chapter 1. Introduction

1.1 Background

1.1.1 *The emergence of app-based shared mobility*

Shared mobility is transportation services and resources that are shared among different users (Shared-Use Mobility Center, 2015). They often grant users short-term access to mobility modes in an on-demand manner. Traditional shared mobility modes, such as public transit, taxi, and social-network-based carpooling, have existed in cities for a long time. In recent years, new app-based shared mobility options, including app-based ride-hailing operated by transportation network companies (TNCs) (e.g., Uber, Lyft), ride-splitting (e.g., UberPool and Lyft Line), car-sharing (e.g., Gig, Turo, Zipcar), bike-sharing (e.g., Lime, JUMP), micro-transit (e.g., Via), scooter-sharing, emerged and have shown phenomenal growth ever since. For example, recent estimates show that the global bookings of app-based ride-hailing, the most commonly used mode of new shared mobility, tripled from 2016 to 2019, and the bookings for scooter sharing, a recently emerged shared mobility mode, doubled from 2018 to 2019 (Heineke et al., 2021).

The critical difference between traditional shared mobility modes and new shared mobility options is that the new mobility options are enabled by the ubiquitous use of smart phones and the mobile information and communication technologies (mobile-ICTs). The new shared mobility options have the following additional distinctive characteristics: 1) they typically draw from a large pool of users, unconfined by one's social network; 2) they allow for real-time mobility matching and sharing; 3) they employ algorithms for service operation, thus are capable of achieving high efficiency; and 4) they are typically owned by profit-driven private companies, thus often operate beyond realms of public transit and transportation planning (Gössling, 2018;

Moudon, 2020; Shaheen et al., 2016). Because of these characteristics, these new app-based services are expected to offer great convenience to users, in particular to those who don't have access to private vehicles.

1.1.2 *Public transit in the US and its challenges*

Transportation researchers and practitioners have recognized a promising direction in which app-based shared mobility modes generates broader societal benefits beyond those directly benefiting individual users, through complementing traditional public transit.

Public transit consists primarily of buses, streetcars, rails, and subways, which operate on fixed routes and schedules, and carry a large number of passengers. In the early-20th century, the electric streetcar was the dominant travel mode in cities in the US and played a significant role in shaping the urban spatial structure, suburbanization, and segregation (Young, 2015). However, the importance of public transit in cities started to decrease in the 1920s with the emergence and popularization of automobiles. Such a decline in the prominence of public transit, in many ways, has continued to the present day, making the US a 'car country' (Young, 2015). Today, the automobile is the most common, and often the only, travel option for people in the US (Manville et al., 2017). On average, an American household takes 2,592 trips by private vehicle and only 80 trips by public transit in a year (Mcguckin et al., 2018: 23). In terms of transit trips' geographical distribution, they are concentrated in a few oldest and largest cities, and within these cities are disproportionally concentrated in dense and mixed-use central-city neighborhoods. In terms of the demographic profiles of transit riders, public transit most commonly serves several population groups who are not able to or do not want to drive.

As a result, transit agencies in the US have long been struggling with providing services with an adequate level of frequency, coverage, and service quality (Watkins et al., 2019). Since the 2010s, with growing concerns on issues related to environmental sustainability and urban revitalization, many cities have voted to increase their spending on transit services, but the increasing political and funding support has not resulted in surges in transit ridership (Manville et al., 2018). The low cost of driving, demographic shifts and neighborhood changes in the central-city neighborhoods, and not surprisingly, the rapid emergence of new shared mobility options, have all contributed to the continuing decline of transit ridership (Lee and Lee, 2022; Manville et al., 2018; Watkins et al., 2019).

In addition, the urban expansion and decentralization facilitated by telecommunications have been a long-lasting trend in the US (Mokhtarian, 2000; Shen, 2000). More recently, the widely adopted work-from-home policy since the COVID-19 pandemic are much likely to further accelerate such a trend (Florida et al., 2021). The resulting declining demand density for public transit, coupled with the growing emphasis on transportation equity, has further challenged transit agencies' capacity (Tirachini and Cats, 2020).

1.1.3 *Incorporating on-demand shared mobility into public transportation provision*

Facing the challenges mentioned above, one could reasonably ask what the role of public transit agencies is and how they should deliver transport services in the era of shared mobility (Feigon and Murphy, 2016). Many transit agencies in the US have started to explore integrating shared mobility modes to supplement traditional fixed-route transit, typically serving as first-mile/last-mile connections, guaranteed ride home, or replacement of some low-efficiency transit services in low-demand areas (Gifford et al., 2021; Grellier, 2020; Gustave et al., 2018; Martin et al., 2020a;

Miller et al., 2021; Nabti, 2020; Shen et al., 2021). Table 1.1 presents examples of such pilots implemented by transit agencies. These pilots often require building partnerships with the shared mobility companies and providing incentives for travelers to adopt the new services. They may also integrate fare payment and/or trip planning of on-demand services and public transit. Many of these existing mobility pilots received funding support from the Federal Department of Transportation (DOT) under the 'Mobility on Demand Sandbox' program (Rodriguez, 2020). In this dissertation, I use the term Transit Incorporating Mobility on Demand (TIMOD) to be consistent with the naming of Federal DOT and accurately capture the supplementary roles played by shared mobility services in enhancing public transit. Similar terminologies, including multimodal integrations, innovative mobility programs, and shared mobility public-private partnerships (King County Metro, 2022; Shaheen et al., 2018; Wang et al., 2022), have appeared in the literature, each with a somewhat different emphasis.

Such TIMOD pilots may have profound implications for the future of urban transportation. Implementing these pilots means changes in the ways public transportation funding is allocated and mobility services are delivered. Instead of investing in the expansion of the fixed-route transit, transit agencies are now exploring whether partnering with shared mobility service providers and having them provide the service to travelers is a more effective approach in some service areas. Furthermore, TIMOD projects indicate a fundamental shift in the role of the public transit agencies, as they are no longer direct transportation service providers but instead mobility facilitators.

Table 1.1 Summary of Selected TIMOD Pilots in the US

Project name	**Region**	**Service to provide**	**Transit agencies**	**On-Demand services to partner**	**Transit to supplement**	**Incentive**	**Major outcomes**
Via to Transit	Los Angeles, CA / King County, WA	First-mile/last-mile solution	Los Angeles County Metropolitan Transportation Authority / King County Metro	Via, on-demand ride service	Subways / Light Rails	Partial fare subsidy	Via itself used frequently by riders; *Appear*s to increase transit ridership
Ride2 Eastgate and West Seattle	King County, WA	First-mile/last-mile solution	King County Metro	Chariot and Hopelink	Bus and water taxi	Partial fare subsidy	More rides in Eastgate than West Seattle; Trip performance met KCM's targets
King County Metro Scoop Carpool Partnership	King County, WA	Transit replacement	King County Metro	Scoop	NA	Partial fare subsidy	Effective in converting SOV to carpool; Benefits high-income groups
Pierce Transit Limited Access Connections	Pierce County, WA	First-mile/last-mile solution; Guaranteed ride home	Sound Transit; Pierce Transit	Lyft	Bus and Light Rails	Full subsidy	Service usage lower than expected
BART Carpool to Transit	Bay Area, CA	First-mile/last-mile solution	BART	Scoop	Light Rails	Guaranteed Parking	Increased BART ridership. Scoop usage concentrated on a few stations
Pinellas Partnership for Paratransit	Pinellas County, FL	On-demand paratransit	Pinellas Suncoast Transit Authority	Lyft and other contractors	Paratransit	NA	Unknown; Evaluation ongoing
Palo Alto and Bay Area Fair Value Commuting	Palo Alto, CA	Transit replacement	City of Palo Alto	Scoop	NA	Partial fare subsidy	Reduced mode share of commuting by SOV

1.2 Problem Statement

Although transit agencies are eager to explore TIMOD by carrying out pilots, to the author's knowledge, few attempts have been made to study these pilots using rigorous analytical methods. There remain substantial research gaps for transit agencies to clearly understand the pros and cons of a TIMOD project and envision the consequences of implementing them, as discussed below.

1. No consensus has been reached in the literature regarding the impacts of app-based ride-hailing, the most commonly used new shared mobility mode. App-based ride-hailing is a transportation service offered by TNCs that allow travelers to request a driver and a vehicle through a smartphone app to get to a given destination (Clewlow and Mishra, 2017). It draws a lot of attention from transportation researchers and there has been a heated debate regarding the impacts of app-based ride-hailing on traditional travel modes, in particular, on whether app-based ride-hailing substitutes or complements public transit (Tirachini, 2020). A primary reason for the lack of consensus is the restricted access to app-based ride-hailing data, which is controlled by private mobility service providers that operate the service. Another important reason is the constraints in prior studies' research methods. Some previous research used regression analysis with aggregated-level data (Boisjoly et al., 2018; Diao et al., 2021; Hall et al., 2018), but they rarely looked at actual app-based ride-hailing usage or ridership; some used intercept surveys targeting app-based ride-hailing users (Henao and Marshall, 2018; Rayle et al., 2016), which did not generate a representative sample and were constrained by various bias throughout the data collection; others have analyzed national or regional household travel survey data, but most limited their analysis at the cross-sectional level (Mitra et al., 2019; Sun et al., 2019). More research is

urgently needed using existing fine-grained app-based ride-hailing trip data that overcome the above constraints, and help us better understand its impacts.

2. The impacts of app-based shared mobility on individual travel and regional mobility are mode-specific, depending very much on each mode's level of mobility sharing. For example, the average distance-weighted vehicle occupancy rate of app-based ride-hailing was found to be less than 1 (i.e., the rate of single-occupancy vehicles) when the empty miles spent on cruising were accounted for (Henao and Marshall, 2018). As a result, statistically significant associations between app-based ride-hailing and increased congestions (Diao et al., 2021; Erhardt et al., 2019; Tarduno, 2021) as well as declined transit ridership (Diao et al., 2021; Graehler et al., 2019) were often reported. Considering these findings, transit agencies should be selective regarding what mobility services to incorporate, as some forms of shared mobility services may not bring the assumed mobility-sharing benefits. More importantly, it is of particular importance for scholars to investigate alternative types of mobility services that can better achieve 'deep sharing' (Shen et al., 2021), where a higher occupancy rate and lower vehicle miles per person can be realized.

3. Not all transit agencies have the resources and capacities for testing TIMOD projects. Although there existed federal support for testing TIMOD projects (Feigon and Murphy, 2016, 2018; Rodriguez, 2020), only a few transit agencies have taken action. Most existing TIMOD pilots are in larger cities with younger, tech-savvy populations, and thus presumably greater local supports for new mobility technologies and innovations. For many other transit agencies, a stronger empirical basis for them to understand, design, and implement TIMOD projects is urgently needed (Shaheen et al., 2018). Questions such as what roles TIMOD projects play in supplementing existing public transit and how newly provided TIMOD services impact the travel behavior of riders need to be addressed.

4. Existing TIMOD pilots need to be more rigorously studied and evaluated. The evaluations of some existing TIMOD pilots often utilized service trip data and user survey data and examined the usage of TIMOD services, trip characteristics, and the socio-demographics of riders (Gifford et al., 2021; Grellier, 2020; Gustave et al., 2018; Miller et al., 2021). However, these evaluations primarily relied on simple descriptive statistics instead of more rigorous analytical methods. More importantly, many positive benefits reported, such as the quick adoption of on-demand services, the shortened travel time, and even the boosted transit ridership, were not surprising given that transit agencies typically offered incentives. The key question should be, instead, how the benefits of TIMOD projects compare to those of traditional fixed-route transit expansions with the same funding.

5. Not all travelers are equally benefited from the TIMOD pilots. One of the primary goals of the TIMOD pilots is to promote equitable mobility access for populations who are socio-economically disadvantaged and experiencing challenges in their mobility, and for neighborhoods that are underserved by fixed-route transit (Gifford et al., 2021; King County Metro, 2020; Miller et al., 2021). However, the nature of app-based, on-demand travel creates technological barriers for people to comfortably access and use the service. It is thus necessary to carefully examine the social equity implications of the TIMOD pilots and fill in this critical gap.

1.3 Objectives

This dissertation is a synthesis of efforts that deepen our understanding regarding first the impacts of new shared mobility modes, and second the incorporation of shared mobility modes into public transportation service provision. The dissertation is part of a collaboration with public transportation agencies and research entities in the Seattle region. It conducts quantitative analysis

with empirical data, and research the opportunities and challenges of urban public transportation in the era of app-based mobility sharing. Specifically, I will investigate three topics that help public transit agencies better utilize the advantages of app-based shared mobility services for a more efficient, flexible, and equitable transportation system, while mitigating the negative effects of the services. The dissertation will advance transportation planning through critically reviewing and synthesizing existing literature, developing new conceptual frameworks that help deepen our understanding, employing innovative datasets that overcome constraints in previous studies, and applying advanced statistical models and transportation simulation methods.

1.4 Dissertation Structure

Figure 1.1 presents the structure of the dissertation and the relation of the three studies included. Each of the three studies is a standalone research project that leads to a paper prepared for peer-reviewed academic publication. And jointly, the three studies will form a coherent theme.

The first study, presented in Chapter 2, will use a dataset collected from the Seattle region to understand the longitudinal impacts of ride-hailing on individual mode choices. The dataset is unique as it is representative of the study area population and longitudinal in nature. The study develops panel regression models to analyze the relations between ride-hailing and traditional travel modes (i.e., driving, public transit, and walking and biking), and more importantly, how such relations change over time as app-based ride-hailing became more and more popular in the region. The objective of this chapter is to provide context for researching transit agencies' policy responses in the next two chapters.

Chapter 3 and Chapter 4 will both use Via to Transit, a TIMOD project in Seattle, as a case study, but each chapter will have its specific focus. Chapter 3 will fill in the gaps in the travel

behavior studies that research riders' adoption, mode switch, and attitude in response to TIMOD projects. It is one of the earliest works that examine the riders' actual responses to a real-world TIMOD pilot, instead of relying on stated preference data as most previous studies did. The study conducts latent class analysis on the survey data collected from the Via to Transit riders and identifies distinct latent rider groups among them. The results of the chapter show rich transportation policy trade-offs regarding the impacts of a TIMOD project on the travel behavior of different rider groups.

Chapter 4 will switch the focus to discuss how transit agencies, from the service providers' perspective, should appropriately understand and evaluate the cost-effectiveness of incorporating on-demand modes versus traditional fixed-route transit expansion. The chapter advances the literature in two ways. First, it clarifies vagueness in the current conceptualization of the cost of mobility service provision by developing a solid, comprehensive theoretical framework based on the economic concept of marginal cost. Second, the chapter will use transportation simulation to show how each component of the cost identified in the theoretical framework can be empirically estimated. The study applies the simulation to Via to Transit as a proof of concept. Jointly, the theoretical framework and the simulation provide an effective approach for transit agencies to determine, contextually, whether the engagement with shared mobility service providers is indeed cost-effective.

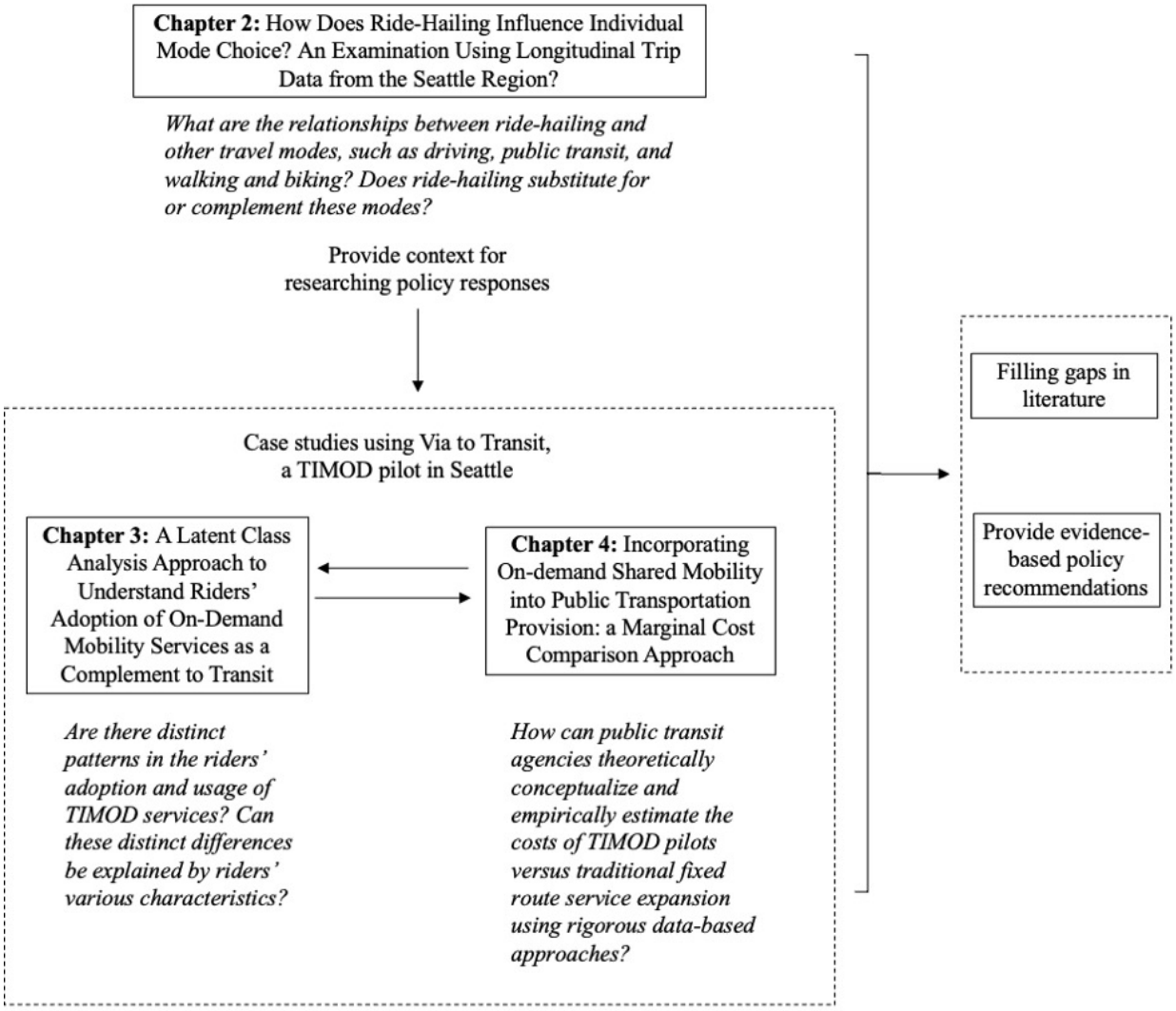


Figure 1.1 Dissertation chapters and their relations

Chapter 2. How Does Ride-Hailing Influence Individual Mode Choice? An Examination Using Longitudinal Trip Data from the Seattle Region

2.1 Introduction

In recent years, the exponential growth of mobile information and communication technology-enabled mobility services offered by TNCs, such as Uber and Lyft, has drawn much attention of transportation scholars and practitioners (Clewlow and Mishra, 2017; Schaller, 2018; Shaheen et al., 2018). TNCs provide a new form of ride-hailing services, which have long existed in major cities, primarily in the traditional form of taxis. Despite the fact that the new form is app-based, it shares many similarities with traditional taxis where drivers are service providers who offer mobility services to riders (Rayle et al., 2016; Schaller, 2018; Wu and MacKenzie, 2021).

Attempts have been made to understand the impacts of the new form of ride-hailing on traditional transportation modes, especially on whether it is substituting for or complementing other modes. Previous studies have employed various data and methodologies to investigate this relationship. Some studies have analyzed aggregated metropolitan-statistical-area (MSA) or transit-agency-level data (Boisjoly et al., 2018; Graehler et al., 2019; Hall et al., 2018; Sadowsky and Nelson, 2017) to examine the relationship between TNCs' entry and regional travel demand. However, most studies lacked data on actual service ridership. In contrast, individual-level studies have used data from intercept surveys targeting ride-hailing users (Gehrke et al., 2019; Henao and Marshall, 2018; Rayle et al., 2016); from household travel surveys targeting ride-hailing users (Clewlow and Mishra, 2017; Coy et al., 2019); and from regional or national household travel

surveys that used travel log (Mitra et al., 2019; Sun et al., 2019; Young and Farber, 2019). However, few of these studies were able to apply rigorous statistical methods that controlled for the various confounders affecting mode choice. And for those that did, most only used one-year cross-sectional data. As a result, in order to reach a consensus on the impacts of ride-hailing on other modes, more research is needed to better prepare cities and the transportation sector for the era of shared mobility (Le Vine and Polak, 2015; McCoy et al., 2018; Watkins et al., 2019).

This study attempts to advance knowledge on this question by utilizing a unique longitudinal travel log and survey dataset from the ACTION (Assessing Choices in Transportation in Our Neighborhoods) project. ACTION is an NIH-funded study that collects primary data on the location and activity of more than 400 individuals in the Seattle region every two years for three times since 2012. These rich data offer a great opportunity to study trends in ride-hailing usage and other individual travel patterns.

The study begins with a review of recent studies on the relationship between ride-hailing and other modes, focusing on their research methods and findings. The subsequent section introduces the data and methodology for this study. Next comes a presentation of the models and estimation results, followed by a discussion and conclusions.

2.2 Literature Review

The lack of consensus on the impacts of app-based ride-hailing on traditional modes is partly explained by the different research methods used in current literature. Therefore, the first section of the literature review summarizes different methods adopted in previous studies and the potential effects of such choices of methods on their results. The second section of this review synthesizes previous research findings.

2.2.1 *Methods to study the impacts of app-based ride-hailing on other modes*

A common approach is to use aggregated data to examine the impact of TNC entry on regional mobility trends such as public transit ridership, vehicle ownership, and average commuting time (Boisjoly et al., 2018; Graehler et al., 2019; Hall et al., 2018; Sadowsky and Nelson, 2017). These studies often take MSA or transit agencies as the unit of analysis. The greater availability and consistency of the data at the aggregated level enable these studies to develop statistical models that can single out the effects of app-based ride-hailing from various confounders. For example, Boisjoly et al. (2018) applied a mixed effect model to investigate factors affecting transit ridership in the service areas of 25 transit agencies in North America. Hall et al. (2018) used a difference in difference model on ridership data for transit agencies in the US to estimate the impact of Uber entry on transit ridership. However, most of the studies measured the effects of app-based ride-hailing using a dummy variable representing whether or not the service is present in the city (Boisjoly et al., 2018; Hall et al., 2018), or a variable capturing the years since the entry (Graehler et al., 2019; Sadowsky and Nelson, 2017). These studies do not present data on actual TNC ridership. Only Hall et al. (2018) used Google search engine 'intensity' as a proxy for the ridership. Furthermore, aggregate level analyses cannot reveal mode choice at the individual level, and therefore are not able to identify different impacts of this new form of ride-hailing on heterogeneous population groups.

An alternative approach is to collect and analyze data at the individual level. A convenient way to do so is to survey ride-hailing riders and gather a convenience sample (Feigon and Murphy, 2016; Gehrke et al., 2019; Henao and Marshall, 2018; Rayle et al., 2016). Such surveys may take place in ride-hailing vehicles during the services, or near ride-hailing hubs, or the ride-hailing service providers may distribute the surveys on their app platforms. This approach can gather data

from a large pool of ride-hailing users and contribute to a better understanding of ride-hailing users' characteristics. However, such survey techniques are not likely to generate a representative sample. Of note, most of these studies asked what modes to choose if ride-hailing was not an option to test the substitution effects, but they did not probe potential complementarity effects.

Clewlow and Mishra (2017) conducted a study on shared mobility users, and they acquired a representative sample of households in seven metropolitan areas. They asked respondents to not only report what alternative modes they would use when app-based ride-hailing was not available, but also to self-estimate changes in the use of transit, walking and biking after the adoption of ride-hailing, thus potentially getting information on mode complementarity. Coy et al. (2019), which is a similar effort, gathered representative cross-sectional travel data with over-sampled app-based ride-hailing users.

There have been efforts to research the impacts of ride-hailing using national or regional household travel surveys (Mitra et al., 2019; Sun et al., 2019; Young and Farber, 2019). Although not created to study the impact of shared mobility solely, many of these travel surveys involved travel logs for more complete and accurate records of participants' travel activities. Some of them, such as the Puget Sound Regional Council (PSRC) Household Travel Survey in the Seattle region, even utilized GPS devices or smartphone apps to ensure accuracy (Puget Sound Regional Council, 2018). Therefore, using data from these sources have a greater potential to overcome bias in stated-preference surveys.

Many studies at the individual level only applied summary statistics, except for a few efforts that developed regression models to better control for various confounders (Gehrke et al., 2019; Mitra et al., 2019; Sun et al., 2019). However, partly due to the fact that the emergence of Uber and Lyft is a recent phenomenon, most of the regression models were based on cross-

sectional data. It is not clear whether the variation in the mode choice among participants is a disruptive effect from TNC services, or a self-selection effect that participants with certain characteristics are more likely to use such services (Sun et al., 2019). Therefore, there is a need to develop models using longitudinal data, which helps to examine how the relationship between ride-hailing and other modes changes over time.

2.2.2 *Impacts of ride-hailing services on driving*

It is more likely that ride-hailing serves as a substitute for driving. For example, In Feigon and Murphy's study (2016), after the adoption of app-based ride-hailing, 35% of the respondents reported driving less for commuting, versus 4% who reported driving more; and 32% reported driving less for errands or recreation, versus 10% who reported driving more. They also found respondents reducing vehicle ownership after the adoption. Similarly, Henao and Marshall (2018) found that, when asked what mode to use if app-based ride-hailing was not available, 19% of respondents in Denver chose driving, ranking second after public transit. Sun et al. (2019) also reported significant substitution effects of ride-hailing on driving in their models. However, other research suggests weaker substitution effects. For example, Rayle (2016) also found few ride-hailing trips in San Francisco replaced driving.

2.2.3 *Impacts of ride-hailing services on public transit*

It is likely that app-based ride-hailing services, with its flexibility and convenience, take some transit customers away in areas where transit services are not efficient. However, such services can also serve as a first-and-last mile solution and thus complement the transit system.

In studies that applied aggregated data, Boisjoly et al. (2018) reported no significant effect of TNC entry on transit ridership, while Graehler et al. (2019) used more recent data and reported a substitution effect. Sadowsky and Nelson (2017) developed a more complicated model and found an initial complementary effect of TNCs after the entry of the first TNC company, but an increasing substitution effect since the entry of the second TNC company. Hall et al. (2018) investigated the heterogeneous effects of app-based ride-hailing on different transit agencies' ridership, and found that such service was more likely to complement small transit systems in large MSAs, and substitute for big transit systems in small MSAs.

In studies based on individual-level survey data, Feigon and Murphy (2016) found that 43% of the respondents reported using public transit more after the adoption of shared mobility options versus 28% who reported less, which suggested a complementary effect. Clewlow and Mishra (2017), using a representative sample, found a 6% reduction in the usage for bus, a 3% reduction for Light Rail, and a 3% increase for commuter rail after the adoption of app-based ride-hailing. These results indicate that the effects are heterogeneous on different transit modes. Also, respondents frequently rank public transit at the top of the list when asked which modes to take if app-based ride-hailing was not available (Coy et al., 2019; Gehrke et al., 2019; Henao and Marshall, 2018; Rayle et al., 2016), suggesting potential substitution effects.

Among studies that used regional or national travel surveys, Young and Farber (2019) found that the new form of ride-hailing has no substantial effects on public transit in the Toronto region, but Sun et al. (2019), using data from Seattle, found that transit and ride-hailing are likely to substitute for each other.

2.2.4 *Impacts of ride-hailing services on walking and biking*

Ride-hailing can also impact walking and biking. On one hand, some forms of shared app-based ride-hailing services (e.g., Uber Pool and Lyft Line) ask riders to walk to/from nearby intersections for pick-up and drop-off. It is also possible that ride-hailing allows people to walk and bike for their outgoing trip and return by ride-hailing should they prefer to do so. On the other hand, ride-hailing trips may directly substitute for some walking and biking trips. Feigon and Murphy (2016) found that 54% of the respondents reported being more physically active since the adoption of shared mobility options. Only 5% reported being less physically active, suggesting a complementary role of ride-hailing on active travel. Young and Farber (2019) reported an association between app-based ride-hailing and an increase in active modes for specific travel demand in the Toronto region. However, Gehrke et al. (2019) found that certain ride-hailing trips, for example, ones that are less expensive and presumably shorter, are likely to substitute for active transportation trips.

2.3 Research Questions

This research aims to utilize a longitudinal dataset to investigate the relationship between ride-hailing, including both traditional taxis and app-based services, and other travel modes, while overcoming some shortcomings of cross-sectional studies. Specifically, this research aims to answer the following questions:

Question 1: What are the relationships between ride-hailing and other travel modes, such as driving, public transit, and walking and biking? Does ride-hailing substitute for or complement these modes?

Question 2: How do these relationships change over time?

2.4 Data and Methodology

2.4.1 *Data*

This study uses data from the ACTION project, an NIH funded study designed to study the impacts of the new E and F Bus Rapid Transit (BRT, called RapidRide service in Seattle/King County) lines on individual physical activity. The study included three waves of data collection, taking place before (2012-2014), soon after (2015-2016), and two years after (2017-2018) the new BRT lines started operation.

Recruitment for ACTION began in July 2012 and continued through January 2014. About half of the participants were selected from among people living within ½ mile of an E or F line BRT stop. The other half were selected from among people living in other neighborhoods within the Seattle region that matched BRT stop-adjacent neighborhoods on household income, racial/ethnic composition, residential property values, residential density, land use mix, bus ridership, and housing type. Households in eligible areas were contacted using the address and phone information obtained from MSG (Marketing Systems Group), a consumer marketing company. Enrollment processes ensured participants were adults 18 years old or older who gave informed consent, were able to walk unassisted for at least 10 min, and completed the travel log and survey in English. The Seattle Children's Research Institute Institutional Review Board approved the study. Figure 2.1 shows the home locations of participants in our sample at the beginning of the study. These individuals are ideal for studying the relationship of new mobility options with other modes, especially with public transit, because: 1) for most of them, transit serves

as a viable travel option; and 2) these individuals were selected through random sampling, thus are more likely to be representative.

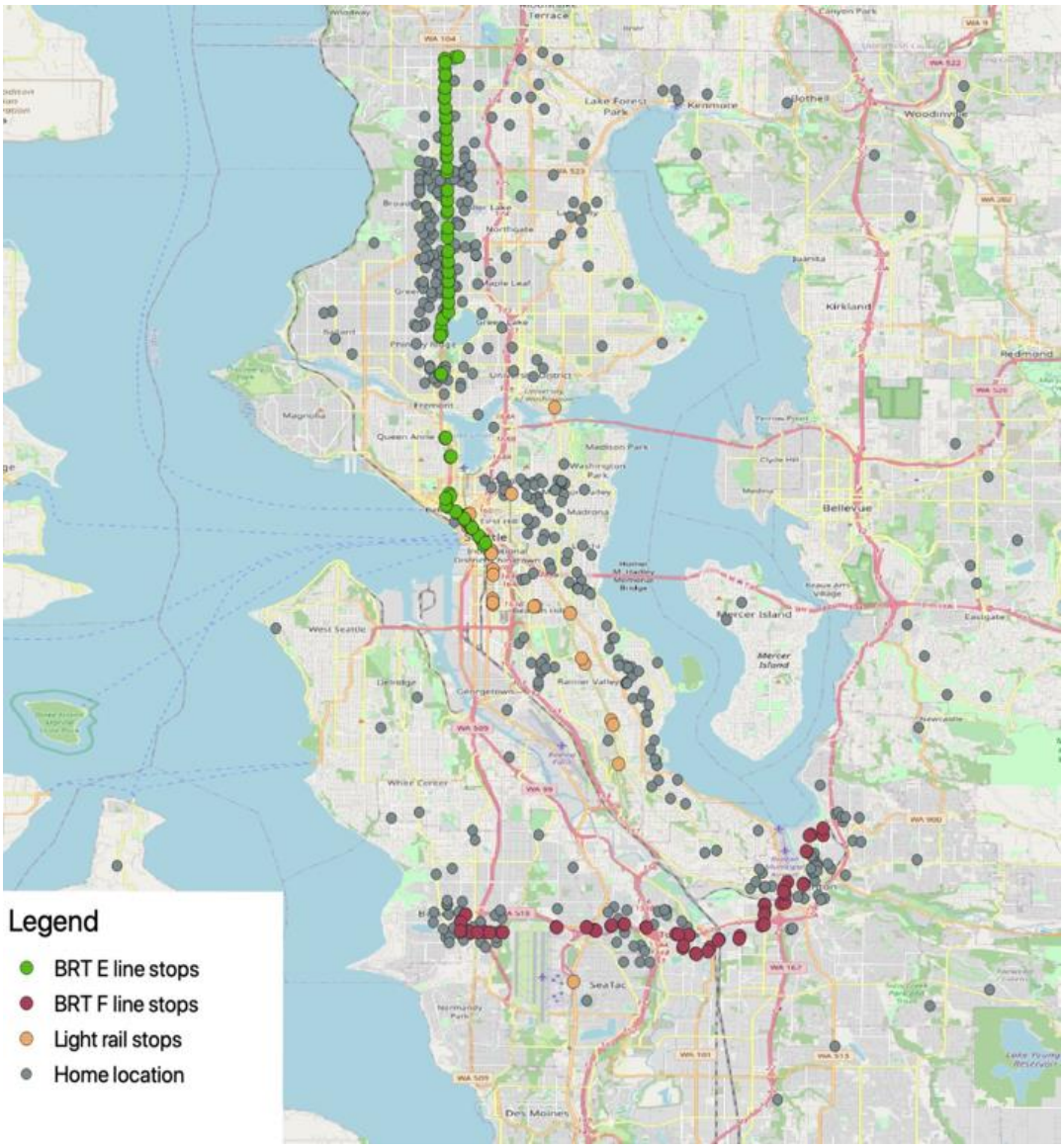
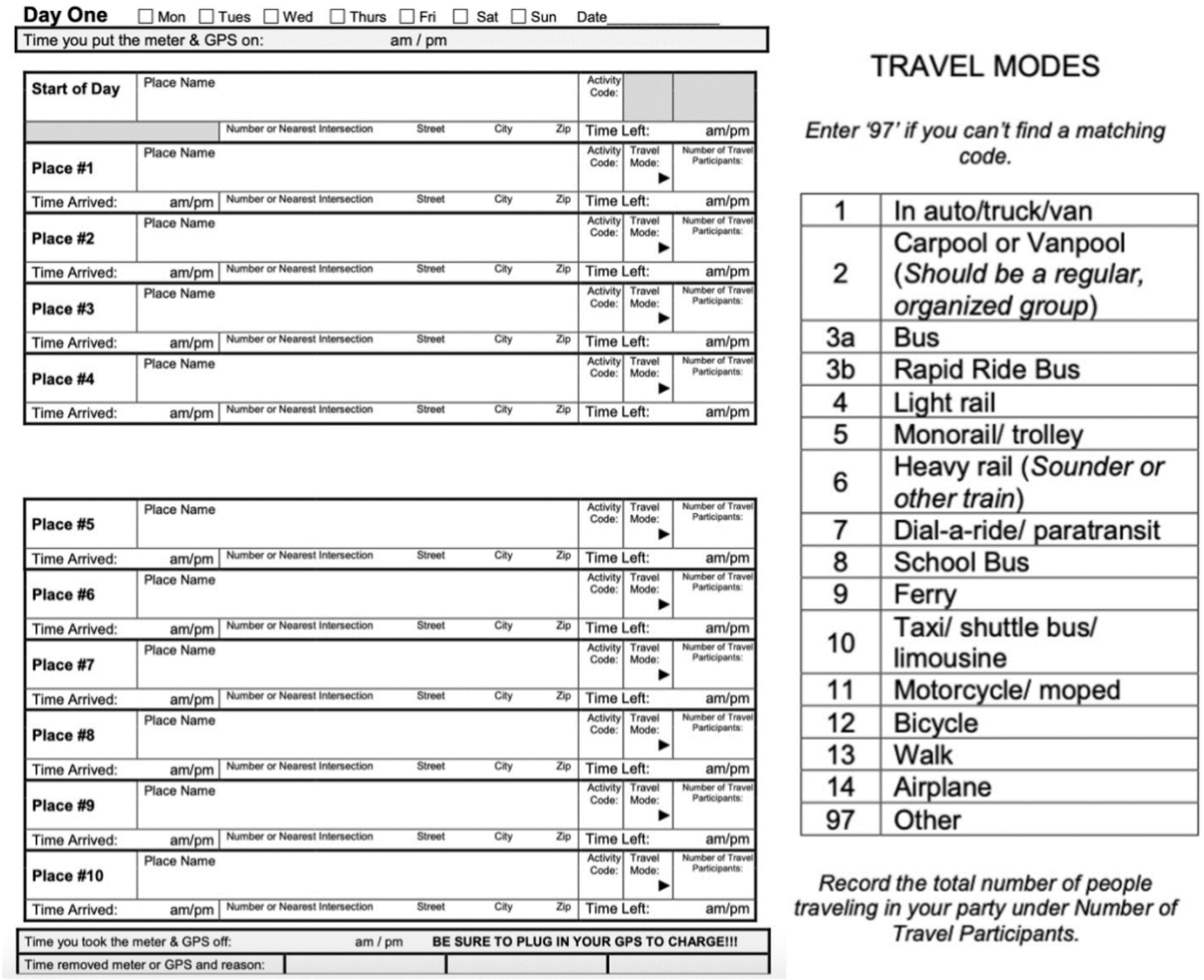


Figure 2.1 Participants' home locations at wave 1 (n=460)

Map Reference: OpenStreet Map

In the extensive survey focusing on socio-demographic and attitudinal factors, participants reported their age, gender, race/ethnicity, height, and educational attainment at baseline (wave 1).

At baseline and each follow-up wave, they reported annual household income, weight, number of other household members, and number of motor vehicles available to the household. For measures of travel behavior, participants were asked at each wave to wear an Actigraph GT3X accelerometer and a QStarz BG-1000XT global positioning system (GPS) data logger for seven days while also recording their travel in a paper diary over the same period (as shown in Figure 2.2). The study team timed contact with participants to maximize monitoring at the same time of the year as prior waves.



Day One ☐ Mon ☐ Tues ☐ Wed ☐ Thurs ☐ Fri ☐ Sat ☐ Sun Date_____

Time you put the meter & GPS on: am / pm

Start of Day	Place Name					Activity Code:		
	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #1	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #2	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #3	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #4	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #5	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #6	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #7	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #8	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #9	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm
Place #10	Place Name					Activity Code:	Travel Mode: ▶	Number of Travel Participants:
Time Arrived: am/pm	Number or Nearest Intersection	Street	City	Zip		Time Left:		am/pm

Time you took the meter & GPS off: am / pm **BE SURE TO PLUG IN YOUR GPS TO CHARGE!!!**

Time removed meter or GPS and reason:

TRAVEL MODES

Enter '97' if you can't find a matching code.

1	In auto/truck/van
2	Carpool or Vanpool (*Should be a regular, organized group*)
3a	Bus
3b	Rapid Ride Bus
4	Light rail
5	Monorail/ trolley
6	Heavy rail (*Sounder or other train*)
7	Dial-a-ride/ paratransit
8	School Bus
9	Ferry
10	Taxi/ shuttle bus/ limousine
11	Motorcycle/ moped
12	Bicycle
13	Walk
14	Airplane
97	Other

Record the total number of people traveling in your party under Number of Travel Participants.

Figure 2.2 ACTION travel log sample page and codes for travel mode

This extensive study generated a series of longitudinal data at three periods, although the number of observations varied somewhat because of participant attrition over the course of the study. Table 2.1 presents the ACTION's timeline and sample size. I obtained a total of 58,901 trips for the three waves.

Table 2.1 ACTION study dates and longitudinal sample size

Wave	Year	Number of participants	Number of trips in the travel log data
1	2012-2014	460	21890
2	2015-2016	371	18591
3	2017-2018	361	18420
Total			58901

Based on online records, Uber launched the service in the Seattle region in 2011 (Uber, 2016), and Lyft first entered the market in 2013 (Cook, 2013). Since then, the two companies rapidly expanded their market in Seattle and other regions; their annual ridership is estimated to pass 20 million in 2017 (Schaller, 2018). The timeline of ACTION's three-wave data collection, which started in 2012 and ended in 2018, aligned well with the emergence and rapid expansion of app-based ride-hailing in the region.

2.4.2 *Methods*

This study uses the travel log data to calculate the total trip count and duration for each mode and examines how the share of ride-hailing has changed over time. Trip count is commonly used in transportation studies to analyze mode choice, while this study also calculates the trip duration to reflect the actual time that participants spent using each mode, which is an important aspect when considering relationships between modes. I followed a data cleaning procedure to process the travel log data, as shown in Table 2.2. First, I removed about 20% of total trips with mode = NA or = blank or = invalid code. The majority of the dropped trips are movements within one's house (e.g., going to the garage, working in the yard). Then, for trip duration statistics, I removed additional trips with duration = NA or = negative values, which tend to be mistakes when participants filled in the travel log. I also excluded a small number of trips with extremely long duration (greater than 5 hours).

Table 2.2 ACTION travel log data cleaning process

Step	**Description**	**Trips**	
		Count	**% removed**
1	Original number of trips in three waves	58,091	
For both trip count and trip duration statistics			
2	Removing trips with mode = NA or = blank or invalid code	46,598	19.8%
For trip duration statistics only			
3	Removing trips with duration = NA	43,835	5.9%
4	Removing trips with duration = negative	41,155	6.1%
5	Removing trips with duration > 5 hours	41,078	0.2%

To answer the research questions, I develop a series of panel models at the person-wave level. The key variables in the model, the travel behavior variables, are derived from the travel log data. The modes are determined according to the codes in Figure 2. Note that ride-hailing in the ACTION survey is described as “taxi, shuttle bus, limousine” and does not explicitly distinguish between the new app-based ride-hailing services (e.g., Uber and Lyft) and traditional taxis. Therefore, the results of the models in the study should be interpreted with caution, as they represent impacts from both traditional taxi services and new ride-hailing services. I will further discuss this limitation in the ‘Discussion and Limitation’ section, and elaborate on why I believe this mode effectively captures the emerging app-based ride-hailing trips in addition to traditional taxis.

For each participant at each wave, I calculate their average trip count per day and the average trip duration per day for each of the following modes: driving, public transit, walking and biking, and ride-hailing. I run the models using the average trip count/duration of driving, public transit, and walking and biking as dependent variables and the average trip count/duration of ride-

hailing as independent variables. I control for other factors that affect mode choice: demographic factors (age, gender, race, household size, and the number of children within the household), socioeconomic factors (educational attainment, income level, employment status, and vehicle ownership), attitudinal factors (whether a participant likes taking public transit and whether s/he likes driving), built environment factor (residential unit density), and time-specific effects of the second and the third waves. Control variables come from the ACTION survey, except for residential unit density, which is calculated as the number of residential units within an 800-meter radius of each individual's home location based on county assessor's data (2014). I calculate density in 2013, 2015, and 2017 for the three data collection waves, respectively. These control variables are commonly adopted in travel behavior and new mode choice adoption studies (Neoh et al., 2017; Young and Farber, 2019). Before running the model, I checked multicollinearity by calculating the variance inflation factor (VIF). All the variables included in the model have VIF less than 3, which suggested that multicollinearity is moderate.

I use negative binomial models that are well-suited for modeling data that are right skewed rather than normally distributed. Three types of panel models are commonly adopted while using longitudinal data: independently pooled model, fixed-effect model, and random effect model. The independently pooled model treats longitudinal data as cross-sectional, and ignores the fact that repeated measures from the same participant tend to be correlated (i.e., serial correlation). Thus, the estimation might be biased due to its inability to account for such correlation. Instead, the fixed-effect model adds an individual effect to the model for each participant and assumes that such an effect is non-random. By doing this, it better controls for the serial correlation. However, the fixed-effect model comes with cost. It purges all the cross-sectional variation from the model and only models the time-variant part of the dependent variables. In our case, the fixed-effect

model can only tell us why a person's usage of transit (or other modes) changes over time, but cannot tell us why person A uses public transit more than person B. Therefore, I first run independently pooled models, and then I run fixed-effect models to verify if the associations between modes still hold after controlling for individual effect. The random effect model is not suitable for our case, because it assumes that the individual effect is not correlated with the X_s (independent variables) in the models, and such an assumption is not met in our models.

2.5 Results

2.5.1 *Longitudinal descriptive statistics*

Table 2.3 presents the total trip count and trip duration for each mode. The ACTION travel log has more than ten modes. I grouped the modes into six broader categories, as listed in the first column in Table 2.3.

Table 2.3 Trip count and trip duration by mode

Category	**Mode in ACTION travel log**	**ACTION Wave**	**Trip count**	**% in all trips**	**Trip duration (min)**	**% in all trips**
Drive alone	Auto/ truck	1	11,099	62.3%	165,947	64.5%
		2	9,355	64.8%	143,351	68.8%
		3	8,868	61.2%	130,046	65.1%
	Motorcycle/ moped	1	94	0.5%	1,334	0.5%
		2	92	0.6%	1,491	0.7%
		3	67	0.5%	994	0.5%
	Total	**1**	**11,193**	**62.8%**	**167,281**	**65.0%**
		2	**9,447**	**65.4%**	**144,842**	**69.5%**
		3	**8,935**	**61.7%**	**131,040**	**65.6%**
Walking/ biking	Walk	1	4,815	36.3%	55,570	21.6%
		2	3,561	34.9%	35,133	16.9%
		3	3,789	37.2%	35,901	18.0%
	Bike	1	327	1.8%	6,434	2.5%
		2	289	2.0%	5,138	2.5%
		3	291	2.0%	5,400	2.7%
	Total	**1**	**5,142**	**38.1%**	**62,004**	**24.1%**
		2	**3,850**	**36.9%**	**40,271**	**19.4%**
		3	**4,080**	**39.2%**	**41,301**	**20.7%**
		1	204	1.1%	3,189	1.2%

Carpool/ Vanpool	Carpool/ Vanpool	2	143	1.0%	3,116	1.5%
		3	263	1.8%	5,285	2.4%
Public Transit	Bus	1	865	4.9%	17,578	6.8%
		2	607	4.2%	12,796	6.1%
		3	769	5.3%	16,051	8.0%
	Bus Rapid Transit	1	0	0.0%	0	0.0%
		2	43	0.3%	695	0.3%
		3	61	0.4%	1,014	0.5%
	Light Rail	1	77	0.4%	1,612	0.6%
		2	92	0.6%	1,618	0.8%
		3	125	0.9%	1,913	1.0%
	Monorail/ trolley	1	39	0.2%	616	0.2%
		2	21	0.1%	412	0.2%
		3	19	0.1%	246	0.1%
	Heavy rail	1	32	0.2%	699	0.3%
		2	4	0.0%	37	0.0%
		3	1	0.0%	30	0.0%
	Total	**1**	**1,013**	**5.7%**	**20,505**	**7.9%**
		2	**767**	**5.2%**	**15,558**	**7.4%**
		3	**975**	**6.7%**	**19,254**	**9.6%**
Ride-hailing	Taxi/ shuttle bus/ limo	1	61	0.3%	787	0.3%
		2	68	0.5%	1,333	0.6%
		3	67	0.5%	1,301	0.7%
Others	Others	1	196	1.1%	3,432	1.3%
		2	161	1.1%	3,379	1.6%
		3	161	1.1%	2,073	1.0%
Total		**1**	17,809	100.0%	257,198	100.0%
		2	14,436	100.0%	208,499	100.0%
		3	14,481	100.0%	199,674	100.0%

Several trends can be observed. First, there had been growth in the percentages of ride-hailing trip count (from 0.3% to 0.5%) and trip duration (from 0.3% to 0.7%). These percentages aligned well with the National Household Travel Survey (0.5% in 2017) and were higher than those in PSRC Household Travel Survey conducted in the Seattle region (0.3% in 2017). However, the percentages were relatively small, suggesting that the new form of ride-hailing was still at the early stage of development. This finding is consistent with results from previous research that uses data from regional household travel surveys (Young and Farber, 2019). Second, Table 2.3 also shows that among ACTION participants, the shares of walking and biking, as well as transit, were high, 2 to 3 times above the national average (Federal Highway Administration, 2017). Third, the

share of driving peaked at wave 2, and then decreased at wave 3. Correspondingly, the share of public transit as well as walking and biking decreased at wave 2 and increased at wave 3. These trends suggest joint effects of the opening of BRT lines and other major transit improvements, and possibly the emergence of new mobility options.

Although ride-hailing's share was relatively small, it almost doubled within six years in terms of trip count and more than doubled in terms of trip duration. If the new form of ride-hailing continues to grow at the current rate, it may play a more substantial role in the future. The next section will examine whether the changes in mode choices observed in the data can be partly attributed to the emergence of app-based ride-hailing.

2.5.2 *Model outcomes*

Table 2.4 presents the summary statistics for the variables in the panel models that examine whether ride-hailing is substituting for or complementing other modes. The travel behavior variables are average trip count and duration per day per person. Some of the control variables show time-variance over the three waves. For example, the average number of children per household decreased while the average number of vehicles owned by households increased. Household income also increased. Over time, participants show a more positive attitude toward public transit, and less positive attitude toward driving. Using these data, I run both independently pooled models and fixed-effect models to examine the association between ride-hailing and other modes. Table 2.5 presents the results of the independently pooled models. Models (1) and (2) use the average count and duration per day by driving as dependent variables, Models (3) and (4) are for public transit, and Models (5) and (6) are for walking and biking. The estimations show changes

in the trip count and trip duration that are associated with a one-unit change in the independent variables.

Table 2.4 Summary statistics by ACTION waves

		Wave 1			Wave 2			Wave 3		
		n	mean	s.d.	n	mean	s.d.	n	mean	s.d.
Travel behavior variables: average trip count or duration (min) per day	Driving count	460	3.09	2.00	371	3.25	2.12	361	3.11	2.21
	Driving duration	460	48.99	32.06	371	52.60	37.25	361	48.89	33.04
	Public transit count	460	0.26	0.61	371	0.26	0.58	361	0.34	0.70
	Public transit duration	460	6.09	16.74	371	5.16	12.57	361	7.22	16.68
	Walking and biking count	460	1.43	1.65	371	1.36	1.55	361	1.45	1.49
	Walking and biking duration	460	18.63	22.94	371	15.09	20.26	361	15.80	18.53
	Ride-hailing count	460	0.01	0.10	371	0.02	0.14	361	0.02	0.12
	Ride-hailing duration	460	0.20	2.02	371	0.50	3.09	361	0.55	3.81
	Total trip count	460	4.90	2.22	371	4.99	2.28	361	5.05	2.39
	Total trip duration	460	76.01	35.06	371	75.75	40.02	361	74.86	33.64
Other variables	Age	453	54.27	12.92	371	56.33	12.85	333	58.70	12.54
	Female (=1)	460	0.62	0.49	358	0.64	0.48	346	0.64	0.48
	White (=1)	460	0.88	0.33	358	0.89	0.32	346	0.88	0.32
	Education: less than college degree (=1)	424	0.30	0.46	368	0.26	0.44	317	0.26	0.44
	Education: college degree (=1)	424	0.37	0.48	368	0.40	0.49	317	0.40	0.49
	Education: graduate degree (=1)	424	0.33	0.47	368	0.35	0.48	317	0.34	0.47
	Household size	449	2.29	1.30	368	2.29	1.41	357	2.29	1.59
	Number of children under 18	450	0.46	0.89	363	0.44	0.89	359	0.38	0.81
	Number of vehicles owned by household	447	1.23	1.02	369	1.68	1.00	359	1.70	1.10
	Income: < $50k (=1)	455	0.38	0.49	371	0.35	0.48	360	0.34	0.47
	Income: $50k - $100k (=1)	455	0.38	0.49	371	0.35	0.48	360	0.35	0.48
	Income: >$100k (=1)	455	0.24	0.43	371	0.29	0.45	360	0.31	0.46
	Work full time (=1)	460	0.54	0.50	371	0.50	0.50	337	0.52	0.50
	Like taking public transit (1 = strongly agree or somewhat agree, 0 = neutral, somewhat disagree or strongly disagree)	456	0.43	0.50	359	0.45	0.50	359	0.46	0.50
	Like driving (1 = strongly agree or somewhat agree, 0 = neutral, somewhat disagree or strongly disagree)	454	0.56	0.50	365	0.54	0.50	358	0.49	0.50
	Residential unit density	456	15.94	11.95	369	17.09	14.24	357	17.26	14.16
Total N		460			371			361		

Table 2.5 Independently pooled model results

	Driving						Public transit						Walking and biking					
	(1)			(2)			(3)			(4)			(5)			(6)		
	Count			Duration			Count			Duration			Count			Duration		
	Est.	SE	Sig	Est.	SE	Sig	Est.	SE	Sig	Est.	SE	Sig	Est.	SE	Sig.	Est.	SE	Sig
Ride-hailing count	-0.36	0.172	**				0.329	0.35					-0.079	0.217				
Total trip count	0.155	0.007	***				0.229	0.024	***				0.193	0.011	***			
Ride-hailing duration				-0.04	0.007	***				0.024	0.028					-0.01	0.014	
Total trip duration				0.013	0.001	***				0.023	0.003	***				0.016	0.001	***
Age	0.002	0.002		0.003	0.002		-0.003	0.006		-0.003	0.009		-0.002	0.003		0.001	0.004	
Female	0.091	0.038	**	0.149	0.042	***	-0.145	0.135		-0.38	0.191	***	-0.144	0.056	**	-0.17	0.092	*
White	-0.01	0.058		0.027	0.065		-0.48	0.189	**	-0.491	0.291	*	0.327	0.108	***	0.305	0.143	**
Education: college degree	0.008	0.048		0.089	0.053	*	-0.209	0.183		-0.052	0.244		0.194	0.08	***	0.155	0.116	
Education: graduate degree	0.111	0.051	**	0.222	0.059	***	-0.32	0.202		0.097	0.267		0.079	0.086		0.037	0.128	
Household size	-0.06	0.023	***	-0.04	0.024	*	0.037	0.04		0.243	0.1	**	0.049	0.019	***	0.045	0.049	
Number of children under 18	0.114	0.032	***	0.068	0.035	*	-0.291	0.108	***	-0.499	0.158	***	-0.111	0.041	***	0.024	0.076	
Number of vehicles owned	0.141	0.022	***	0.173	0.025	***	-0.608	0.089	***	-0.755	0.118	***	-0.226	0.034	***	-0.21	0.055	***
Income: $50k - $100k	0.063	0.048		0.068	0.054		-0.166	0.18		-0.143	0.243		-0.103	0.075		-0.07	0.117	
Income: > $100k	-0.002	0.057		-0.02	0.065		0.065	0.209		-0.308	0.295		0.015	0.087		0.048	0.142	
Work full time	-0.01	0.042		0.038	0.049		0.231	0.168		0.389	0.22	*	0.005	0.068		0.021	0.106	
Like taking transit	-0.28	0.038	***	-0.27	0.043	***	1.314	0.161	***	1.474	0.191	***	0.464	0.058	***	0.474	0.093	***
Like driving	0.145	0.038	***	0.169	0.043	***	-0.337	0.143	**	-0.283	0.194		-0.174	0.059	***	-0.31	0.093	***
Residential unit density	-0.01	0.002	***	-0.01	0.002	***	-0.001	0.004		0.01	0.007		0.008	0.002	***	0.017	0.003	***
ACTION wave 2	-0.06	0.044		-0.06	0.049		0.346	0.158	**	0.484	0.224	**	0.043	0.068		-0.11	0.108	
ACTION wave 3	-0.09	0.046	**	-0.05	0.052		0.355	0.168	**	0.267	0.239		0.05	0.071		-0.02	0.114	
Constant	0.198	0.146		2.534	0.158	***	-2.036	0.485	***	-0.339	0.702		-0.987	0.222	***	0.97	0.342	***
N	983			983			983			983			983			983		
Log-Likelihood	-1,743.99			-4,567.02			-476.944			-1,655.11			-1,306.32			-3,437.44		
AIC	3525.98			9172.04			991.888			3,348.21			2,650.64			6,912.88		
Note: *p<0.1; **p<0.05; ***p<0.01																		

Models (1) and (2) show that, respectively, when controlling for the count and duration of total trips and other control variables, more ride-hailing usage is significantly associated with less driving at 0.05 level. This is consistent with previous research findings that suggest ride-hailing can serve as a viable alternative to driving (Feigon and Murphy, 2016; Henao and Marshall, 2018). Total trip count and duration show an expected positive association with driving, as individuals with stronger travel demand tend to drive more. Other control variables also help explain the count and duration of driving. Females tend to drive more than males. It is likely that females share more household chores such as chauffeuring children or grocery shopping that often require driving. Higher educational attainment is associated with a greater likelihood to drive. Household composition is a significant factor, as shown by more driving by participants from smaller households, and households with more children. To elaborate, when controlling for the number of children, the household size variable captures the number of adults in the household. Therefore, the negative sign of the household size variable suggests that when there are more adults in the households, each individual adult needs to shoulder less household responsibility and drive less. Attitudinal variables show significant and strong effects. Participants who have a more positive attitude toward driving and a less positive attitude toward transit are more likely to drive. Participants who live in denser built environments are also less likely to drive. This may either indicate that a denser built environment allows individuals to access destinations with modes other than driving, or that self-selection is taking place where individuals who do not like to drive choose to live in denser neighborhoods. Lastly, the wave dummies capture the second and third waves' time-specific impacts on the entire sample. The significant negative estimation at wave 3 in the count model suggests a reduction in driving. It is possibly a reflection of the opening of the BRT lines. There were other infrastructure, service, and policy changes in the region during the time

period, which all could have contributed to fewer driving trips. However, such an effect is not observed in the duration model, suggesting that participants tend to make fewer but longer driving trips at wave 3.

Models (3) and (4) both show a positive association between ride-hailing and public transit, which suggests complementarity between ride-hailing and public transit. However, this relationship is not statistically significant. This is different from the results reported in many previous studies based on convenience sample surveys. Many other variables that are significant in these two models are also significant in Models (1) and (2), but with opposite directions of effect, reflecting that driving and transit may be competing modes. One exception is the race variable, which is not a significant variable in the first two models. The negative association between being white and public transit usage suggests that the non-whites are more likely to rely on transit in the Seattle region, and thus transit serves as an important mobility option for them.

Models (5) and (6) suggest a weak and not significant negative association between ride-hailing and walking and biking. Again, many control variables show the expected directions of effect that are opposite to those in Models (1) and (2), because driving and active transportation modes are options typically taken by different population groups with distinctive demographic and socioeconomic characteristics. Racial differences also exist in the mode choices for walking and biking, indicating that being white is associated with more walking. Also, household size and the number of children are significantly related to walking and biking in the count model, but not in the duration model. It shows that individuals from smaller households and with more children tend to make fewer walking trips. Lastly, the positive estimation of residential density suggests that participants who live in denser neighborhoods are more likely to choose walking and biking.

Independently pooled models assume that observations are drawn independently and ignore serial correlation in the data. Therefore, I estimate additional fixed-effect models to test if the identified relationships between ride-hailing and other modes still hold after controlling for serial correlation. Table 2.6 presents the results, which show that how, at the participant level, a one-unit change in an independent variable would affect the dependent variable over time. The models include all variables shown in Table 2.5, except for those that are time-invariant. Table 2.6 displays the results for the travel behavior variables. Most control variables show the same directions of effect as in the independently pooled models and hence are not included in this table to save space.

Table 2.6 confirms the key findings from independently pooled models. As shown in Models (7) and (8), ride-hailing is negatively associated with driving, and the relationship is statistically significant. These results tell us that for a specific participant, over time, an increase in the average daily ride-hailing trip count and duration is associated with a decrease in the average daily driving trip count and duration. No statistically significant association is found between ride-hailing and transit use or walking and biking in Models (9) to (12).

Table 2.6 Fixed-effect model results

	Driving						**Public transit**						**Walking and biking**					
	(7)			**(8)**			**(9)**			**(10)**			**(11)**			**(12)**		
	Count			**Duration**			**Count**			**Duration**			**Count**			**Duration**		
	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.
Ride-hailing count	-0.35	0.21	*				-0.02	0.02					0.00	0.30				
Total trip count	0.16	0.01	***				0.01	0.00	***				0.19	0.02	***			
Ride-hailing duration				-0.03	0.01	**				-0.01	0.01					0.00	0.01	
Total trip duration				0.01	0.00	***				0.01	0.00	***				0.01	0.00	***
N	983			983			983			983			983			983		
Log-Likelihood	-203.97			-2,379.63			-137.58			-400.88			-484.43			-1,649.65		
AIC	435.94			4,787.26			301.15			829.76			996.85			3,327.30		

Note: *p<0.1; **p<0.05; ***p<0.01

Variables in the control group were included in all models as in Table 2.5, except for those that are not time-variant, but are not shown here.

2.6 Discussion and Limitation

The estimated models show that cross-sectionally, participants who take more ride-hailing trips tend to make fewer driving trips. The association remains longitudinally in that for a specific participant, an increased number of ride-hailing trips over time is also associated with a decreased number of driving trips. This finding provides evidence that ride-hailing may be a viable substitute for driving. However, the models do not show any statistically significant impact of ride-hailing on public transit or walking and biking.

These empirical results are based on data that bundle traditional taxi and new (e.g., Uber and Lyft) forms of ride-hailing into a single variable. The inability to distinguish among Uber, Lyft, or taxi trips is a limitation because it is not possible to confirm changes in the use of the different ride-hailing options. However, it appears that the data effectively capture the new app-based ride-hailing trips for the following reasons:

1) Average daily count and duration of ride-hailing trips in the ACTION data doubled within the six years, which implies the growing presence of the new form of ride-hailing, as traditional taxi ridership first declined after the entry of the new ride-hailing services (Vaughn, 2014).

2) While it is possible that some participants enter their app-based ride-hailing trips into the survey's last category 'other', the observed data suggest this is unlikely to be the case, because the mode share of 'other' did not increase during the study time period.

3) The shares of trip count and trip duration for ride-hailing in the ACTION data aligns with those of the National Household Travel Survey (NHTS) data, and are higher than those of the PSRC travel survey data. Ride-hailing options in NHTS and PSRC surveys include separate entries

for trips taken by traditional taxi or by Uber/Lyft. This alignment is another indication that the ACTION data adequately capture both traditional and new ride-hailing options.

4) It should be noted that taxi companies in the Seattle region quickly became app-based after Uber and Lyft entry into the marketplace (Vaughn, 2014). Since 2014, they function in a way that greatly resembles Uber and Lyft.

Finally, this study data come from populations living in transit-rich areas of a major metropolitan region. As a result, research findings cannot be generalized and further analyses will be required using data from different population groups and geographical areas.

2.7 Conclusion

This study uniquely attempts to apply longitudinal data to probe the impacts of ride-hailing, consisting of both taxis and app-based services, on other modes at the individual level. The findings deepen our understanding of the substitution and complementarity effects of new mobility services. The results suggest that ride-hailing substitutes for driving, but does not have a significant relationship with transit or walking and biking. In other words, these services so far generate rather limited direct impacts on the more environmentally sustainable travel options. The identified substitution effect of ride-hailing on driving is two-fold: first, among participants, those who use more ride-hailing tend to drive less; and second, over time, the increase of ride-hailing usage is also associated with fewer driving trips.

I believe that this study is informative for transportation professionals who want to better understand how new mobility options fit within the range of available mode choices. This knowledge is essential for policymaking in the era of app-based mobility sharing. Since ride-hailing shows a significant substitution effect on driving, it may create opportunity to reduce

dependency on private automobile as the new form of ride-hailing becomes more prevailing. Planners and policymakers should actively monitor the changing usage of app-based mobility services, and be prepared to facilitate the transition. On the other hand, our study does not find a substitution effect of ride-hailing on public transit or walking and biking. This result suggests that transportation planners should explore the potential for integrating on-demand, app-based mobility options into urban transportation systems.

To gain a deeper understanding of the impacts generated by the growing use of app-based ride-hailing, existing survey collection methods need to be updated. Survey instruments should be modified to explicitly ask about the usage of app-based ride-hailing as a mode choice. In addition, longitudinal data should be collected for monitoring urban mobility trends, which can better inform future transportation planning and policymaking.

Chapter 3. A Latent Class Analysis Approach to Understand Riders' Adoption of On-Demand Mobility Services as a Complement to Transit

3.1 Introduction

As mentioned in Chapter 1, early evaluations suggest many existing TIMOD pilots achieved promising results. For example, many evaluations reported that the on-demand services provided were popularly adopted by riders (Gifford et al., 2021; King County Metro, 2020; Martin et al., 2020a; Miller et al., 2021). However, the exact impacts of incentivizing on-demand shared mobility on rider's travel behavior remain largely unknown, and more rigorous examinations are needed for the following reasons.

First, introducing and incentivizing on-demand mobility services offers riders in the service area a competitive option for travel, and draws riders from different travel modes. However, most of the evaluations of existing TIMOD pilots were limited to simple descriptive statistics, and little is known about riders' heterogeneous responses to the pilots and subsidies. For example, the implications of adopting on-demand modes are different between riders who switch from walking from those who switch from taking buses, between riders who travel alone for commuting and riders who travel in groups for recreational purposes, or between riders who value convenience and riders who value cost. Without a granular understanding of whom TIMOD pilots primarily serve, it is difficult for transit agencies to better tailor future mobility policy innovations to specific rider groups.

Second, TIMOD pilots often invest a substantial amount of funds to incentivize on-demand shared modes, with the hope that such subsidies can benefit those who are socioeconomically disadvantaged and mobility challenged (Gifford et al., 2021; King County Metro, 2020; Miller et

al., 2021). However, the social equity implications in the distributions of the investments remain a question, as the nature of the app-based travel creates technological barriers for people to comfortably access and use the service (Moudon, 2020). For example, Shen et al. (2021) found that incentivizing app-based carpooling for commuting in the Seattle region had unintended consequences such as disproportionally benefiting high-income employees. Therefore, it is important to analyze and compare among different groups of riders who adopt the on-demand services, and make sure that socio-economically disadvantaged riders at least benefit equally from the pilots.

This research aims to fill in the gaps as one of the first studies examining the impacts of TIMOD pilots on riders' travel behavior. The study uses a TIMOD pilot, Via to Transit in the Seattle region as a case study. Specifically, the study aims to answer the following questions:

1) Are there distinct patterns in the adoption and usage of on-demand mobility services among riders?

2) Can these distinct differences be explained by riders' socio-demographic statuses and built environment characteristics?

3) Learning from the answers to the above two questions, what should transit agencies consider when designing and implementing TIMOD pilots in the future?

To answer these questions, this study conducts latent class analysis (LCA) on the survey data from Via to Transit riders. LCA is a statistical modeling technique that can systematically identify latent (unobserved) subgroups that share certain (observed) commonalities within a population. The chapter proceeds with a literature review of how riders perceive and use the on-demand services as complements to traditional transit. Then the chapter will introduce Via to

Transit program, data, and the methodological details of LCA. Next, the chapter will present and interpret the latent classes identified by the LCA. The chapter concludes with discussions and policy implications derived from the LCA results.

3.2 Literature Review

3.2.1 *On-demand shared mobility modes as complements to public transit*

Even without transit agencies' explicit efforts to integrate and incentivize shared mobility modes, riders have 'naturally' adopted them (often app-based ride-hailing) as complementary modes to public transit, most commonly to mass transit such as Light Rail and bus rapid transit. At the individual level, correlations between a person's usage of shared mobility modes and public transit use were often reported (Grahn et al., 2020; Tirachini, 2020; Young and Farber, 2019). At the aggregate level, the introduction of app-based ride-hailing was shown by some researchers to be positively associated with transit ridership, in particular for small transit agencies in larger cities, which strongly implied the use of app-based ride-hailing as a first-mile/last-mile solution for longer transit trips (Hall et al., 2018). However, these studies only indicated an association between shared mobility modes and transit, instead of evidence that the two modes are taken in junction with each other.

A few recent studies directly modeled the mode choices of access and egress modes for transit using discrete choice models. For example, Zgheib et al. (2020) modeled the choices of feeder modes to transit with stated-preference data collected from Beirut, and their results show that app-based ride-hailing was perceived as a popular choice, especially among younger commuters. Azimi (2021) employed data from an onboard transit rider survey in Orlando, FL, and

identified the associations between using app-based ride-hailing as a feeder to transit and various socio-demographics, trip-related factors, and built environment characteristics.

3.2.2 *Why are TIMOD pilots desirable?*

These results from the above literature demonstrate the potential of integrating on-demand shared mobility modes with public transit. However, I argue that only 'natural' or purely market-driven adoptions may fail to fully achieve the potential of on-demand shared mobility modes.

First, both Zgheib et al. (2020) and Azimi (2021) suggest that the 'natural' adoption of on-demand modes as feeder modes is constrained to a niche market. The riders of TIMOD largely overlap with the early adopters and frequent users of new transportation technologies in general, who are young, central-city dwellers, and tech-savvy (Circella et al., 2018; Clewlow and Mishra, 2017; Vij et al., 2020; Young and Farber, 2019). Even among them, the use of on-demand modes is still occasional (Tirachini, 2020), and only for specific trip purposes such as getting to airports or avoiding drunk-driving (Azimi et al., 2021; Young and Farber, 2019). A major barrier to choosing on-demand modes to access/egress transit is the high market-priced fare of on-demand modes, as Zgheib et al. (2020) demonstrated. Other barriers may include the lack of an integrated payment system and difficulties in multi-modal trip planning. It is thus interesting to know with the subsidies provided and better-integrated services, whether TIMOD projects can overcome some of the barriers and provide more inclusive mobility access.

Second, a 'natural' adoption of using on-demand shared mobility modes may not be sufficient to promote the use of transit for societal benefits. From an urban economics perspective, public transit is known to have positive externalities because of its impacts on reducing congestion, environmental pollution, and road collision when compared with private car use (O'Sullivan,

2012: 11). TIMOD pilots are essentially a new form of transit subsidies that reduce a rider's total generalized cost for accessing/egressing public transit. They may therefore help internalize the positive externalities of the transit.

Third, literature has realized that not all shared mobility modes are beneficial to the cities. Among shared mobility modes, app-based ride-hailing is the most adopted mode (Heineke et al., 2021). However, literature has pointed out that the level of mobility sharing (i.e., the passenger occupancy rate) of app-based ride-hailing tends to be low (Henao and Marshall, 2018; Shen et al., 2021). As a result, they exacerbated road congestion instead of reducing it (Diao et al., 2021). TIMOD pilots can thus be opportunities for transit agencies to strategically select alternative mobility service providers (i.e., ride-pooling, micro-transit) to partner with, and thus encourage greater mobility sharing. They can also purposefully deploy vehicles with a high level of capacity (Tirachini et al., 2020). This is, in particular, promising in the case of first-mile/last-mile solutions, as riders would share the same origins or destinations (i.e. the transit stops), and thus the trips can be more 'sharable'.

Riders' preferences and adoptions of TIMOD pilots

As most of the TIMOD pilots in the United States are still under development, few studies were able to use real-world trip and survey data collected from these pilots to examine riders' adoption. Alternatively, many studies have used a stated preference survey to collect riders' preferences and choices if a hypothetical on-demand service was offered instead of traditional transit. Yan et al. (2019) forecasted the adoption of a proposed TIMOD project on a college campus using data collected from surveying students, staff, and faculty. Yan et al. (2021) and Wang et al. (2022) were a series of efforts that analyzed the attitude of residents in low-income neighborhoods toward

TIMOD, where they found associations between preferences towards the proposed TIMOD pilot and population characteristics, and identified major barriers if the pilot was implemented. These studies, although offering timely insights for transit agencies, were largely exploratory as they asked about riders' adoption of the service in hypothetical scenarios, instead of observing riders' behavior and experience after actually using the service provided in the TIMOD pilot. This study is an attempt to fill in this gap by using survey data collected from riders of a real-world TIMOD pilot, supplemented by riders' complete service usage records.

3.3 Background, Data, and Methodology

3.3.1 *Via to Transit program*

Via to Transit is a TIMOD pilot that allows people located within the specified service areas to request rides to/from one of five Link Light Rail stations: Mount Baker, Columbia City, Othello, Rainier Beach, and Tukwila International Blvd Station. The program - employs on-demand, accessible shared mobility services as a first-mile/last-mile connection to Link Light Rail. Figure 3.1 shows the five Link stations and the corresponding service areas. Before the COVID-19 pandemic in 2020, the service operated daily from 5 AM to 1 AM from Monday to Saturday, and from 6 AM to 12 AM on Sunday in stations except for Tukwila station. At Tukwila station, the service operated between 6 AM and 9 AM and between 3:30 PM and 6:30 PM on weekdays.

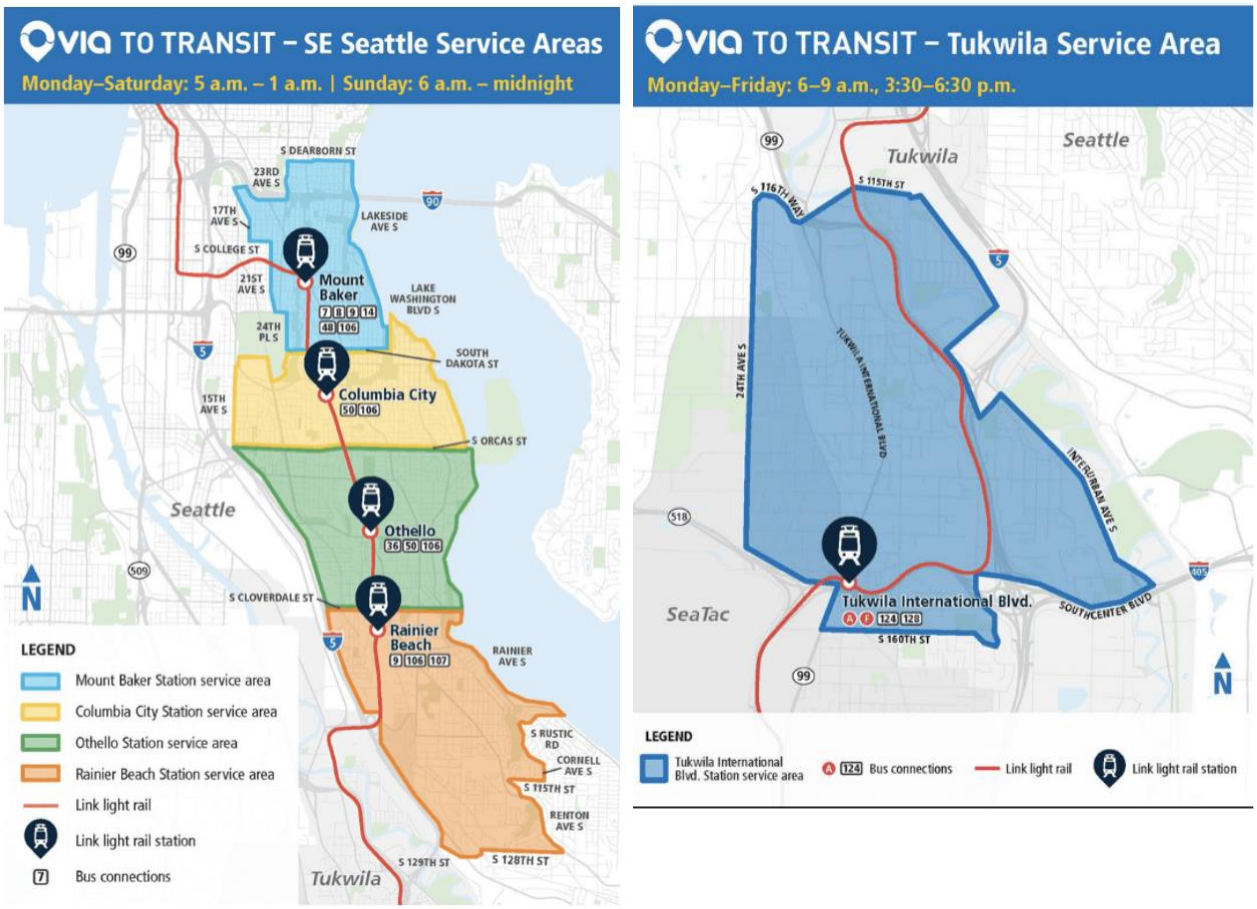


Figure 3.1 Via to Transit service areas and Link Light Rail stations

Source: King County Metro (2021)

KCM partners with Via, an on-demand mobility service provider, to operate the service with Via's drivers, fleets, Via apps, and call centers. Via to Transit service uses minivans to operate, and Figure 3.2 shows the exterior and interior of such a vehicle. Travelers typically book the Via to Transit rides through the Via app[1]. To travelers, Via to Transit costs the same as KCM's fixed-route services, as shown in Figure 3.3. Riders typically paid the fare with an ORCA card (the smartcard for paying transit fare in the region), while other payment options such as credit

[1] A call center was available for travelers who did not have access to a smartphone or data plan

cards, debit cards, and mobile payment through KCM's Transit GO app were available. KCM was responsible for the remaining portion of Via's operating cost.

Figure 3.2 Exterior and Interior of the vehicles that provide Via to Transit service
Source: King County Metro and Toyota

Adults (19 and older)	$2.75
Youth (6-18 yrs)	$1.50
ORCA LIFT Cardholders (Income qualified)	$1.50
RRFP cardholders (registered seniors, Medicare, disabled)	$1.00

Figure 3.3 Via to Transit fare (same as KCM standard transit fare)

Studying the adoption and usage of riders of Via to Transit offers timely, transferrable insights for both KCM and other transit agencies. KCM is a transit agency that serves a medium-to-large sized U.S city, and the Link Light Rail is currently the only Light Rail line and the 'backbone' of the public transit system in the region. Via to Transit thus provide meaningful mobility access in the service areas. Instead of a short-term, small-scope experiment, Via to Transit lasted for a year from April 16, 2019, to March 23, 2020, carrying about 230,000 trips[2]. As shown in Figure 3.4, the ridership of Via to Transit quickly increased since April 2019, peaked around October 2019, and stabilized thereafter. Therefore, its outcomes can shed light on the long-term impacts of such mobility pilots on riders. In addition, the five service areas consist of neighborhoods with a relatively high percentage of racial minorities and low-income populations. Studying Via to Transit thus offers invaluable knowledge regarding the social equity implications of such mobility pilots.

In addition, there are a few characteristics of the Via to Transit service that are worth highlighting:

- Via to Transit rides can only be booked on-demand. When successfully booking a ride, the app informs travelers about the estimated time of arrival.
- Via to Transit serves any number of travelers, i.e., there is no minimum number of riders for booking the trip.
- Via to Transit rides are commonly shared by multiple groups of travelers.
- Riders are usually asked to walk a short distance to/from a convenient location for pick-up/drop-off.

[2] The service was suspended due to the COVID-19 pandemic. In 2021, the service was partially resumed. The data used in this dissertation were from the service operation prior to the pandemic.

- At the pick-up location, Via drivers would wait for travelers for maximum two minutes beyond pick-up time before proceeding to the next traveler.
- Via to Transit is not available for trips to or from locations within a quarter mile of the stations except for travelers with disabilities.

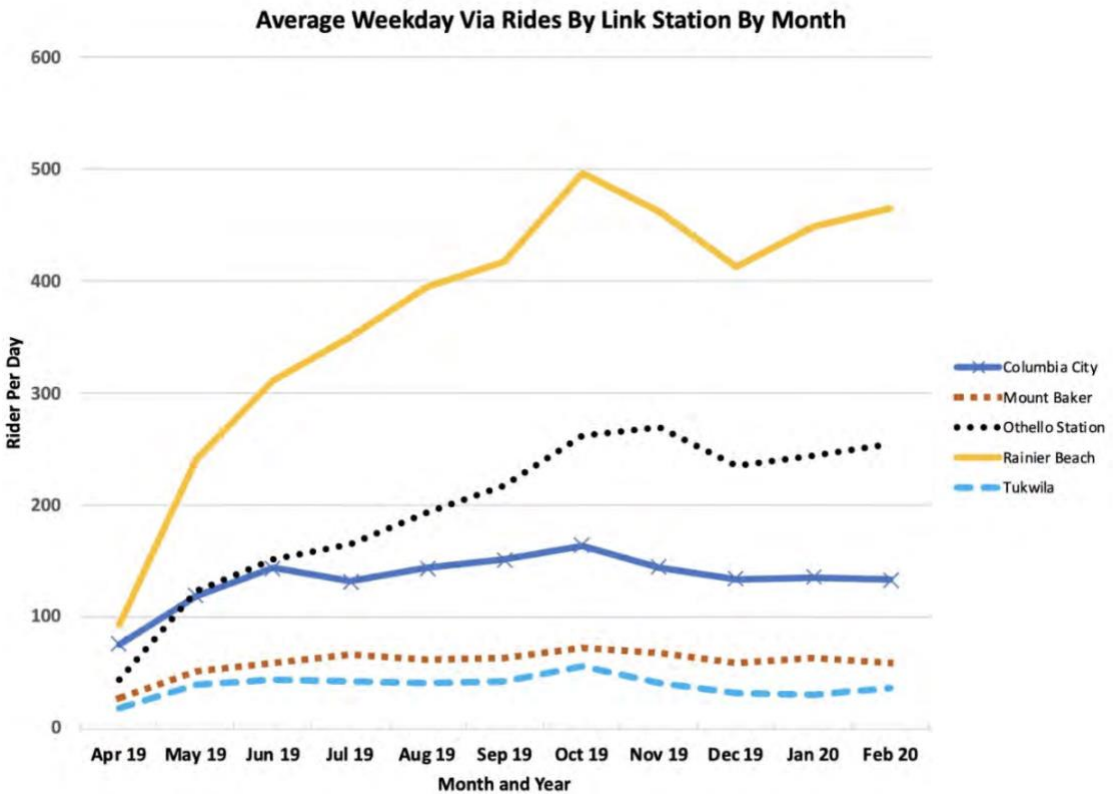


Figure 3.4 Via to Transit average weekday ridership by station

Source: Gifford et al. (2021)

Figure 3.5 shows the distribution of Via to Transit riders' most frequent travel location, where the darker color indicates locations that a higher number of riders traveled to. This is obtained from the Via to Transit trip data. Since trip purpose information is not available for each trip, I am not able to know whether the most frequent travel location was the rider's home, workplace, favorite restaurants, or other places. The only thing I know for sure is that this was one

end (either origin or destination) of the Via to Transit trip (the other end is the Light Rail station), and this was the location that the riders most traveled to. Figure 3.5 shows that there were more riders in the four service areas upper on the map, and fewer riders from the Tukwila International Blvd Station service area. Within the four service areas, riders were in general spread out while there existed a few 'hotspots' where riders were concentrated.

Figure 3.6 shows the median household income of Census Block Groups in the service areas. Neighborhoods with relatively high median income are those in the north of the area and close to the waterfront on the east, while many neighborhoods in the south are with lower income.

Figure 3.7 is the land use map of the Via to Transit service areas, excluding the one of Tukwila International Blvd Station. The area consists primarily of land zoned as single-family residential. There are commercial/mixed-use and multi-family residential lands along major transportation corridors.

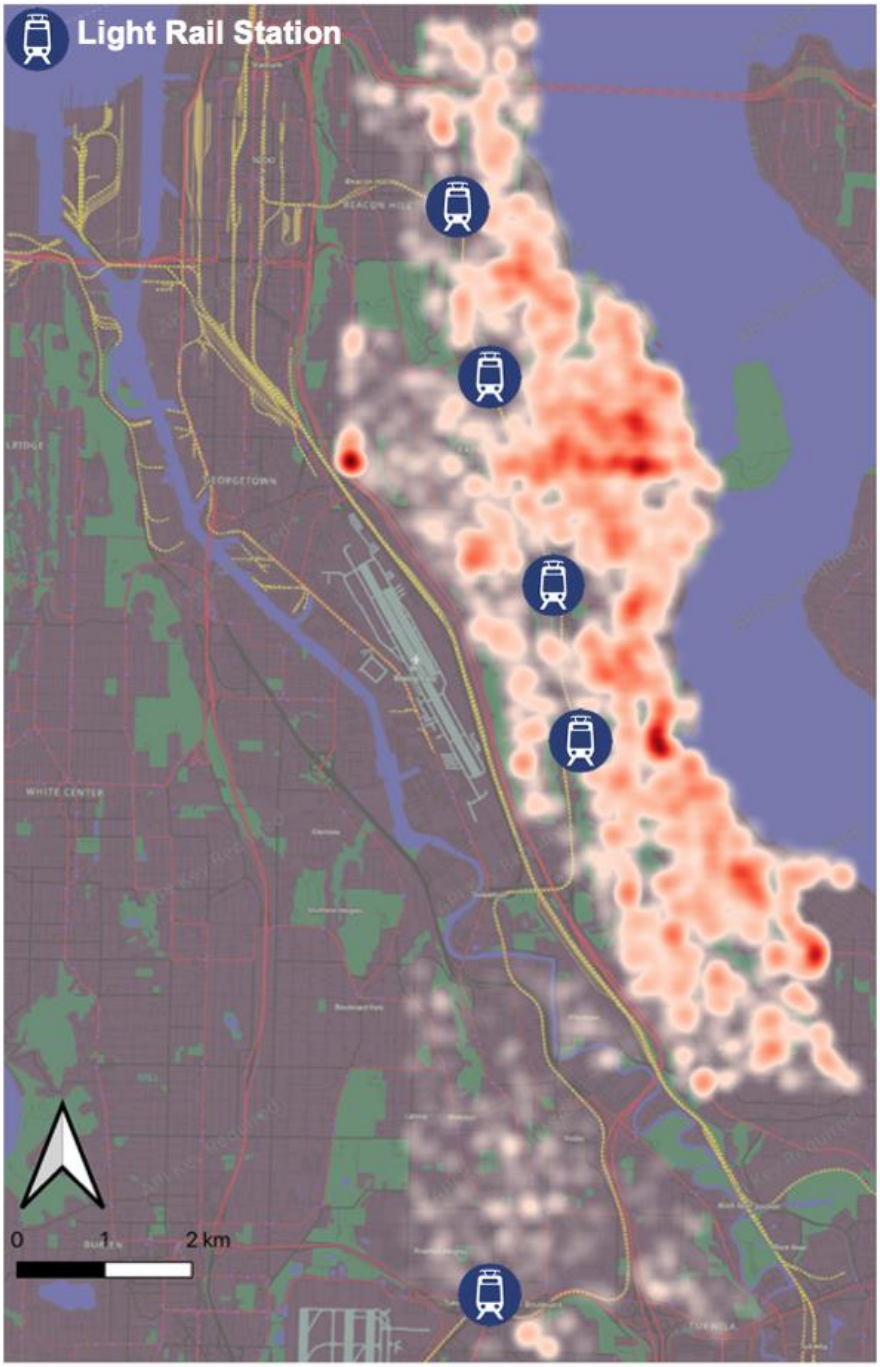


Figure 3.5 Heatmap of Via to Transit riders' most frequent travel location (darker color = higher rider counts)

Source of the base map: Open Street Map

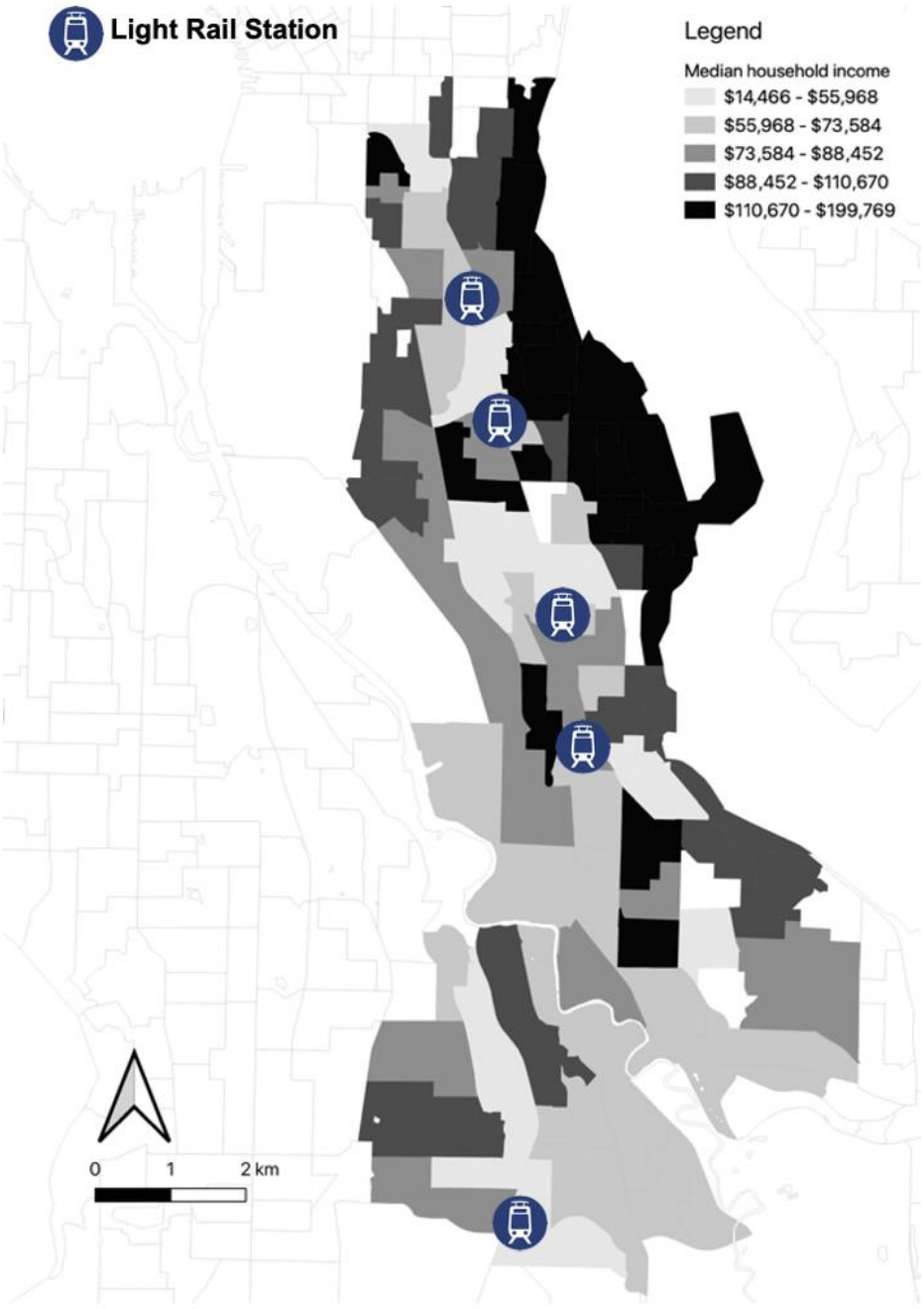


Figure 3.6 Median household income of Census Block Groups in the Via to Transit service areas (with 5-quantile classification)

Data Source: US Census Bureau (2022)

Figure 3.7 Land use in the Via to Transit service areas (excluding Tukwila International Blvd Station)

Source: City of Seattle (2019)

3.3.2 *Data*

This research primarily uses Via to Transit rider survey data while integrating some information from Via to Transit trip records. Via rider survey was administrated by King County Metro and distributed to Via to Transit riders by sending an email with the survey link. The survey collection started on December 3, 2019, about 8 months after the launch of the Via to Transit project, and ended on January 20, 2020. Survey respondents were offered a chance to draw a $100 Visa gift card. The survey questionnaire consisted of two sections, one asking questions related to Via to Transit service and Link Light Rail usage, and the other covering respondents' basic personal and household information. Survey respondents can be linked to Via trip data through a unique, anonymous ID. The raw data contains 1272 samples. I followed a data cleaning procedure as in Table 3.1 and obtained an effective sample size of 925.

Table 3.1 Via rider survey data cleaning process

	Step	N (remaining)
1	Original raw data	1272
2	Riders who had at least one completed Via trip record[3]	1208
3	Riders who did not skip the socio-demographic section of the survey	1110
4	Riders who took Via for first-mile/last-mile solution for Link Light Rail[4]	988
5	Riders who responded to all survey questions except for income[5]	925

[3] The remainder could be riders who used the app and requested rides, but did not complete the trip. Or it could be riders who used credit card instead of the ORCA card (the transit smart card in the region) to pay Via to Transit, which results in survey data unable to be linked to the trip records.

[4] The remainder did not use Via to Transit as the access/egress mode to public transit. It is possible that their travel origins/destinations are near the Light Rail stations. These riders did not answer questions related to Link Light Rail usage, and thus needed to be dropped.

[5] Due to the fact that a large number of survey respondents (n=227) chose not to disclose their household income, I tested two models, one with N = 698 and the income variable containing three levels: 0 - $49,999, $50,000 - $100,000, and >$100,000), and the other one with N = 925 and the income variable four income levels: 0 - $49,999, $50,000 - $100,000, >$100,000, and prefer not to answer income. The latent classes identified in LCA between the two models are largely consistent. The one with larger sample comes with smaller standard errors, which helps interpret and explain the identified classes. In this chapter, I present the model with N = 925.

3.3.3 *Methodology*

This study employs LCA, a statistical technique that identifies latent, unobserved subgroups (or classes) within a population using manifested, observed characteristics (Vermunt and Magidson, 2004). LCA has two components, as illustrated in Figure 3.8, a measurement model that determines/generates latent classes from observed indicators, and a membership model that predicts/explains the identified latent classes using a series of covariates. In this study, the indicators are variables related to the service usage and travel behavior changes associated with Via to Transit, and therefore the latent classes represent heterogeneity in the riders' responses to the TIMOD service provided. The measurement model detects latent groups by maximizing the differences in indicators across latent classes. In the second component, the covariates are riders' socio-demographics and built environment characteristics, and thus the membership model explains the associations between these covariates and the probability of a rider belonging to a specific class. The two components of LCA are estimated jointly.

LCA and its extensions are increasingly popular in travel behavior research, and in particular, on the attitude, adoption, and usage of new transportation technology (Alemi et al., 2018; Lee et al., 2022; Vij et al., 2020; Wang et al., 2022). However, its pros and cons, in particular when compared to commonly used regression models, need to be more thoroughly discussed. The most distinct feature of LCA is that it is 'person-oriented' (Weller et al., 2020). Instead of being 'variable-oriented' and finding associations between variables, LCA finds associations across individuals and groups them. This approach thus better informs the outcomes of transportation policy at the individual level. Second, as a direct result of the above feature, instead of narrowly focusing on a limited number of dimensions of the travel behavior (i.e., mode choice or service

use frequency), the results of the LCA gives us an elegant, interpretable representation of individuals' variations in much greater dimensions. With that being said, unlike traditional regression models, it is not easy to obtain some quantities that might be of interest to policy-makers, such as marginal effects and elasticities between variables, from the LCA model.

A few additional features of the LCA make it an appropriate method for our study: 1) the LCA uses individuals' responses to categorical indicator variables, which works well with data collected from survey questionnaires; 2) LCA determines class from the data, and does not require prior assumptions regarding the model specifications (Alemi et al., 2018; Weller et al., 2020).

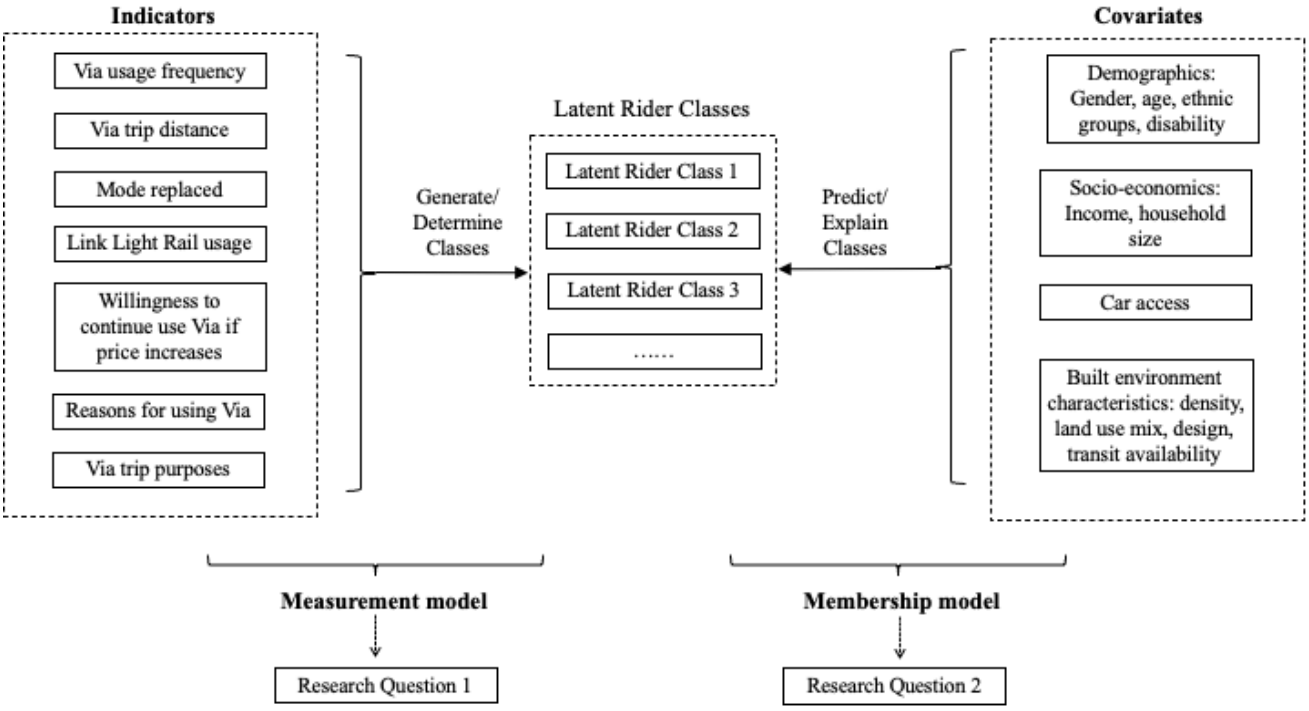


Figure 3.8 LCA model framework

Table 3.2 and Table 3.3 show the list of indicators and covariates used in the LCA of this study, respectively. Most indicators came directly from the Via to Transit rider survey. I regrouped the categories of several indicators from raw survey data to ensure the distributions among categories

were balanced. Two additional indicators, the number of Via to Transit trips and average Via to Transit trip distance, were obtained from the Via trip data and transformed from a continuous scale to a categorical one, as LCA requires the indicators in the measurement model to be categorical. Regarding covariates, in addition to using the information from the Via to Transit rider survey, I obtained four additional built environment measures for each Via to Transit rider's most frequent travel location [6] from the Smart Location Database (Chapman et al., 2021). These built environment variables are at the Census Block Group (BG) level and represent the location's density, land use diversity, street design, and frequencies of transit services. I log-transformed three of them because the original distributions are severely right-skewed, as shown in Table 3.4. Variance inflation factors (VIF) of all covariates in the membership model were screened, and all variables had a VIF of less than 3, which suggests the extent of multicollinearity was moderate.

Table 3.2 List of indicators – variables used to determine class membership

	Categories	Source
Number of Via to Transit trips (one-year period)	K = 5 (1 – 4; 5 – 14; 15 – 49; 50 – 99; >100)[7]	Via Trip Data
Avg. Via to Transit Trip Distance of the rider	K = 2 (< 1.5 miles; >= 1.5 miles)	Via Trip Data
Mode replaced	K = 5 (Personal car; Bus; Walk and Bike; Ride-hailing; Others)	Via Survey Data
Days of using the Link Light Rail per week	K = 4 (Less than once; 1 or 2 days; 3 or 4 days; 5 or more days)	Via Survey Data
Via usage if the price doubles	K =3 (Won't use anymore; Use less; Use the same)	Via Survey Data

[6] This is obtained by joining the unique ID of the survey data to Via to Transit trip data. Since trip purpose information is not available for each trip, I am not able to know whether the most frequent travel location is the rider's home, workplace, favorite restaurants, or other places. The only thing I know for sure is that this is one end (either origin or destination) of the Via to Transit trip (the other end is the Light Rail station), and this is the location that the riders most traveled to.

[7] I chose K=5 to make sure that there are sufficient numbers of samples in each category (i.e. K is not too large), and categories together represent rich variation in number of Via to Transit trips (i.e., K is not too small).

Safety is one of the reasons for switching to Via	K = 2 (Yes; No)	Via Survey Data
Convenience/faster travel is one of the reasons for switching to Via	K = 2 (Yes; No)	Via Survey Data
Cost is one of the reasons for switching to Via	K = 2 (Yes; No)	Via Survey Data
Has utilitarian trip purpose (work, school, errands)	K = 2 (Yes; No)	Via Survey Data
Has recreational trip purpose	K = 2 (Yes; No)	Via Survey Data

Table 3.3 List of covariates – variables used to explain class membership

	Variable Type	Source
Rider's socio-demographics		
Gender	Categorical, K = 2 (Female; male and other)	Via Survey Data
Age	Categorical, K = 4 (<25; 25-44; 45-64; >65)	Via Survey Data
Race	Categorical, K = 2 (White; other)	Via Survey Data
Household size	Categorical, K = 3 (1; 2; 3 or more)	Via Survey Data
Income	Categorical, K = 4 (< $50,000; $50,000 - $100,000; >$100,000; *Prefer not to answer)	Via Survey Data
Car available for the trip	Categorical, K = 2 (Yes; No)	Via Survey Data
Having a checking account	Categorical, K = 2 (Yes; No)	Via Survey Data
Disability	Categorical, K = 2 (Yes; No)	Via Survey Data
Census BG's Built Environment Characteristics of Rider's Most Frequent Travel Location		
Population density (log)	Continuous Gross population density (people/acre) on unprotected land[8]	EPA Smart Location Data, 2021
Employment and household entropy	Continuous This variable uses five-tier employment categories and the number of occupied housing units to calculate the entropy. It represents land use mix	EPA Smart Location Data, 2021

[8] Unprotected land means land that is not protected from development, for example, a park or conservation land. It's used by EPA to calculate density-related measures.

Street intersection density (log)	Continuous Number of street intersections (auto-oriented intersections eliminated) per square mile	EPA Smart Location Data, 2021
Frequency of transit service per square mile (log)	Continuous Aggregate frequency of transit service per hour per square mile[9]	EPA Smart Location Data, 2021

Table 3.4 Descriptive statistics for built environment variables (in their original values)

Built environment variables	Mean	Min	Median	Max
Population density (people/acre)	11.6	0.5	13.4	31.5
Employment and household entropy	0.4	0.1	0.4	0.8
Street intersection density (number of intersections/square mile)	137.5	25.8	147.1	320.2
Frequency of transit service (frequency/square mile)	218.2	14.0	178.3	960.4

For LCA, the number of latent classes needs to be pre-determined. Model fit and interpretability are two important factors when making such a decision. One common approach is to run LCA with different numbers of classes and choose the one with the best model fit, measured by the Akaike information criterion (AIC) or Bayesian information criterion (BIC). Table 3.5 shows the model fit with different classes, where a smaller AIC or BIC suggests a better fit. Based on the results, AIC favors 4 classes and BIC favors 3 classes. After examining the model outputs in these two models, I choose the one with 3 classes because its classes are more distinctive from

[9] The frequency of transit service is calculated by aggregating the frequency per hour of all transit routes within 0.25 miles of the boundary of the CBG during weekday peak hours. The frequency is then divided by land area to get frequency per square mile.

each other and thus the results are more interpretable. The model is estimated using the 'poLCA' package in R.

Table 3.5 Model fit with different number of classes

	2 Classes	3 Classes	4 Classes
AIC	15024	14710	14589
BIC	15275	15125	15169

3.4 Results

3.4.1 *Results of the measurement model*

Table 3.6 shows the three classes identified by the measurement model[10]. The first row shows that the sizes of Class 1, 2, and 3 are 34%, 39%, 27% of the total sample size (N = 925), respectively. Each value starting from the second row is the posterior probability of riders within the class being in the corresponding category of the indicator. For example, the first number, 0.59, indicates that 59% of riders in Class 1 conducted 1-4 Via to Transit trips during the one-year pilot. The bold numbers are the highest values for each row. For example, among three classes, Class 1 has the highest percentage of riders that conducted 1-4 Via to Transit trips. Table 3.6 thus presents an easy-to-interpret way to understand the three classes by reading the class-specific distribution of indicators.

Class 1 has the highest share of riders who used Via to Transit occasionally, with 59% of them only taking 1-4 Via to Transit trips, and 31% of them taking 5-14 trips. The class had the highest share of riders who switched from private motorized modes, i.e., personal car (41%) and ride-hailing (14%). It was the class that was least dependent on the Light Rail, with 82% of riders

[10] The algorithm of LCA is sensitive to the initialization. I therefore had 'poLCA' package re-run the model for multiple times, which automated the search for the global, rather than local optimum.

only using the Light Rail less than once a week, which also explained the infrequent use of Via to Transit. The class was least sensitive to price with the highest percentage of riders indicating they would still use Via to Transit even if the price increased. This class was least likely to adopt Via to Transit because of safety (19%), least likely to travel for utilitarian purposes (52%), and most likely to travel for recreational purposes (70%).

Class 2 consists mostly of riders whose Via to Transit trip distance was on average less than 1.5 miles (99%), which makes sense as the class had the highest share of riders who previously walked or biked to the station (60%). Riders in this class needed to access the Light Rail frequently as 35% of them rode the Link 5 or more days a week. The class was price-sensitive, with 39% of them would stop using Via to Transit if the price increased. The class had the highest share of riders who switched because of safety (44%). Almost all of them had utilitarian trip purposes (i.e., work, school, or personal errands) (99%).

Class 3 contained frequent Via to Transit riders, as 19% of them took 50-99 Via to Transit trips and 30% of them took more than 100 trips in a year. They were more likely to be riders whose trip distance on average exceeded 1.5 miles (75%). They were likely to be frequent transit riders with the highest share of riders who previously took the bus to access Link stations (46%) and a relatively high percentage of riders who took Link Light Rail 3 or 4 days (32%) or 5 days or more (34%) in a week. Similar to Class 2, Class 3 was also price sensitive as 39% of them would stop using Via to Transit if the price increased. A large proportion of riders (84%) in Class 3 switched because of Via to Transit's convenience and savings in travel time. Regarding trip purpose, almost all riders in Class 3 had utilitarian purposes (98%), and this class was the least likely group to have recreational purposes (37%).

To summarize, three latent classes identified in the measurement model were distinctive from each other and represented substantial variations in their Via to Transit usage, mode choices, reasons for switching, and trip purposes. I will further discuss the role Via to Transit played in their travel and the corresponding policy implications in the discussion section.

Table 3.6 Results of the estimated LCA measurement model (N = 925)

Indicators	Categories	Class 1	Class 2	Class 3
Class size		34%	39%	27%
Number of Via to Transit trips (one-year)	1-4	**0.59**	0.19	0.10
	5-14	**0.31**	0.25	0.17
	15 – 49	0.08	**0.30**	0.25
	50 – 99	0.01	0.14	**0.19**
	>100	0.00	0.11	**0.30**
Avg. Via to Transit Trip Distance	<1.5 miles	0.64	**0.99**	0.25
	>= 1.5 miles	0.36	0.01	**0.75**
Mode replaced	Personal car	**0.41**	0.13	0.31
	Bus	0.12	0.21	**0.46**
	Walk/bike	0.27	**0.60**	0.08
	Ride-hailing	**0.14**	0.01	0.09
	Other	0.05	0.05	**0.06**
Days of using the Link station per week	Less than once	**0.82**	0.14	0.15
	1 or 2 days	0.17	**0.21**	0.20
	3 or 4 days	0.02	0.30	**0.32**
	5 or more days	0.00	**0.35**	0.34
Via usage if the price doubles	Won't use it anymore	0.19	**0.39**	**0.39**
	Use less	**0.48**	0.45	0.43
	Use the same	**0.32**	0.16	0.18
Reason for switching – safety	Yes	0.19	**0.44**	0.33
	No	**0.81**	0.56	0.67
Reason for switching – convenience & faster travel	Yes	0.70	0.78	**0.84**
	No	**0.30**	0.22	0.16
Reason for switching – cost	Yes	**0.22**	0.07	**0.22**
	No	0.78	**0.93**	0.78
Trip purpose: utilitarian	Yes	0.52	**0.99**	0.98
	No	**0.48**	0.01	0.02
Trip purpose: recreation	Yes	**0.70**	0.46	0.37
	No	0.30	0.54	**0.63**

Note: bold numbers indicate the highest value for each row

3.4.2 *Results of the membership models*

Table 3.7 presents the second component of the model, where socio-demographics and built environment covariates were used to explain the membership of three latent classes identified from the measurement model. The reference class is Class 1.

Among socio-demographics, the model finds that riders who were older (over 45 years old) and who had greater access to cars were significantly less likely to be in Class 2, while riders with larger household sizes were significantly more likely to be in Class 2. Riders who traveled to places that were denser with greater land-use mix and transit service were more likely to belong to Class 2 than to Class 1, and these associations were statistically significant. These findings were in general consistent with the travel behavior of Class 2, as Class 2 consists of more pedestrians and bikers whose origins or destinations were closer to the Light Rail stations.

Regarding the coefficients for Class 3 versus Class 1, the model finds that older riders were significantly less likely to be in Class 3. Being a racial minority was significantly associated with a greater likelihood of belonging to Class 3. Having access to a car and access to a checking account were both negatively associated with the likelihood of belonging to Class 3. All these results suggested that riders in Class 3 were more likely to be more disadvantaged compared to Class 1, which was consistent with their dependency on transit and price sensitivity, as reflected in the measurement model. The results for the built environment covariates for Class 3 were particularly interesting, as riders who traveled to places with lower land use mix, lower street intersection density, and lower frequencies of transit services were significantly more likely to belong to Class 3. One possible explanation is that Via to Transit greatly expanded the travel destination options for those who were previously transit-dependent (i.e., Class 3). Before Via to

Transit was available, their travel was constrained to narrow corridors along the bus lines. And Via to Transit allowed them to freely travel to places that existing buses could not reach. Another possible explanation is that such associations were a reflection of Class 1 and Class 3's distinct trip purposes. Class 1 mainly took Via to Transit for non-utilitarian purposes and therefore they traveled to places where social and commercial activities took place. While Class 3 mainly took Via to Transit for utilitarian purposes, and their trips mostly started or ended at their homes, where the built environments were more residential. Either way, the results strongly suggest that Via to Transit better connected Class 3 to Link stations from places with limited convenient access to jobs and services, unfriendly street design to active travel, and relatively poor transit services, as shown by the results for the built environment covariates in Table 3.7.

Table 3.7 Results of the estimated LCA membership model (N = 925)

Coefficient	Class 2 (ref. Class 1)	Class 3 (ref. Class 1)
Gender: female	-0.011	-0.36
Age: < 25 (ref. 25- 44)	0.54	0.23
Age: 45-64 (ref. 25-44)	-0.48*	-0.78**
Age: > 65 (ref. 25-44)	-2.35***	-1.63***
Race: racial minorities (ref. white)	0.31	1.20***
HH size: 1 (ref: 2)	-0.26	0.265
HH size: 3 or more (ref: 2)	0.61**	-0.00
Income: < $ 50,000 (ref: $50,000 - $100,000)	0.51	0.13
Income: > $ 100,000 (ref: $50,000 - $100,000)	-0.20	0.32
Income: prefer not to answer (ref: $50,000 - $100,000)	-0.1	-0.118
Car available: yes	-0.59**	-0.82**
Having a checking account: yes	-0.27	-1.04*
Disability: yes	-0.12	-0.36
Population density (log)	0.79**	-0.37
Employment and household entropy	2.29***	-4.71***
Intersection density (log)	-0.003	-2.10***
The total frequency of transit service per sq. mile (log)	0.83***	-0.98***
Intercept	-6.34***	18.35***

Note: *p<0.1; **p<0.05; ***p<0.01

3.4.3 *Mapping three classes*

Figure 3.9 shows the spatial distributions of the most frequent travel locations of riders belonging to each class, as well as the median household income of census block groups in the area.

The travel locations of riders in Class 1 were in general dispersed across the area, reflecting their travel was less spatially constrained because of their better access to personal vehicles. There were a few concentrations of riders belonging to Class 1 in relatively high-income neighborhoods along the waterfront on the right of the map. Compared to Class 1, Class 2's travel locations were in areas immediately surrounding the Light Rail stations, reflecting the fact that Class 2 consisted primarily of riders who previously walked or biked to stations. Class 3, which consisted of riders who were previously bus riders, had travel needs from and to areas in the bottom-right of maps, where many neighborhoods were with lower median household income. Their locations were also further away from the Light Rail stations. Such clustering of riders of Class 3 further demonstrates the equity implications of Via to Transit, which enables riders in socio-economically disadvantaged neighborhoods to get better connected to the Light Rail stations.

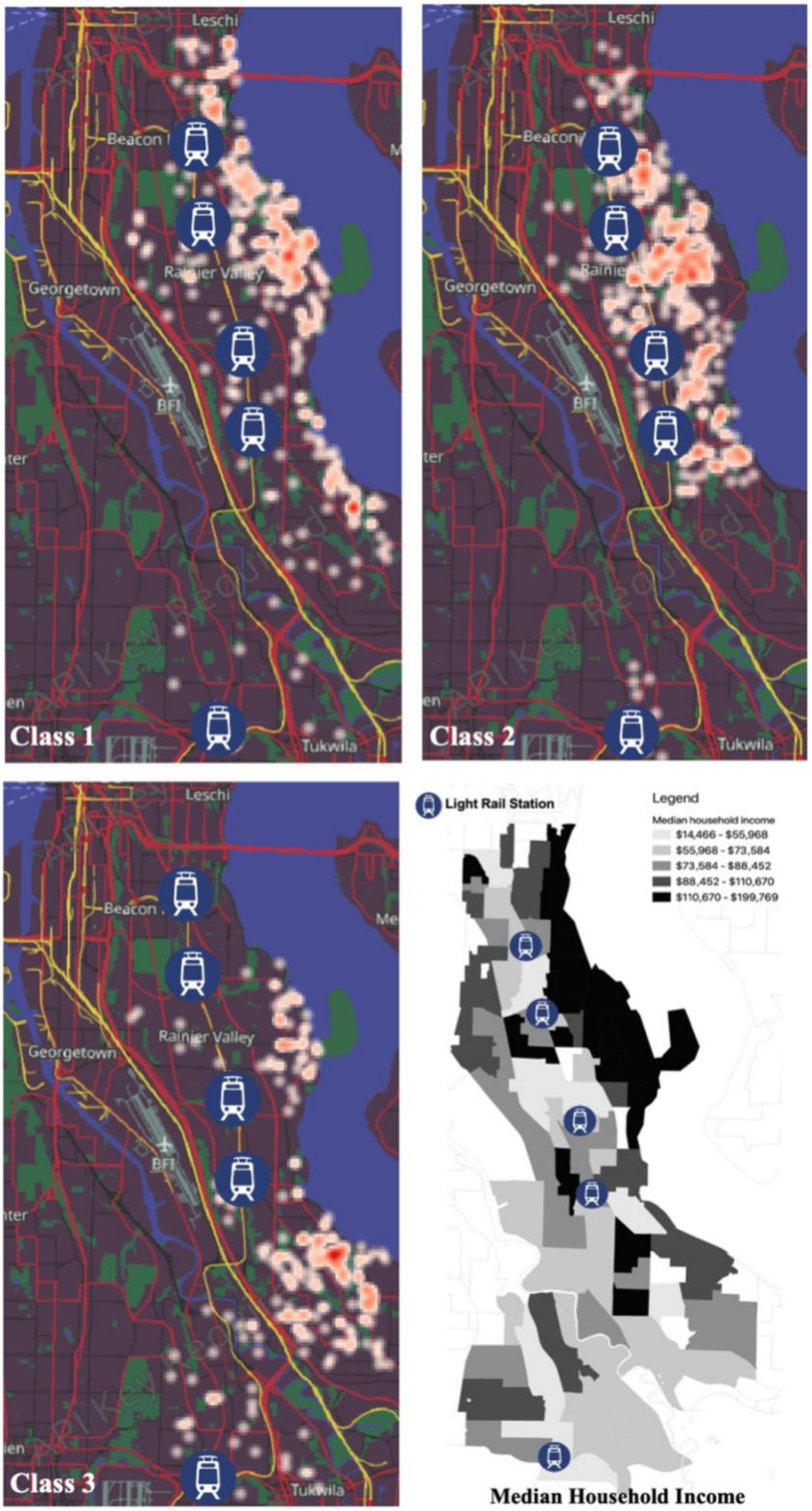


Figure 3.9 Heatmaps of three identified classes (darker color = higher rider counts) and median household income

3.5 Discussion and Policy Recommendations

This section draws from the above results and discusses how the three distinctive latent classes identified can offer rich policy implications.

Class 1 was the class with the least frequent use of Via to Transit. It consisted of riders who were previously personal car or ride-hailing users, infrequent Link Light Rail riders, less price-sensitive, less safety-concerned, and primarily recreational travelers. Socio-demographically, they tended to be older and had better access to cars compared to the other two groups. Via to Transit converted many riders in Class 1 from driving alone and ride-hailing to Via to Transit. For travelers who did not take Link Light Rail prior to the pilot, such conversion came with many social and environmental benefits because it could reduce the use of vehicles and the number of vehicle trips. And for travelers who previously used personal cars as first-mile/last-mile solutions to Link, Via to Transit reduced the demand for parking facilities near the Light Rail stations. This class's profile to some degree aligned with the early adopters of on-demand shared mobility modes (Tirachini, 2020; Vij et al., 2020; Young and Farber, 2019), as members were likely to be wealthier and to use Via to Transit for recreational purposes, likely, for avoiding drunk-driving. However, the fact that riders in Class 1 were older shows that with subsidies and greater integration between transit and on-demand modes, TIMOD pilots have the potential to expand rider groups beyond what can be achieved in a natural, market-driven adoption, where in general riders are young and tech-savvy.

Riders in Class 2 and Class 3 shared some similarities. For example, they were sensitive to prices, needed to access the Light Rail frequently, and used Via for utilitarian purposes. However, the two classes adopted Via to Transit for different reasons. For riders in Class 2, they tended to

be pedestrians and bikers who were concerned about safety[11] when walking and biking to or from the stations, especially during late nights or early mornings. Therefore, Via to Transit offered a safer travel means for this class of riders. By doing this, Via to Transit took riders away from non-motorized, active modes, which may have adverse environmental consequences. While encouraging mode switch might be an effective temporary solution, long-range planning and transportation policies that directly address travelers' safety concerns are also needed. For example, providing and maintaining adequate streetlight to ensure the neighborhoods are safely lit and creating mixed-use streets that are welcoming to pedestrians and bikers. If such safety issues can be properly addressed, alternative on-demand modes (e.g., bike-sharing or scooter-sharing) might be more suitable to meet the needs of these riders, given the fact that Class 2's trip distance were relatively short. I recommend that future TIMOD pilots and future research should evaluate these alternatives.

Riders in Class 3 were likely to be those who faced mobility challenges in travel. On one hand, they lacked access to personal vehicles and previously relied on buses to access to/egress from the Light Rail. On the other hand, they had needs to travel to/from places that were hard to access without a personal vehicle. In addition, this class consisted of a higher percentage of racial minorities. These findings suggested that Via to Transit provided a more convenient and faster first-mile/last-mile solution for riders in Class 3. Furthermore, Via to Transit expanded the places that they could access beyond corridors along the bus lines, although admittedly Via to Transit trips were still bounded by the service area boundary that KCM designated. However, Via to Transit service directly took riders away from existing bus lines in the service areas as it provided

[11] Although the exact meaning of the 'safety' was not clearly articulated in the survey questionnaire, the authors believe it is more likely to refer to concerns over crime/harassment than traffic safety. One evidence to support this belief is that the KCM learned from community feedback that late-night safety was an prominent issue in the service areas.

a much more convenient service. When implementing future TIMOD pilots, transit agencies should investigate ways to better design and deploy the pilots so that the newly provided TIMOD services can better fill in the gaps of existing bus transit, and the comparative advantages of both bus and on-demand modes can be realized.

To summarize, the results of the LCA model show that the TIMOD service in the Via to Transit pilot impacted the travel behavior of three rider groups and benefited them in different ways. Such benefits may not be possible if KCM chose to expand the fixed-route transit services to meet the same demands in the study area. Public transit agencies should recognize the flexibility of the TIMOD service, and consider exploring TIMOD projects to fill in the gaps in existing transit.

In addition, we recommend transit agencies clearly define their policy goals before implementing TIMOD projects and design the TIMOD projects accordingly with an in-depth understanding of the socio-demographic and geographic characteristics of the areas they intend to serve. They should also actively engage with riders to better understand their travel needs and barriers for them to access transit. For example, if the primary goal of the TIMOD service is to provide a safe alternative for riders who need to walk or bike at night, then the areas surrounding the public transit stations should not be excluded from the service area. If the primary goal is instead to provide better access to disadvantaged populations underserved by the public transit, then transit agencies need to carefully identify neighborhoods that have poor connections to major transit routes and deploy the service there.

3.6 Conclusion

This work is one of the first studies that used methods beyond simple descriptive statistics to evaluate riders' responses to a completed TIMOD pilot. Employing LCA on survey data collected

from riders of the Via to Transit program in the Seattle region, the result revealed transportation policy trade-offs for each of the three latent rider classes identified. I found that the TIMOD service in Seattle converted riders who previously would use private cars or ride-hailing to a public transit service, provided a safer mobility option for those who were pedestrians and bikers, and made accessing Light Rail stations more convenient for those who previously relied on the bus.

Although the study offers timely insights for KCM and other transit agencies that are exploring integrating shared mobility modes to complement traditional fixed-route transit, I acknowledge a few data and analysis limitations. First, since the data was collected by KCM and was primarily focused on the first-mile/last-mile travel, it was not sufficient to fully understand the impacts of a TIMOD pilot on riders' travel behavior in a broader context beyond this first-mile/last-mile segment. Future research should consider designing a more comprehensive rider survey, and perhaps employing travel logs, to fill in this gap. Second, although the policy recommendations of the study are transferable to other cities, transit agencies can greatly benefit from future research that compares different TIMOD pilots and evaluates how different pilot designs (i.e., on-demand modes partnered, incentive amount and structure, service integration strategies) may affect riders' responses. Third, this study draws evidence-based policy recommendations retrospectively by evaluating a completed TIMOD pilot. Future research should explore predictive methods that help identify potential TIMOD riders in an ex-ante manner, so that transit agencies can envision the outcomes of TIMOD projects without the needs of carry out a pilot.

Chapter 4. Incorporating On-demand Shared Mobility into Public Transportation Provision: A Marginal Cost Comparison Approach

4.1 Introduction

As briefly discussed in Chapter 1, even though cost-saving is one of the primary arguments to advocate for implementing TIMOD projects rather than traditional fixed-route service expansion, the cost-saving potentials of TIMOD projects have not been fully demonstrated for the following two reasons:

1) Theoretically, the concept of cost is often vague. While some studies explored the potential for shared mobility to help public transit agencies achieve cost savings, they usually compared the average cost of fixed-route services to the cost of shared mobility options (Lazarus et al., 2017; Zhou, 2019). This approach may misinform decision-making because the marginal cost of running a fixed-route transit in low-demand areas or for the first-mile/last-mile travel can be substantially higher than the system-wide average cost.

2) Practically, only a few programs evaluated the cost-effectiveness of TIMOD versus alternatives. Of those that did, the evaluation was very limited as they typically compared the pilot service with non-performance-equivalent alternatives, for example, with past transit lines serving the areas, or with different mobility pilots in other areas (Gifford et al., 2021; Grellier, 2020; Ong, 2019). As such comparisons did not control for the performance, the results may not reflect the actual cost-saving by the pilots.

In light of these research gaps, this study is initiated in collaboration with King County Metro (KCM), the primary transit operator in the Seattle region. The study uses KCM's recent TIMOD pilot, Via to Transit, which connects people located within the specified service areas to

one of the five Link Light Rail stations. Based on this unique policy experiment, which has generated rich data, the study aims at introducing a rigorous approach that compares TIMOD with expanding fixed-route services based on their marginal costs. It will address the following questions:

1) What are the conceptual differences between the marginal cost and the average cost of providing mobility service? What are the major components of the marginal costs?

2) How do marginal costs differ between traditional transit service expansion (e.g., increasing bus frequencies on existing routes, increasing fleet size, or increasing route density by adding new routes) and providing on-demand services?

3) How can public transit agencies empirically estimate and compare the marginal costs of different options using rigorous data-based approaches?

The chapter proceeds with a literature review of the impacts of app-based shared mobility on urban mobility. I also review research works that analyzed integrating app-based shared mobility with public transit. Then the chapter will present a theoretical framework based on the economic concept of marginal cost that I believe provides more pertinent information for decision-making on TIMOD projects. Next, the chapter will introduce a transportation simulation procedure that allows transit agencies to empirically compare the marginal costs of traditional service expansion and a TIMOD project. Applying this approach to the case of Via to Transit, the chapter will demonstrate how the results can effectively evaluate TIMOD projects and inform future decision-making. The chapter closes with discussions and conclusions.

4.2 Literature Review

4.2.1 *Emerging app-based ride-hailing and its impacts on urban transportation*

It remains a question whether app-based ride-hailing, the most popular form of shared mobility, can benefit urban transportation as a whole (Tirachini, 2020). Studies have found that app-based ride-hailing usage is negatively associated with automobile usage, and therefore, app-based ride-hailing has the potential to reduce car ownership and parking needs (Clewlow and Mishra, 2017; Henao and Marshall, 2018, 2019; Wang et al., 2021). Some studies suggested that app-based ride-hailing has equity benefits as it grants socioeconomically disadvantaged neighborhoods adequate automobile access (Brown, 2019). However, many other assumed benefits of app-based ride-hailing were rarely empirically supported. Evidences from both individual-level travel survey analysis and aggregated-level regression analysis found that app-based ride-hailing directly competes with public transit and is likely to take transit riders away (Clewlow and Mishra, 2017; Diao et al., 2021; Graehler et al., 2018; Henao and Marshall, 2018; Rayle et al., 2016). Furthermore, studies found that app-based ride-hailing has exacerbated road congestion (Diao et al., 2021; Erhardt et al., 2019; Tarduno, 2021)

One of the important reasons that app-based ride-hailing has failed to deliver its theoretical benefits is its low passenger occupancy rate. In addition. The benefits of such limited mobility sharing are often offset by the empty miles drivers spend on cruising for customers. It is thus important to investigate alternative types of mobility services that can better achieve ‘deep sharing’ (Shen et al., 2021). In Shen et al. (2021), they studied app-based carpooling in a TIMOD pilot and encouraged transit agencies to explore partnering with app-based carpooling, which has a much higher level of passenger occupancy rate than app-based ride-hailing. Another study, Tirachini et

al. (2020), called for integrating shared modes in bigger vehicles (e.g., vans) rather than app-based ride-hailing.

Considering these findings, transit agencies should be selective regarding what mobility services to incorporate, as some forms of shared mobility services may not bring the assumed mobility-sharing benefits. Transit agencies also need to be strategic about where to launch the pilots, what specific services to offer, what incentives to provide, and how to rigorously evaluate the outcomes.

4.2.2 *Exploring the integration of app-based shared mobility into transit*

Although empirical cases are limited as many TIMOD pilots are still under development, several studies have developed innovative approaches to come up with useful recommendations for designing such pilots.

Some studies have analyzed or simulated scenarios where supply-side fixed-route transit is supplemented with on-demand shared mobility services. Zhou (2019) introduced a procedure to identify low-demand service routes using smart card data, and suggested that replacing them with shared mobility modes can generate cost-savings if the on-demand modes have an occupancy rate greater than two. Studies such as Shen et al. (2018) and Gurumurthy et al. (2020) used agent-based modeling to simulate performance gains under scenarios of on-demand services (in their case, automated vehicles) replacing buses as first-mile/last-mile connections to urban rails.

Other studies have conducted travel surveys to understand the potential of shared mob from the demand side. Yan et al. (2019) analyzed commuters' responses to a proposed TIMOD system and predicted the resulting mode choices, and found that the proposed TIMOD service can lower the transit' operation costs primarily by reducing riders' waiting time. Zgheib et al. (2020)

collected stated preference data for the three stages of transit trips (i.e., access, in-transit, and egress) and modeled the mode choice of using app-based ride-hailing to access transit. They estimated that the introduction of app-based ride-hailing as feeder mode to transit could attract additional 2% commuters to transit, and the effect would be greater if subsidies were provided. Focusing on low-income neighborhoods, Yan et al. (2021) and Wang et al. (2022) conducted in-depth analyses of low-income travelers' preferences for a proposed TIMOD service. They found strong preferences for the TIMOD service over the traditional fixed-route transit, in particular among respondents who were underserved by the existing transit and who had adopted app-based ride-hailing. They also identified that low-income travelers' technological self-efficacy can be a major barrier to adopting TIMOD.

While contributing to the early understanding of TIMOD projects, these prior studies were exploratory. The supply-side simulations assumed that a hypothetical new mobility service was introduced, while the demand-side survey analysis mostly relied on respondents' stated preferences. Therefore, the insights obtained by these studies have limited practical values to guide current transportation decision-making.

4.2.3 *Examining the cost of TIMOD projects*

Cost-efficiency is a key argument for initiating TIMOD projects. However, the concept of cost in related literature is often vague due to two reasons:

1) The total economic costs of mobility service consist of both the service provider's cost and the users' cost. However, not all these components were explicitly accounted for in existing studies. For example, for research that examined hypothetical services (Gurumurthy et al., 2020;

Shen et al., 2018; Wang et al., 2022; Yan et al., 2019), service provider's cost was often not considered. Similarly, users' cost may not be fully estimated (Yan et al., 2019; Zhou, 2019).

2) While it is critically important to differentiate between the average cost and the marginal cost, existing studies have not clearly made the distinction (Lazarus et al., 2017; Zhou, 2019). The system-wide or route-wide average cost of traditional transit was often implicitly - and inappropriately - compared with marginal cost associated with the incremental improvement of the TIMOD projects.

4.2.4 *Evaluating existing TIMOD pilots*

Another group of studies consist of transit agencies' self-evaluation or third-party evaluation of the existing TIMOD pilots (Gifford et al., 2021; Grellier, 2020; Gustave et al., 2018; Martin et al., 2020b; Miller et al., 2021). Most studies utilized TIMOD service trip records and user survey data, and examined the usage of TIMOD services, trip characteristics, and the socio-demographics of riders. Some studies probed the effects of the on-demand services in boosting transit ridership (Gifford et al., 2021), and others looked at the cost-efficiency of the TIMOD pilots (Martin et al., 2020b; Miller et al., 2021). Ong (2019) was one of the most comprehensive efforts, where the author compared the service provider's cost of operating on-demand mobility services in a TIMOD pilot versus that of running fixed-route transit. The result showed that the pilot had a relatively high operating cost. However, as the author acknowledged, the comparison did not consider the users' costs, and such costs are very likely to differ substantially among different types of services.

In general, evaluations of existing TIMOD pilots were not satisfactory for two reasons. First, many reported benefits, such as the quick adoption of on-demand services, the shortened travel time, and even the boosted transit ridership, were not surprising given that transit agencies

typically offered special incentives. Second, the costs of TIMOD pilots were often compared against that of non-comparable alternatives, such as fixed-route transit and TIMOD projects in a substantially different setting. This is because transit agencies can only observe implemented TIMOD pilots and their outcomes, without knowing what the costs would be in the counterfactuals, i.e., when the TIMOD pilots were not provided, and traditional fixed-route transit was deployed to meet the demands.

The key question should be, instead, how the benefits of TIMOD projects compare to those of traditional fixed-route transit expansions with the same funding. To address this question, this study develops a rigorous and effective approach. It will first present a theoretical framework built upon fundamental economic principles, and then apply this framework to make comparisons among different mobility service delivery options.

4.3 Theoretical Framework

Figure 4.1 illustrates our proposed theoretical framework for quantifying the total economic costs of expanding the mobility service to a new or underserved area with either traditional fixed-route service options (e.g., increasing bus frequencies/service hours on existing routes, increasing vehicle size, and/or adding new routes), TIMOD projects (e.g., incorporating ride-hailing, ride-splitting, micro-transit, carpooling, and/or bike-sharing), or any other types of service provision options. The diagram illustrates the three aspects of vagueness in current conceptualization of cost, each addressed by an argument from the economic perspective.

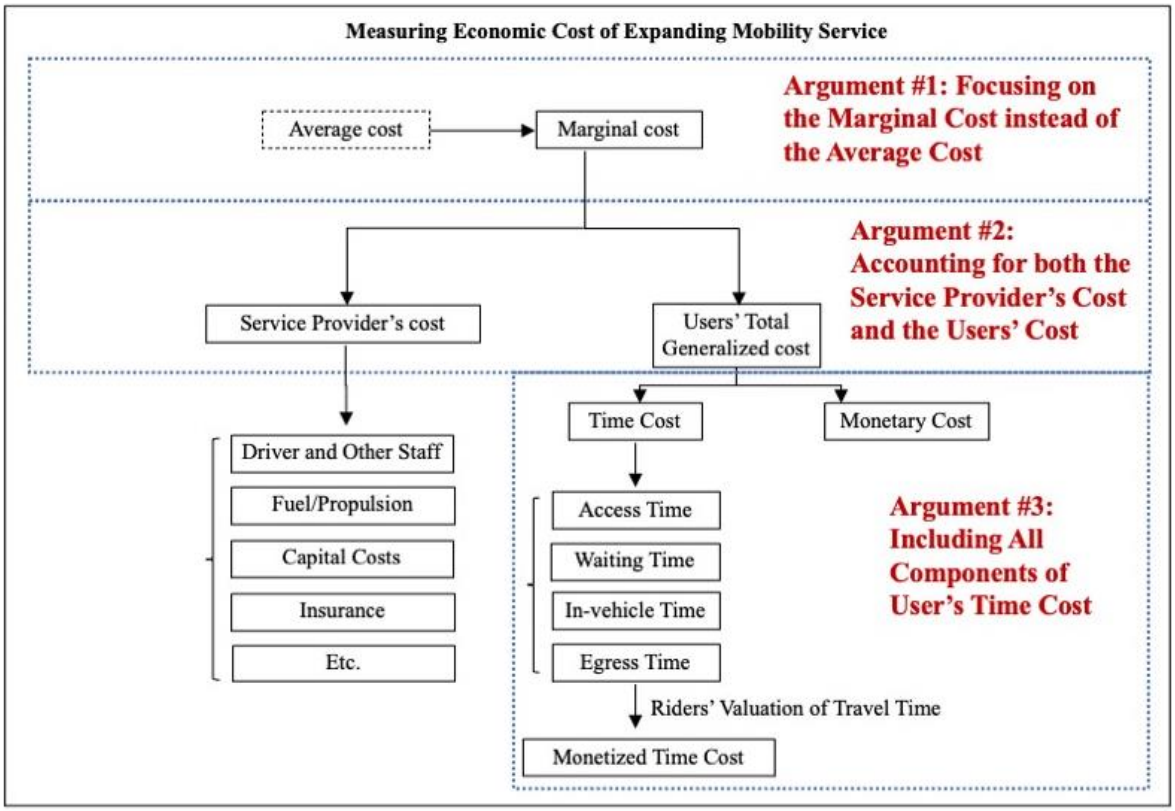


Figure 4.1 Theoretical framework for conceptualizing the economic costs of different service provision options

4.3.1 *Argument #1: focusing on the marginal cost instead of the average cost*

When public transit agencies consider expanding current services or adding new mobility options, they are thinking at the margin. Therefore, compared to the average cost, which is the total system-wide cost divided by the total number of services provided, the concept of marginal cost provides more pertinent information for decision making. The marginal cost refers to the extra cost associated with one-unit increase in an economic activity, which in our case means one additional unit of mobility service.

The marginal principle guides an economy entity to make optimal decisions. In the context of TIMOD projects, switching from average cost to marginal cost as the basis for decision-making

is of particular importance because the projects are typically deployed in areas where extending fixed-route transit would be too costly. In such areas, the marginal cost of operating fixed-route transit is likely to be much higher than the system-wide average cost. Switching our perspective from comparing average costs to marginal costs may help transit agencies identify areas - especially low-demand areas - where shared mobility modes have real competitive advantages.

In real-world decision-making, it is not practical for transit agencies to estimate the marginal cost for a one-unit increase in the service. It is largely because the mobility service, as a typical example of public goods, is naturally indivisible. That is, the transit agency is not likely to supply mobility service in one single bus ride or for a single on-demand trip. Therefore, in practice the decision-making units are often more aggregated, such as adding a new bus route, increasing bus schedules, or launching TIMOD service in a new area. In other words, marginal cost is approximated.

4.3.2 *Argument #2: accounting for both the service provider's cost and the users' cost*

To thoroughly estimate the marginal cost of different service options, one needs to decompose the marginal cost to the service provider's cost and the users' cost and account for both components. For public transportation, the service provider's cost is the cost for transit agencies to operate the service, which typically includes the cost of labor (i.e., drivers, service managers, and planning staff), fuel/propulsion, capital costs, insurance, etc. The users' cost is made up of the monetary cost and the time cost of travel, which is commonly known as generalized travel cost.

In the case of comparing TIMOD pilots with traditional fixed-route transit, transit agencies typically can estimate the service provider's cost based on the amount billed to them. Similarly, the TIMOD service users' cost can be obtained by observing their travel time and payment.

However, as discussed in the literature review, it is challenging to measure both the service provider's cost and the users' cost for unobserved counterfactuals, where TIMOD services were not offered and transit agencies instead chose to expand traditional fixed-route transit. Consequently, transit agencies may overlook the reduction in users' generalized travel cost when comparing TIMOD with other options.

4.3.3 *Argument #3: including all components of user's time cost*

A user's travel time consists of not only the in-vehicle travel time but also the following components:

- Access time from one's origin to the transit stop or on-demand service's pickup location
- Waiting time for the transit or the on-demand vehicle to arrive
- Egress time from the transit stop or on-demand service's drop-off location to one's destination

Accurately estimating the users' travel time cost requires all the above components to be included. Furthermore, each component can be converted to monetary value based on user's valuation of travel time.

Figure 4.1 and the three arguments, collectively, clarify the conceptualization of the total economic cost of mobility service provision. The framework includes the capital costs and operation costs for the transit agencies as providers of public goods (i.e., the mobility service), and time costs and monetary costs for users to undertake trips to fulfill their travel needs. The framework, however, does not explicitly include some external costs of transit agencies, users and

the society associated with the service provision. For transit agencies, the framework does not consider:

- The external impacts of providing one service on other services that the agencies offer, for example, offering TIMOD service may take riders away from existing bus lines;
- Positive externalities of public transit, commonly known as the 'Mohring Effect', i.e., the increasing return to scale of transit service.

For users, the framework does not consider:

- Long-term behavioral and attitudinal changes of users and their corresponding economic and societal costs, for example, mode switch from walking and biking to TIMOD may discourage active transportation and its environmental and health benefits.

For the societal cost, the framework does not consider:

- Externalities associated with the vehicle use, including local environmental pollution, global warming, road congestion, oil dependency, road accidents, etc.;
- Long-term maintenance cost for road and other infrastructure.

The following sections will use Via to Transit, a TIMOD pilot in the Seattle region, to demonstrate how such a conceptual framework can be applied to the policy evaluation of real-world TIMOD projects.

4.4 Data and Methodology

The conceptual framework can be applied to analyzing any mode of travel. In the empirical evaluations of Via to Transit I will compare the cost of the TIMOD pilots versus two plausible counterfactual service provision options: expanding traditional fixed-route bus transit and providing park and ride facilities near the Light Rail stations. I estimate the service provider's (i.e., transit agency's) cost and users' (i.e., travelers') cost for each option. For the agency's cost, I work with KCM staff and obtain their cost measures for each counterfactual scenario. For the travelers' cost, I simulate travelers' travel time when Via to Transit was not available, and travelers needed to take alternative modes (specifically, fixed-route transit and drive alone) instead. This section introduces the data and our simulation methodology.

For estimating travelers' generalized cost, this study uses Via to Transit Trip data, a dataset that records every completed Via to Transit trip (N = 229,133). The data include each Via to Transit trip's request, pick-up, and drop-off times (in minutes), origin and destination geo-coordinates (rounded to 3 decimals), trip distance, number of seats requested, etc.

Using this dataset, I apply a transportation simulation approach to model the scenarios where Via to Transit was not an option, and all current Via to Transit riders needed to choose alternative modes instead. I used Eclipse SUMO, a free and open-source software for the simulation. SUMO is highly customizable and can directly model real-world road networks and individual-traveler-level traffic flows (Lopez et al., 2018). It also allows for modeling multi-modal travel.

Figure 4.2 illustrates our simulation framework. I obtained the road network map and related information on the number of lanes, speed limit, permitted vehicle types, sidewalks,

pedestrian crossings, and traffic lights from the OpenStreetMap, and the bus stop and route information from KCM. In the simulation, travelers would depart at the same time when they requested for Via to Transit, but instead of taking Via, they take fixed-route bus or drive alone. The outputs of the simulation are the access, waiting, in-vehicle travel, and egress times needed for travelers using the either one of the two alternative modes.

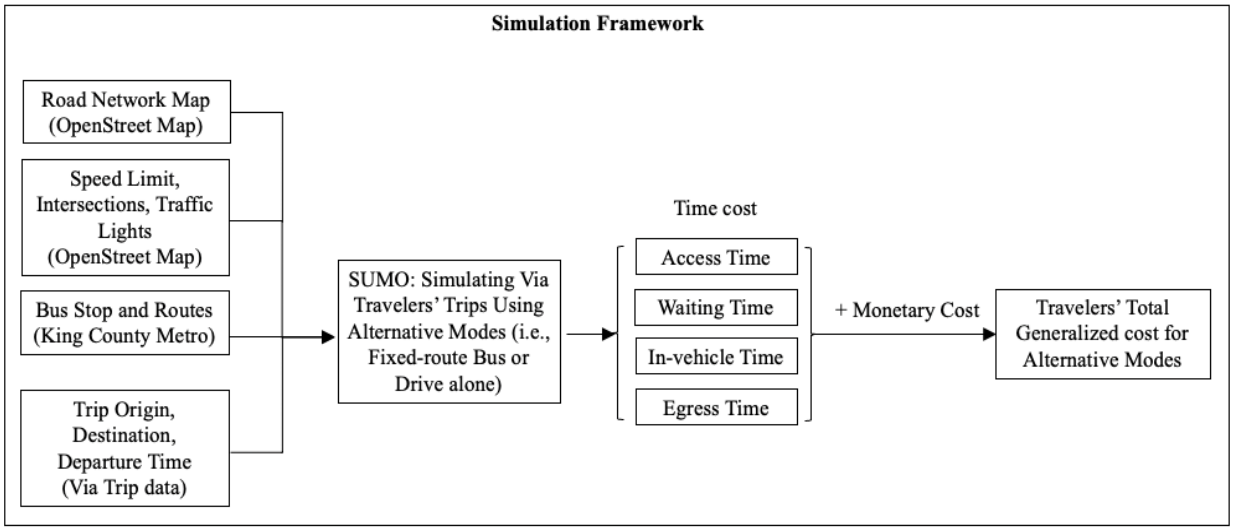


Figure 4.2 Simulation framework for estimating travelers' total generalized costs using alternative modes

For this simulation, I picked the Rainier Beach station and its service area for the following reasons. First, Rainier Beach had the highest number of Via Transit rides throughout the pilot period out of the five stations, which indicates that Via to Transit has real comparable advantages for riders in the area. Second, Rainier Beach station is one of the stations that Via to Transit service got resumed recently after its suspension as a response to the COVID-19 pandemic. Therefore, choosing it as the study area has greater practical value than stations where Via to Transit was not

resumed. I will discuss how our simulated results might change if a different service area is selected in the 'Discussion' section. I chose September 9, 2019, as the date for simulation, because its daily trip count was representative for Via to Transit's operation[12].

I simulated four fixed-route bus transit scenarios and one drive alone scenario. In the four transit scenarios, KCM would invest in expanding the two existing bus lines, Line 106 and Line 107, by offering more frequent bus services[13]. Line 106 and Line 107 are the only two bus lines that connect the service area to the Rainier Beach Light Rail station, as shown in Figure 4.3. The details of the scenarios are:

- Scenario 1: bus running at current service frequency. Line 106 runs about every 15 minutes between 7 AM and 7 PM, and about every 30 minutes in early-morning and late-night hours. Line 107 runs about every 30 minutes throughout the day.
- Scenario 2: bus with a '10/15' service frequency. Bus frequency is increased to every 10 during peak hours and every 15 minutes during off-peak hours. For this and the following scenarios, I define peak hours as 7-9 AM and 4-6 PM[14].
- Scenario 3: bus with a '5/10' service frequency.
- Scenario 4: bus with a '5/5' service frequency.
- Scenario 5: drive alone. All Via to Transit users would drive alone. Instead of providing transit services, KCM would provide free parking facilities for them to park their cars near the station and ride the Link Light Rail. Free park-and-ride services are currently provided by KCM in peripheral transit hubs.

[12] Strictly speaking, it is a representative date for Via's operations from September 2019 to February 2020. Before September 2019, Via to Transit ridership was still quickly growing. After September 2019, the ridership stabilized.
[13] It is conceivable that KCM could expand the existing transit services by adding new stops or routes. However, I believe that the two existing bus lines are providing sufficient coverage for the service area with sufficiently high stop density, but the service frequency is inadequate. Therefore, I focus on increasing bus frequency for the simulation.
[14] This is defined by observing peak hours in Via to Transit trip data.

The simulation was built on several additional assumptions:

- The travel speed for buses and private vehicles during peak hours is 80% of their free-flow travel speed.
- Scenarios 1-4: travelers' travel consists of access phase (including walking to bus stops and waiting), in-bus travel phase, egress phase (walking to destination). This scenario assumes everyone can walk, and their walking speed is 3 miles per hour.
- Scenario 5: every traveler has access to a car[15]; there is a transfer access time (i.e., time spent on walking between park and ride facility and the Link Light Rail station platform) of 4 minutes.

I validated SUMO modeling outcomes in Scenario 1 (transit service running at current frequency) by comparing the resulting travel times with those estimated from Google Transit (Gifford et al., 2021). The two results aligned well with each other, suggesting that the simulation model is appropriately set up.

[15] This scenario is hypothetical for simulation purpose. In reality, about 30% of Via to Transit riders in the Rainier Beach service area reported that they did not have access to a car.

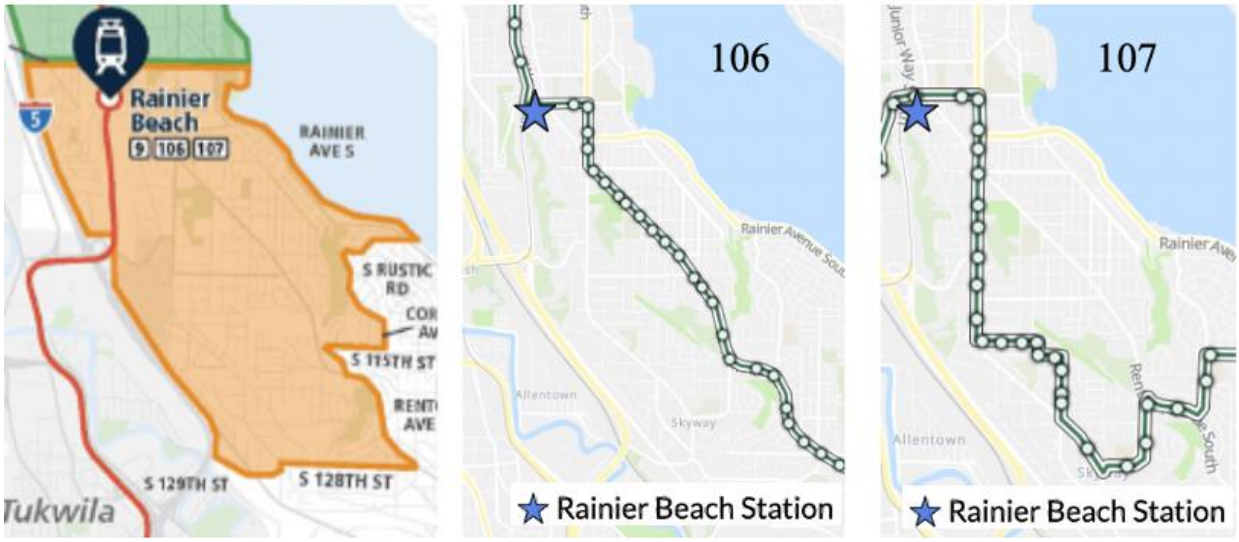


Figure 4.3 Via to Transit Rainier Beach service area (left), bus line 106 (middle), and bus line 107 (right)

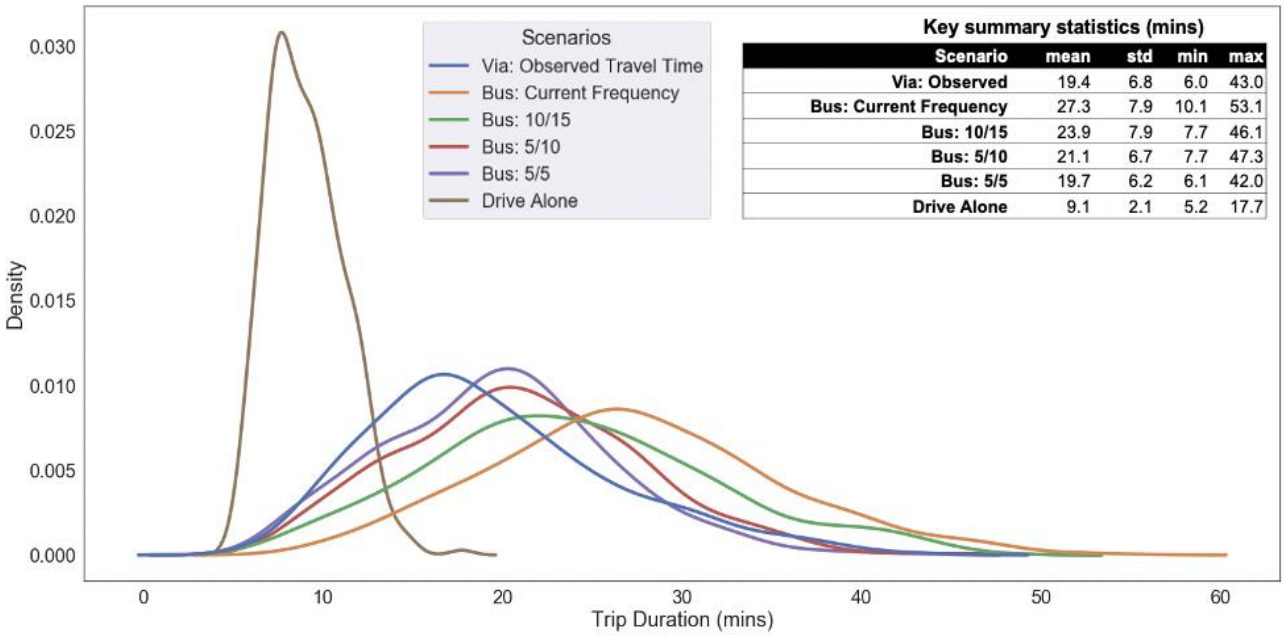
4.5 Simulation Results and Analysis

4.5.1 *Simulated travel time*

Figure 4.4 shows travelers' total travel time for a trip in each scenario. Via trip travel time was based on observed trip data, while the travel times for the other scenarios were generated by the SUMO simulation.

On average, Via to Transit's travel time is 19.4 minutes. If trips were diverted to two bus lines with their existing service frequency, the average travel time would increase to 27.3 minutes, and the longest trip would increase to 53.1 minutes from 43.0 minutes. The average travel time would decrease as the bus service became more frequent. If the frequency reached a high level with a 5-min headway, the bus would become approximately performance-equivalent to Via (19.4 mins versus 19.7 mins). This finding confirms the travel time saving of Via to Transit due to its

on-demand, flexible nature compared to the fixed-route bus. Driving alone, on the other hand, has a much shorter average travel time than any other option, which is not surprising because driving alone does not require waiting and detouring as Via does.



Key summary statistics (mins)

Scenario	mean	std	min	max
Via: Observed	19.4	6.8	6.0	43.0
Bus: Current Frequency	27.3	7.9	10.1	53.1
Bus: 10/15	23.9	7.9	7.7	46.1
Bus: 5/10	21.1	6.7	7.7	47.3
Bus: 5/5	19.7	6.2	6.1	42.0
Drive Alone	9.1	2.1	5.2	17.7

Figure 4.4 Travelers' total travel time (mins) and distribution in each scenario

Figure 4.5 and Figure 4.6 show the distribution of travelers' total travel time by trip start hour and by trip distance, respectively. The two figures offer more details on the performance of each option than Figure 4.4. Figure 4.5 shows that Via to Transit underperforms fixed-route bus service with a 5-min headway during daytime hours (7-10 AM and 12 – 2 PM), but substantially outperforms at late night hours (after 5 PM). It can be explained by the fluctuation of the travel demand throughout the day. During peak hours, Via to Transit riders need to wait longer for their rides and have a higher chance of sharing rides with others, both resulting in longer travel time. However, after 5 PM, Via to Transit trips have shorter waiting times and a lower chance of detouring. Figure 4.6 shows the comparative advantages of each mode at different trip distances.

Via to Transit outperforms transit for relatively long-distance trips. However, for trips with a distance shorter than 1.5 miles, Via to Transit no longer has the advantages over buses when the bus frequency is increased to ‘5/10’ or ‘5/5’.

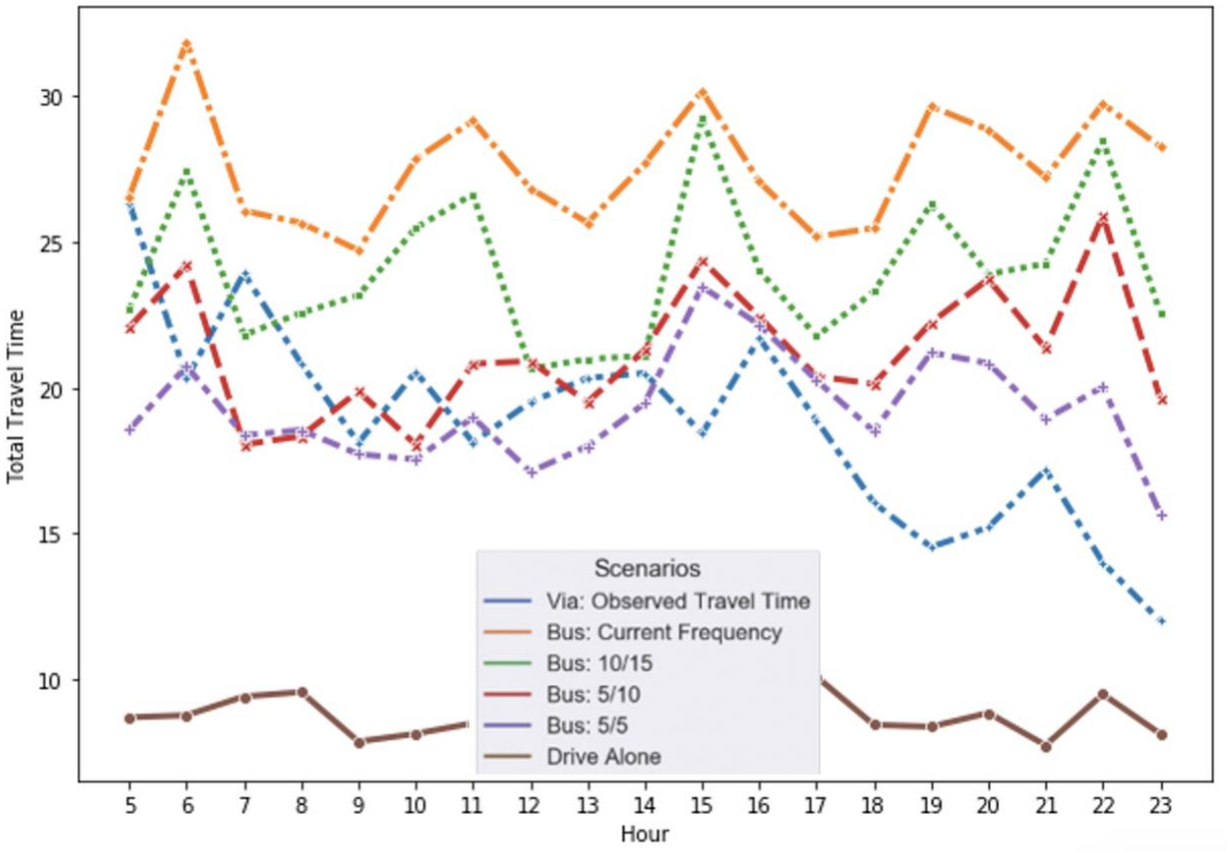


Figure 4.5 Travelers’ total travel time by trip start hour

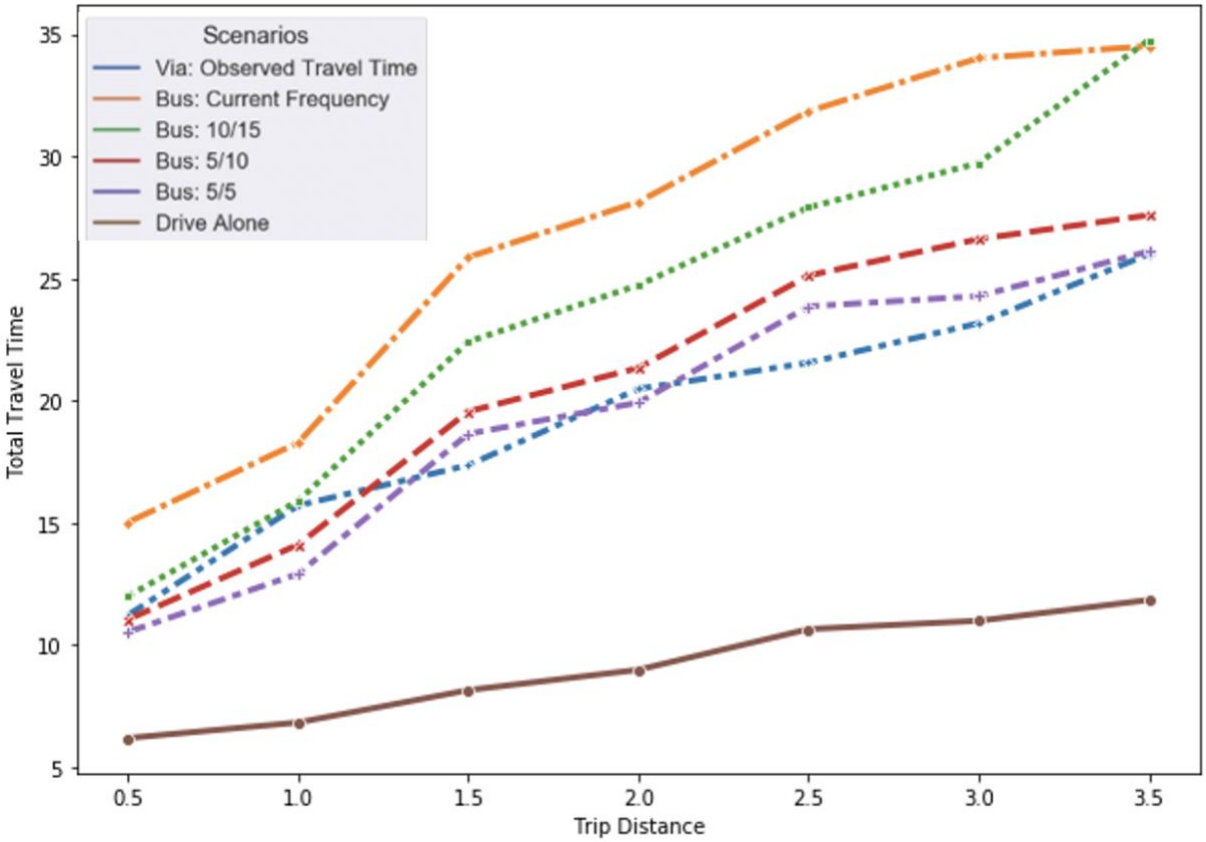


Figure 4.6 Travelers' total travel time by trip distance

4.5.2 *Estimating travelers' total generalized costs*

Based on the SUMO simulation outcomes above, this section converts travel times into monetary values through travelers' valuation of travel time. Travelers' average hourly wage was assumed to be $35.74 per hour, which is the average wage for workers in the Seattle Metropolitan Statistical Area (Bureau of Labor Statistics, 2020). Travelers' valuation of travel time, in terms of percentages of their hourly wage for each segment of travel, is listed in Table 4.1. These parameters were determined based on: 1) DOT's guidance on valuation of travel time (White, 2016); 2) current literature that measures or synthesizes value of travel time for traditional and new shared mobility

modes (Schwieterman, 2019; Victoria Transport Policy Institute, 2020); 3) unique characteristics of Via to Transit service as described previously in Section 3.3.1 Via to Transit program.

Some of these parameters were determined with the additional considerations as follows:

- For in-vehicle travel time, the percentage for transit was set higher (50% of travelers' hourly wage) than that for Via (40%) considering the level of comfort, such as the availability of seats. The percentage for driving was the highest (60%) because drivers cannot freely use the time as passengers. These numbers were determined following the recommendations of White (2016).
- For waiting time, the percentage for transit was set higher (75%) than for Via (50%). This is because Via allows travelers to have much better control on where and how to use their waiting time than bus. These numbers were determined following the recommendations of Schwieterman (2019).
- Monetary cost of driving was estimated at $0.64 per mile (AAA, 2021). The number included the costs of fuel, insurance, vehicle depreciation and maintenance, license, and registration. The average trip distance of Via to Transit on the selected date was 2 miles, therefore the per-trip monetary cost of driving is $1.28. For Via to Transit and bus transit, travelers' monetary cost was $2.75, assuming they all paid standard transit fare.

Table 4.1 Assumptions about travelers' valuation of travel time and monetary cost

	Via to Transit	**Transit (bus)**	**Drive**
In-vehicle travel time	40%	50%	60%
Waiting time	50%	75%	NA

Walking time	100%	100%	100%
Monetary cost	$2.75	$2.75	$ 0.64 per mile

Column C in Table 4.2 shows the estimates for the travelers' total generalized cost. Not surprisingly, driving alone has the lowest generalized cost on the travelers' side. It reflects the reality when a traveler has access to a personal vehicle and can drive, driving is typically the mode that minimized one's total generalized cost, primarily because of travel time advantages. Via to Transit's total generalized cost, although higher than that of driving, is lower than those for the four transit scenarios.

Table 4.2 Estimated travelers' total generalized cost, agency's cost, and the total economic cost

		Cost for the Selected Day (N of Vehicle Trips = 371, N of Person Trips = 392)			Cost for Six Months
A	B	C	D	E	F
	Scenarios	Travelers' Total Generalized Cost	Agency's Economic Cost	Total Economic Cost	Total Economic Cost
Observed	Via: Observed Travel Time	$3,850	$2,506	$5,278	$955,298

Alternative 1: Driving	Park and Ride: Last 50 Years	$2,571	$2,654	$5,225	$945,708
	Park and Ride: Last 30 Years	$2,571	$4,027	$6,598	$1,194,149
Alternative 2: Fixed-route Transit	Bus: Current Frequency	$6,110	$1,697	$6,729	$1,217,949
	Bus: 10/15	$5,336	$2,729	$6,987	$1,264,647
	Bus: 5/10	$4,765	$4,746	$8,433	$1,526,373
	Bus: 5/5	$4,447	$8,526	$11,895	$2,152,995

4.5.3 *Estimating the agency' cost*

This section describes our procedure for estimating the agency's (i.e., KCM's) cost of providing each service option, using the information provided by KCM, which includes: 1) information that KCM reported to the Federal Transit Administration following the federal standard of transit cost reporting; 2) cost figures of recent transit service expansion cases in the Seattle region.

For Via to Transit, I used the per-vehicle-hour cost provided by KCM. Such cost includes the wages of drivers and supporting staff, fuel, insurance, and other regular costs such as vehicle maintenance, but not capital costs such as the vehicles and the fare collection device. The intent is to remain consistent with the standard that transit agencies are required to report the cost of the

fixed-route transit[16]. I multiplied the per-vehicle-hour cost and the total vehicle hours of Via for the selected day, September 9, 2019, to get the daily operating cost, which is $2,506[17].

For fixed-route bus, our KCM collaborators used REMIX, a public transit planning software to estimate the operating costs. The detailed procedure is described in Table 4.3 Estimating KCM's cost for operating bus line 106 and 107 with different frequencies. For each scenario, REMIX took the schedules of the 106 and 107 lines as inputs and computed daily operating costs for the schedules (Column C). Such costs measure route-wise total costs serving riders within and beyond the Rainier Beach area. To obtain the marginal costs for serving the Via to Transit riders, I multiplied the total costs (Column C) by the percentage share of rides attributed to Via riders (Column E divided by Column D). The final estimations are in Column F. Column G is the sum of the costs of two routes in Column F for each scenario. Again, the costs do not include capital costs such as the bus vehicles and the fare collection device.

[16] When reporting to the National Transit Database, transit agencies include operating costs that are directly identifiable to each mode/type of service.

[17] The per-vehicle-hour cost is confidential per data sharing agreement with Via, and therefore in the study I only report the daily operating cost in Table 4.

Table 4.3 Estimating KCM's cost for operating bus line 106 and 107 with different frequencies

Scenarios	Route	Adjusted Route-Wise Daily Cost	Number of Daily Rides	Number of Rides from Pre-existing Via Riders	Cost for Meeting Via Demand	Scenario Total
A	*B*	*C*	*D*	*E*	*F*	*G*
Source:		*KCM, Estimated Using REMIX*	*KCM 2019 Route Performance Report*	*SUMO Simulation*	*= Column C / COLUMN D * COLUMN E*	
Current Frequency	106	$22,317	5800	234	$898	$1,697
Current Frequency	107	$15,703	2700	137	$799	
10/15	106	$30,275	5800	228	$1,191	$2,729
10/15	107	$28,891	2700	144	$1,538	
5/10	106	$49,305	5800	204	$1,734	$4,746
5/10	107	$47,229	2700	172	$3,013	
5/5	106	$81,656	5800	182	$2,559	$8,526
5/5	107	$78,196	2700	206	$5,967	

For driving alone, I assumed that transit agencies provided free park-and-ride spaces. If one parking space serves two rides per day, serving 371 rides would require at least 186 parking. I determined that 225 parking spaces would be provided at the Light Rail station to make sure that 1) travelers would not need to spend an excessive amount of time cruising for parking, and 2) the parking spaces would be sufficient to meet the growing demand in the near future. KCM uses

$167,000 as price per parking stall for permanent, dedicated, structured transit parking, and the cost includes property acquisition, design, and construction. I assumed two alternative scenarios regarding the lifespan of a park and ride facility, one for 50 years and the other for 30 years, each operating 365 days a year. In the case of 50 years, the daily cost of 225 parking stalls would be $167,000/50/365*225 = $2,059. In addition, I assumed one staff member is needed during the service hour for parking enforcement and on-site maintenance, and thus the daily cost for providing parking would be $2,059 + $35*17 = $2,654. In the alternative 30-year-lifespan scenario, the daily cost would be $4,027.

The estimated agency's cost is shown in Column D in Table 4.2. Although Via's cost to agency is higher than that of running fixed-route bus at current frequency, it is lower than that of every other scenario. In particular, increasing bus frequency to '5/5' results in a much higher agency's cost ($8,265). Column E in Table 4.2 presents the total economic cost for each service option. For driving alone, the total economic cost is simply the sum of travelers' total generalized cost and the agency's cost. For Via to Transit and fixed-route bus scenarios, each traveler pays $2.75 to KCM, which is revenue for KCM that actually offsets part of the agency's cost. Therefore, for these five scenarios, the total economic cost is the sum of travelers' total generalized cost and the agency's cost minus the fare-box revenue, which is $2.75 * 392 person trips. Column F shows the cumulated cost for six months, based on the assumption that the daily cost is representative of the Via to Transit's operation from September 2019 to February 2020.

Based on the above analysis, under reasonable assumptions, Via to Transit has a lower total economic cost than all four scenarios of bus transit. But it is slightly higher than the cost of providing park and ride facilities for driving alone, if the parking structure lasts 50 years. We will discuss in detail what this result means in the next section.

We performed some additional sensitivity tests, including an analysis focusing on low-income travelers who are minimum wage earners. The results are shown in Table 4.4. Via to Transit remains to be more cost effective than all four scenarios of bus transit, and its cost is also lower than the those of both driving alone scenarios. This analysis demonstrates greater potentials of TIMOD pilots like Via to Transit to serve lower income travelers.

Another additional sensitivity test is for scenarios when the park and ride facilities were not free to travelers. For example, KCM could charge travelers $2.75 to use the facilities, the same amount that travelers needed to pay for using Via to Transit or taking buses. In such scenario, the travelers' total generalized cost in Column C will increase by $2.75 * 392 persons = $1,078. However, the total economic costs in Column E would remain the same because the fare was collected by KCM and can offset part of the agency's cost. In addition, riders would be discouraged to drive if the cost for using park and ride facilities increased to a level that the generalized cost of driving exceeds the generalized cost of taking alternative modes. I will discuss how future study can explicitly incorporate such a mode choice into the simulation framework in the 'Discussion' section.

Table 4.4 Estimated travelers' total generalized Cost, agency's Cost, and the total economic cost, assuming a minimum wage ($ 17.2 per hour)

		Cost for the Selected Day (N of Vehicle Trips = 371, N of Person Trips = 392)			Cost for Six Months
A	B	C	D	E	F

	Scenarios	Travelers' Total Generalized Cost	Agency's Economic Cost	Total Economic Cost	Total Economic Cost
Observed	Via: Observed Travel Time	$2,440	$2,506	$3,868	$700,088
Alternative 1: Driving	Park and Ride: Last 50 Years	$1,812	$2,654	$4,466	$808,329
	Park and Ride: Last 30 Years	$1,812	$4,027	$5,839	$1,056,770
Alternative 2: Fixed-route Transit	Bus: Current Frequency	$3,551	$1,697	$4,170	$754,770
	Bus: 10/15	$3,170	$2,729	$4,821	$872,601
	Bus: 5/10	$2,890	$4,746	$6,558	$1,186,998
	Bus: 5/5	$2,734	$8,526	$10,182	$1,842,942

4.6 Discussion

The previous sections show how to appropriately compare the cost-effectiveness of TIMOD projects versus traditional fixed-route service expansions. This new approach is built upon fundamental economic principles. Instead of arbitrarily choosing among non-comparable service provision options and making comparisons based on incomplete or inaccurate costs, it accounts for all the components of the service provision cost, and quantifies these cost components based on transportation simulation. Such an approach leads to rich policy implications, discussed below.

4.6.1 *Incorporating all cost components prevents misleading findings*

The results in Table 4.2 highlight the importance of incorporating all components of costs. Many prior efforts that compared TIMOD pilots and traditional fixed-route service expansions only included the agency's cost (Miller et al., 2021; Ong, 2019) but not the travelers' cost because the time costs in counterfactual scenarios could not be easily estimated.

By including both travelers' and agency' costs, the results in this study clearly show that prior studies generated potentially misleading findings. Considering only the agency's cost would be equivalent to comparing exclusively the numbers within Column D in Table 4.2. More specifically, the comparison would be between the agency's costs for scenarios 'Bus: Current Frequency' ($1,697) and 'Via: Observed Travel Time' ($2,506). One would then find the TIMOD project to be more costly than operating fixed-route transit.

However, such comparison overlooks the substantially higher costs for travelers when taking the existing low-performance fixed-route transit. Our theoretical framework clarifies that traveler's total generalized cost should also be included in an appropriate cost comparison. Our simulation outcomes for counterfactual scenarios demonstrate that when incorporating travelers' total generalized costs, the TIMOD pilot is the more economically cost-effective option ($5,278) compared to the fixed-route transit running at the current frequency ($6,729). Such a result shows the advantages of a TIMOD service over traditional fixed-route transit in our service area. In addition, transit agencies should follow our approach and appropriately assess the outcomes of future TIMOD projects.

4.6.2 *Cost-effectiveness of on-demand mobility options should not be taken for granted*

Although Table 4.2 indicates that Via to Transit is justifiable based on its comparatively lower total economic cost, this does not suggest that providing TIMOD services would make economic sense everywhere. For example, information provided by KCM shows that the average agency's cost per Via ride for all five service areas is almost twice as high as that for Rainier Beach, mostly due to the other areas' lower service demand. In these other areas, Via is unlikely to have as much cost advantage; it may even be more costly than simply expanding fixed-route buses. Indeed, KCM recently resumed Via to Transit program after temporarily suspending operation in responding to the COVID-19 pandemic, but the resumed service covers only three out of the five original station areas.

In addition, Via to Transit may not have similar travel time advantages over traditional fixed-route transit as shown in Figure 4.4 in other places. Whether TIMOD can offer faster service than traditional transit depends on the spatial and temporal distributions of the demand, as well as how agencies deploy and operate the two services.

Therefore, providing on-demand mobility services may not be optimal everywhere. Implementing TIMOD projects requires careful decision-making, including especially proper identification of areas where on-demand modes have cost advantages over traditional modes. More importantly, transit agencies should consider using pilots such as Via to Transit to experiment and help delineate ideal service areas.

4.6.3 *The unaccounted externalities and barriers to automobile access*

It may be surprising that the cost for driving alone with park and ride facilities is lower than the cost for providing fixed-route transit in Table 4.2, assuming the facilities would last for 50 years.

One possible explanation is that, our analysis does not include externalities. It is known that in the US drivers do not pay all the societal costs of driving, for example, road congestion, environmental pollution, and inefficient use of the land as parking facilities. Using Parry et al. (2007)'s estimate that externality cost of driving is $0.26 per mile in 2020 dollar, which include local pollution, global climate change, congestion, accident, and oil dependency. On our selected simulation day, travelers would drive 775.7 miles if all chose to drive alone, which would result in an externality cost of $201.68 in addition to the $5,225 economic cost in Table 4.2. Although the externality cost seems to be small for our one-day simulation, they could be substantial if travelers continue to drive every day to access the Link station. The $0.26 per mile may also increase exponentially as global warming continues to accelerate.

Another factor not explicitly accounted for is that access to a personal car is not universal. Our simulation assumes that all travelers have access to cars and can drive, which is inconsistent with the general idea that TIMOD projects need to be implemented in areas where many residents face great mobility challenges primarily due to the lack of automobile access.

4.7 Conclusion

This study deepens our understanding of how to appropriately evaluate the costs of TIMOD projects with a theoretical framework. The research builds a simulation model as a proof of concept for the theoretical framework and applies it to a real-world TIMOD program. Together, the theoretical framework and the simulation serve as an effective approach for public transit agencies to determine, contextually, whether the engagement with shared mobility service providers is indeed cost-effective.

There are several limitations in this study. First, although the simulation has served as a proof of concept that our theoretical framework has practical value, there certainly remain gaps between what I have simulated and how individuals make mode choices in real world. In each counterfactual scenario, I assumed all pre-existing Via to Transit riders used the same mode, while in real world riders could choose among a variety of options. The Via to Transit data we obtained were not sufficient for us to develop a discrete choice model to predict the mode choices when Via to Transit was not an option. In addition, our simulation framework could not examine riders' demand elasticity to changes in the service and incentives, for example, to a different number of incentives. Future research will benefit from developing discrete choice models that better resemble how travelers choose among travel modes, and coupling the choice models with the simulation model presented in this study.

Second, our study advanced the literature by thoroughly examining components of total economic cost for expanding mobility services, but not all societal costs were included. Although incorporated in our conceptual framework, the capital costs of acquiring service vehicles and devices were not accounted for in our simulation and empirical analysis for scenarios of Via to Transit and bus transit. In addition, both our conceptual framework and simulation models do not include costs such as positive and negative externalities associated with different modes, costs of building and maintaining road infrastructure, and costs associated with long-term behavioral and attitudinal changes of users.

In addition, although providing cost-effective transit service is an important goal, transit agencies, as public service providers, often prioritize other goals such as ensuring equitable mobility services. These additional considerations should be better incorporated into future studies. For example, the simulation and empirical analysis in this study focus on travelers who have

adopted the Via to Transit services. Future studies should consider incorporating those who did not adopt the Via to Transit services, and help understand and address their concerns.

Third, our empirical demonstration was restricted to one service area of one TIMOD pilot. Therefore, future research can build upon this work by estimating and comparing the economic costs in different service areas and/or with different on-demand service options, which will help better understand factors affecting the economic outcomes of supplementing fixed-route transit with on-demand shared mobility services.

Chapter 5. Synthesis

5.1 Summary of three studies

This dissertation is a collection of timely and innovative studies that contribute to important and understudied areas in transportation planning and service provision in the era of app-based shared mobility. On one hand, the exponential growth of app-based shared mobility has challenged the public transit agencies' role as the primary transportation service provider in the cities. On the other hand, app-based shared mobility creates new opportunities to be better integrated with traditional fixed-route transit through TIMOD projects. The dissertation aims at, first, advancing our knowledge regarding the impacts of app-based shared mobility on individual travel behavior, and second, facilitating our understanding of TIMOD projects by examining the outcomes of an existing pilot on the travel behavior of riders and on the cost-effectiveness of transportation service provision.

Chapter 2 applied a longitudinal dataset, which overcame many constraints in the cross-sectional analysis used in prior studies. The study investigates the impacts of ride-hailing on individual travel behavior. Using panel regression, the study shows that the substitution effect between ride-hailing and driving is two-fold: first, among participants, those who use more ride-hailing tend to drive less; and second, over time, the increase in ride-hailing usage is also associated with fewer driving trips. Ride-hailing does not have a significant relationship with using transit or walking and biking.

Chapters 3 and 4 are the first studies that examine a real-world TIMOD pilot using rigorous analytical methods. Specifically, Chapter 3 conducted latent class analysis on riders of the TIMOD

pilot and identified three rider groups, each impacted by the TIMOD pilot in distinctive ways. The first group was older riders, recreational travelers, infrequent transit riders, and those who previously used personal cars. For these riders, the TIMOD pilot provided an alternative to personal vehicle use and converted them to taking public transit, even though only occasionally for most of them. The second group was primarily former pedestrians and bikers whose travel locations were close to the Light Rail stations. They traveled for utilitarian purposes and rode Link Light Rail frequently. The TIMOD pilot provided a safer solution to this group of riders. The last group consisted of riders who faced the greatest mobility challenges among the three groups. They were transit-dependent and needed to travel, mostly for utilitarian purposes, to or from places that were hard to access by fixed-route buses. They were also more likely to be socio-economically disadvantaged. To these riders, the TIMOD pilot provided a relatively affordable option for them to easily access the Light Rail. Informed by these rich policy implications of the TIMOD projects, transit agencies should carefully study riders' needs before implementing a TIMOD project, so that the new service can better fill in the gaps of existing transit.

Chapter 4 introduced a new approach to conceptualizing and estimating the costs of TIMOD projects, and comparing such costs with those of traditional fixed-route service expansions. The approach consisted of a theoretical framework built upon economic principles and a simulation model that estimates costs of different service provision options. The approach highlights the importance of comparing the service provision costs of traditional and new options at the marginal cost level, and including all components of the economic costs. The chapter applied the approach to the real-world TIMOD pilot and demonstrated its practical values. By accounting for both the service provider's cost and the users' cost, the study obtained a more complete and

accurate measure for the cost of on-demand modes in comparison to that of expanding fixed-route transit.

5.2 Contributions

5.2.1 *Supporting findings with empirical evidence for researching TIMOD projects*

Prior studies in the literature have recognized the potential of TIMOD projects, but few of them examined a real-world, existing TIMOD pilot. The insights obtained from their simulations and stated-preference surveys have limited practical values for current transportation decision-making. This dissertation overcomes this critical constraint and conducts solid analyses on a TIMOD pilot that has already been implemented. Therefore, the findings of this dissertation are well supported by empirical evidence.

5.2.2 *Applying economic thinking to transportation research*

This dissertation demonstrates the value of applying economic theories to advance our understanding of individual travel behavior and transportation policymaking. Economic theories of individual's travel mode choice are the basis of analyzing the impacts of ride-hailing in Chapter 2 and the adoption of the new TIMOD service in Chapter 3. More importantly, Chapter 4 shows that the economic concepts of marginal cost and generalized travel cost can effectively inform public transportation agencies regarding the appropriate approach to understanding the cost-effectiveness of TIMOD services.

5.2.3 *Making use of innovative data in transportation and travel behavior research*

The dissertation leverages datasets that were rarely used in previous literature on shared mobility and TIMOD services. The longitudinal datasets used in Chapter 2 allow us to gain a deeper understanding of the relationships between ride-hailing and traditional travel modes. Chapter 3 and Chapter 4 evaluate the TIMOD pilot by collaborating with the public transit agencies and obtaining timely data, including both complete TIMOD service trip records and rider survey data from the TIMOD pilot.

5.2.4 *Applying statistical methods suitable to the research question and the data*

Statistical methods, including panel regressions and latent class analysis, are applied in this dissertation. The dissertation clearly explains how these methods compare to traditional regression models and introduces types of research questions that these methods can be effectively applied in transportation research. The dissertation serves as a useful reference, methodologically, for other researchers working in this field.

5.3 Discussions and Future Research

5.3.1 *Opportunities of public transportation in the era of shared mobility*

While many existing studies on app-based shared mobility focus primarily on how shared mobility impacts individual travel behavior, this dissertation studies take the perspectives of both individual travelers and public transportation policymaking. As shared mobility is quickly changing how mobility services are provided, more research is urgently needed to inform the public sector to make use of its advantages while mitigating its negative effects. One clear lesson from this

dissertation for the public transportation sector is that app-based shared mobility may not always take riders away from transit, and transit agencies should actively consider integrating shared mobility services and creating synergies between emerging on-demand modes and traditional public transit. Transit agencies need to realize that when expanding mobility services into low-demand areas, fixed-route transit is no longer the only service provision option. Instead, TIMOD projects can be a better option, as supported by the empirical evidence in the dissertation.

5.3.2 *Potential challenges of implementing TIMOD*

While demonstrating TIMOD's opportunities, this dissertation indicates that realizing the potential of shared mobility in supplementing public transit requires careful policy-making and an in-depth understanding of the service areas. Specifically, Chapter 3 shows that transit agencies need to be aware of the fact that individuals benefit from a TIMOD service in different ways, depending on their prior travel behavior, socio-demographic characteristics, and travel locations. And some of the outcomes of a TIMOD project may not be desirable. Although confirming that the on-demand mode indeed has a cost advantage over traditional fixed-route expansions in a selected case, Chapter 4 suggests that such a cost advantage may not exist in other places with lower demand for the on-demand service. It is thus important for public transit agencies to identify areas where the comparative advantages of TIMOD can be realized and the TIMOD service can better play a supplementing role to the transit.

In addition, implementing TIMOD projects involves building mobility partnerships with private mobility service providers, negotiating contracts and data sharing agreements, engaging local communities, marketing, determining the type and the number of incentives, managing service operations, and collecting data for evaluations. All these factors will contribute to a

successful TIMOD project, but they are out of the scope of this dissertation. I encourage future research to examine them, possibly through directly surveying or interviewing planners and decision-makers, and to identify best practices for future TIMOD projects.

5.3.3 *Advancing transportation research and practice in the era of app-based shared mobility*

The analytical approaches in the dissertation can be easily transferable to other regions in the US for understanding the impacts of on-demand modes and evaluating future TIMOD projects. The longitudinal data and panel regression used in Chapter 2 is an excellent example for studying changes in travel behavior. Transportation researchers and practitioners should continue to systematically collect longitudinal travel surveys and closely observe any new trends in the adoption and usage of shared mobility modes. Public transit agencies can also easily utilize the latent class analysis framework in Chapter 3 to identify patterns in rider groups of any transport services. In particular, I encourage future research to apply the theoretical framework and the simulation model developed in Chapter 4 to appropriately evaluate other TIMOD projects.

Bibliography

AAA (2021) Your driving costs 2021. Available at: https://newsroom.aaa.com/wp-content/uploads/2021/08/2021-YDC-Brochure-Live.pdf.

Alemi F, Circella G, Mokhtarian P, et al. (2018) Exploring the latent constructs behind the use of ridehailing in California. *Journal of Choice Modelling* 29: 47–62. DOI: https://doi.org/10.1016/j.jocm.2018.08.003.

Azimi G, Rahimi A, Lee M, et al. (2021) Mode choice behavior for access and egress connection to transit services. *International Journal of Transportation Science and Technology* 10(2): 136–155. DOI: https://doi.org/10.1016/j.ijtst.2020.11.004.

Boisjoly G, Grisé E, Maguire M, et al. (2018) Invest in the ride: A 14 year longitudinal analysis of the determinants of public transport ridership in 25 North American cities. *Transportation Research Part A: Policy and Practice* 116(January). Elsevier: 434–445. DOI: 10.1016/j.tra.2018.07.005.

Brown A (2019) Redefining Car Access. *Journal of the American Planning Association* 85(2). Routledge: 83–95. DOI: 10.1080/01944363.2019.1603761.

Bureau of Labor Statistics (2020) Occupational Employment and Wages in Seattle-Tacoma-Bellevue — May 2020. Available at: https://www.bls.gov/regions/west/news-release/occupationalemploymentandwages_seattle.htm (accessed 14 April 2022).

Chapman J, Fox EH, Bachman W, et al. (2021) *Smart Location Database Technical Documentation and User Guide, Version 3.0*. *Environmental Protection Agency EPA*.

Circella G, Alemi F, Tiedeman K, et al. (2018) The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior. UC Davis: National

Center for Sustainable Transportation. Available at: https://escholarship.org/uc/item/1kq5d07p

City of Seattle (2019) CIty of Seattle Generalized Zoning. Available at: https://www.seattle.gov/dpd/Research/gis/webplots/smallzonemap.pdf (accessed 26 April 2022).

Clewlow RR and Mishra GS (2017) *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. *Institute of Transportation Studies, University of California, Davis*. DOI: UCD-ITS-RR-17-07.

Cook J (2013) Ride sharing service Lyft buys assets of Cherry, sets April 12 launch for Seattle. Available at: https://www.geekwire.com/2013/lyft-set-launch-ride-sharing-service-seattle-april-12th/.

Coy C, Greene E and Bradley M (2019) *First large-scale survey of TNC users, a case study from the SF Bay Area*. *TRB Planning Application Conference*. Available at: https://www.trbappcon.org/2019conf/138_D4_138_TNCSurvey_3June2019.pdf

Diao M, Kong H and Zhao J (2021) Impacts of transportation network companies on urban mobility. *Nature Sustainability*. DOI: 10.1038/s41893-020-00678-z.

Erhardt GD, Roy S, Cooper D, et al. (2019) Do transportation network companies decrease or increase congestion? *Science Advances* 5(5). DOI: 10.1126/sciadv.aau2670.

Federal Highway Administration (2017) 2017 National Household Travel Survey. Available at: https://nhts.ornl.gov

Feigon S and Murphy C (2016) *Shared Mobility and the Transformation of Public Transit*. *TCRP Research Report 188*. Washington, DC: The National Academies Press. DOI: 10.17226/23578.

Feigon S and Murphy C (2018) *Broadening Understanding of the Interplay Between Public Transit, Shared Mobility, and Personal Automobiles*. DOI: 10.17226/24996.

Florida R, Rodríguez-Pose A and Storper M (2021) Cities in a post-COVID world. *Urban Studies*. SAGE Publications Ltd: 00420980211018072. DOI: 10.1177/00420980211018072.

Gehrke SR, Felix A and Reardon TG (2019) Substitution of Ride-Hailing Services for More Sustainable Travel Options in the Greater Boston Region. In: *Transportation Research Record*, 2019, pp. 438–446. DOI: 10.1177/0361198118821903.

Gifford C, Chazanow A and Hallenbeck ME (2021) *Mobility on Demand Sandbox Demonstration: Puget Sound First/Last Mile Partnership with Via, Final Report*. *Federal Transit Administration, U.S. Department of Transportation*. Washington, D.C. DOI: 10.21949/1520669.

Gössling S (2018) ICT and transport behavior: A conceptual review. *International Journal of Sustainable Transportation* 12(3). Taylor & Francis Ltd: 153–164. Available at: http://10.0.4.56/15568318.2017.1338318.

Graehler M, Mucci R and Erhardt G (2018) Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes? In: *98th Annual Meeting of the Transportation Research Board*, 2018.

Graehler M, Mucci RA and Erhardt GD (2019) Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes? *98th Annual Meeting of the Transportation Research Board* (January): 1–19.

Grahn R, Harper CD, Hendrickson C, et al. (2020) Socioeconomic and usage characteristics of transportation network company (TNC) riders. *Transportation* 47(6): 3047–3067. DOI: 10.1007/s11116-019-09989-3.

Grellier P (2020) *Mobility on Demand (MOD) Sandbox Demonstration : Limited Access Connections, Final Report*. *Federal Transit Administration, U.S. Department of Transportation*. Washington, D.C. DOI: 10.21949/1518350.

Gurumurthy KM, Kockelman KM and Zuniga-Garcia N (2020) First-Mile-Last-Mile Collector-Distributor System using Shared Autonomous Mobility. *Transportation Research Record* 2674(10). SAGE Publications Inc: 638–647. DOI: 10.1177/0361198120936267.

Gustave C, Shaheen S and Martin E (2018) *Mobility on Demand (MOD) Sandbox Demonstrations Independent Evaluation (IE) – Pinellas Suncoast Transit Authority (PSTA) – Public- Private-Partnership for Paratransit Mobility on Demand Demonstration (P4-MOD) Evaluation Plan*. *Federal Transit Administration, U.S. Department of Transportation*. DOI: FHWA-JPO-18-682.

Hall JD, Palsson C and Price J (2018) Is Uber a substitute or complement for public transit? *Journal of Urban Economics* 108. Academic Press: 36–50. DOI: 10.1016/j.jue.2018.09.003.

Heineke K, Kloss B, Moller T, et al. (2021) *Shared mobility: Where it stands, where it's headed*. *McKinsey & Company*. Available at: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/shared-mobility-where-it-stands-where-its-headed

Henao A and Marshall WE (2018) The impact of ride-hailing on vehicle miles traveled. *Transportation* 46(6). Springer US: 2173–2194. DOI: 10.1007/s11116-018-9923-2.

Henao A and Marshall WE (2019) The impact of ride hailing on parking (and vice versa). *Journal of Transport and Land Use* 12(1 SE-). DOI: 10.5198/jtlu.2019.1392.

Hurvitz PM, Moudon AV, Kang B, et al. (2014) Emerging technologies for assessing physical activity behaviors in space and time. *Frontiers in Public Health* 2(JAN): 1–15. DOI: 10.3389/fpubh.2014.00002.

King County Metro (2020) *Ride2 Fact Sheet*. Available at: https://kingcounty.gov/~/media/depts/metro/accountability/reports/2020/ride2-summary-report-03-02-20.pdf

King County Metro (2022) Innovative Mobility Program - Programs & Projects - King County Metro Transit - King County Metro. Available at: https://kingcounty.gov/depts/transportation/metro/programs-projects/innovation-technology/innovative-mobility.aspx (accessed 15 March 2019).

Lazarus J, Shaheen S, Young S, et al. (2017) *Shared Automated Mobility and Public Transport*. DOI: 10.7922/G2HQ3X3V.

Le Vine S and Polak J (2015) Introduction to special issue: new directions in shared-mobility research. *Transportation* 42(3): 407–411. DOI: 10.1007/s11116-015-9603-4.

Lee Y and Lee B (2022) What's eating public transit in the United States? Reasons for declining transit ridership in the 2010s. *Transportation Research Part A: Policy and Practice* 157: 126–143. DOI: https://doi.org/10.1016/j.tra.2022.01.002.

Lee Y, Chen GY-H, Circella G, et al. (2022) Substitution or complementarity? A latent-class cluster analysis of ridehailing impacts on the use of other travel modes in three southern U.S. cities. *Transportation Research Part D: Transport and Environment* 104: 103167. DOI: https://doi.org/10.1016/j.trd.2021.103167.

Lopez PA, Behrisch M, Bieker-Walz L, et al. (2018) Microscopic Traffic Simulation using SUMO. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC* 2018-November: 2575–2582. DOI: 10.1109/ITSC.2018.8569938.

Manville M, King DA and Smart MJ (2017) The Driving Downturn: A Preliminary Assessment. *Journal of the American Planning Association* 83(1): 42–55. DOI: 10.1080/01944363.2016.1247653.

Manville M, Taylor B and Blumenberg E (2018) Transit in the 2000s: Where Does It Stand and Where Is It Headed? *Journal of Public Transportation* 21(1): 104–118. DOI: 10.5038/2375-0901.21.1.11.

Martin E, Cohen A, Yassine Z, et al. (2020a) Mobility on Demand (MOD) Sandbox Demonstration: BART Integrated Carpool to Transit Access Program Evaluation Report. *Federal Transit Administration* (February). Available at: https://www.transit.dot.gov/research-innovation/mobility-demand-mod-sandbox-demonstration-bart-integrated-carpool-transit-acce-0

Martin E, Cohen A, Yassine Z, et al. (2020b) *Mobility on Demand (MOD) Sandbox Demonstration: BART Integrated Carpool to Transit Access Program Evaluation Report*. *Federal Transit Administration*. Available at: https://www.transit.dot.gov/research-innovation/mobility-demand-mod-sandbox-demonstration-bart-integrated-carpool-transit-acce-0

McCoy K, Andrew J, Glynn R, et al. (2018) *Integrating Shared Mobility into Multimodal Transportation Planning: Improving Regional Performance to Meet Public Goals*. *Federal Highway Administration*. Available at: https://rosap.ntl.bts.gov/view/dot/34689

Mcguckin N, Fucci A and Jenkins DE (2018) *Summary of Travel Trends: 2017 National Household Travel Survey*. Available at: https://nhts.ornl.gov/.

Miller S, Huang E, Sullivan M, et al. (2021) *Mobility on Demand (MOD) Sandbox Demonstration: LA Metro First/ Last Mile Partnership with Via*. *Federal Transit*

Administration, U.S. Department of Transportation. Washington, D.C. DOI: 10.21949/1520687.

Mitra SK, Bae Y and Ritchie SG (2019) Use of Ride-Hailing Services among Older Adults in the United States. *Transportation Research Record* 2673(3). SAGE Publications Inc: 700–710. DOI: 10.1177/0361198119835511.

Mohtarian PL (2000) Telecommunications and Travel. A1C08: Committee on Telecommunications and Travel Behavior. *Transportation in the New Millennium.* Available at: https://onlinepubs.trb.org/onlinepubs/millennium/00115.pdf

Moudon AV (2020) Epilogue, looking into near future of information and communication technology–enabled travel. In: Plaut PO and Shach-Pinsly D (eds) *Digital Social Networks and Travel Behaviour in Urban Environments*. Routledge, pp. 221–229.

Nabti J (2020) *Mobility on Demand (MOD) Sandbox Demonstration : BART Integrated Carpool to Transit Access Program*. *Federal Transit Administration*. Available at: https://www.transit.dot.gov/research-innovation/mobility-demand-mod-sandbox-demonstration-bart-integrated-carpool-transit-access

Neoh JG, Chipulu M and Marshall A (2017) What encourages people to carpool? An evaluation of factors with meta-analysis. *Transportation* 44(2). Springer US: 423–447. DOI: 10.1007/s11116-015-9661-7.

Ong LW (2019) *Microtransit as First/Last Mile Connection to Transit Hub: An Evaluation of King County Metro's Ride2 Eastgate Service*. University of Washington.

O'Sullivan A (2012) *Urban Economics*. 8th ed. New York, NY: New York, NY : McGraw-Hill/Irwin.

Puget Sound Regional Council (2018) *2017 Puget Sound Regional Travel Study*. Available at: https://www.psrc.org/household-travel-survey-program

Rayle L, Dai D, Chan N, et al. (2016) Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy* 45. Elsevier: 168–178. DOI: 10.1016/j.tranpol.2015.10.004.

Rodriguez EA (2020) *FTA Annual Report on Public Transportation Innovation Research Projects for FY 2019*. *Federal Transit Administration*. Available at: https://www.transit.dot.gov/research-innovation/fta-annual-report-public-transportation-innovation-research-projects-fy-2019

Sadowsky N and Nelson E (2017) The Impact of Ride-Hailing Services on Public Transportation Use: A Discontinuity Regression Analysis. *Economics Department Working Paper Series*: 28. Available at: https://digitalcommons.bowdoin.edu/cgi/viewcontent.cgi?article=1012&context=econpapers

Schaller B (2018) The New Automobility: Lyft, Uber and the Future of American Cities. Available at: http://www.schallerconsult.com/rideservices/automobility.htm

Schwieterman JP (2019) Uber Economics: Evaluating the Monetary and Travel Time Trade-Offs of Transportation Network Companies and Transit Service in Chicago, Illinois. *Transportation Research Record* 2673(4). SAGE Publications Inc: 295–304. DOI: 10.1177/0361198119839344.

Shaheen S, Cohen A and Zohdy I (2016) *Shared Mobility: Current Practices and Guiding Principles*. *Federal Highway Administration*. DOI: FHWA-HOP-16-022.

Shaheen S, Totte H and Stocker A (2018) *Future of Mobility White Paper*. DOI: 10.7922/G2WH2N5D.

Shared-Use Mobility Center (2015) *Shared-use Mobility Reference Guide*. Available at: https://6c6.77f.myftpupload.com/wp-content/uploads/2019/08/Reference-Guide-Editsweb-version-10.24.2016_1.pdf (accessed 12 May 2022).

Shen Q (2000) New Telecommunications and Residential Location Flexibility. *Environment and Planning A: Economy and Space* 32(8). SAGE Publications Ltd: 1445–1463. DOI: 10.1068/a3292.

Shen Q, Wang Y and Gifford C (2021) Exploring partnership between transit agency and shared mobility company: an incentive program for app-based carpooling. *Transportation*. DOI: 10.1007/s11116-020-10140-w.

Shen Y, Zhang H and Zhao J (2018) Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. *Transportation Research Part A: Policy and Practice* 113: 125–136. DOI: https://doi.org/10.1016/j.tra.2018.04.004.

Sun F, Moudon AV, Shen Q, et al. (2019) The Impact of Shared Mobility Options on Travel Demand. In: *99th Annual Meeting of the Transportation Research Board*, 2019.

Tarduno M (2021) The congestion costs of Uber and Lyft. *Journal of Urban Economics* 122(October 2019). Elsevier Inc.: 103318. DOI: 10.1016/j.jue.2020.103318.

Tirachini A (2020) Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation* 47(4): 2011–2047. DOI: 10.1007/s11116-019-10070-2.

Tirachini A and Cats O (2020) COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation* 22(1): 1–34. DOI: 10.5038/2375-0901.22.1.1.

Tirachini A, Chaniotakis E, Abouelela M, et al. (2020) The sustainability of shared mobility: Can a platform for shared rides reduce motorized traffic in cities? *Transportation Research Part C: Emerging Technologies* 117: 102707. DOI: https://doi.org/10.1016/j.trc.2020.102707.

Uber (2016) It's been a great 5 years, Seattle. Available at: https://www.uber.com/blog/seattle/its-been-a-great-5-years-seattle/.

US Census Bureau (2022) American Community Survey 2016-2020 5-Year Estimates. Available at: https://www.census.gov/newsroom/press-kits/2021/acs-5-year.html.

Vaughn A (2014) Seattle Yellow Cab on the comeback path. Available at: https://www.seattletimes.com/seattle-news/seattle-yellow-cab-on-the-comeback-path/.

Vermunt JK and Magidson J (2004) Latent class analysis. *The sage encyclopedia of social sciences research methods* 2. Sage Publications Thousand Oakes, CA: 549–553.

Victoria Transport Policy Institute (2020) *Transportation Cost and Benefit Analysis II – Travel Time Costs*. Available at: https://www.vtpi.org/tca/tca0502.pdf.

Vij A, Ryan S, Sampson S, et al. (2020) Consumer preferences for Mobility-as-a-Service (MaaS) in Australia. *Transportation Research Part C: Emerging Technologies* 117: 102699. DOI: https://doi.org/10.1016/j.trc.2020.102699.

Wang X, Yan X, Zhao X, et al. (2022) Identifying latent shared mobility preference segments in low-income communities: Ride-hailing, fixed-route bus, and mobility-on-demand transit. *Travel Behaviour and Society* 26: 134–142. DOI: https://doi.org/10.1016/j.tbs.2021.09.011.

Wang Y, Moudon AV and Shen Q (2021) How Does Ride-Hailing Influence Individual Mode Choice? An Examination Using Longitudinal Trip Data from Seattle Region. In: *Transportation Research Record*, 2021.

Watkins K, McDonald N, Ruth S, et al. (2019) *Transit in the Era of Shared Mobility*. *Southeastern Transportation Research, Innovation, Development and Education Center (STRIDE)*. Available at: https://stride.ce.ufl.edu/wp-content/uploads/2017/03/STRIDE-Project-G-Final.pdf.

Weller BE, Bowen NK and Faubert SJ (2020) Latent Class Analysis: A Guide to Best Practice. *Journal of Black Psychology* 46(4). SAGE Publications Inc: 287–311. DOI: 10.1177/0095798420930932.

White V (2016) *Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis*. U.S Department of Transportation. Available at: https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic

Wu X and MacKenzie D (2021) The evolution, usage and trip patterns of taxis & ridesourcing services: evidence from 2001, 2009 & 2017 US National Household Travel Survey. *Transportation*. DOI: 10.1007/s11116-021-10177-5.

Yan X, Levine J and 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. DOI: https://doi.org/10.1016/j.trc.2018.07.029.

Yan X, Zhao X, Han Y, et al. (2021) Mobility-on-demand versus fixed-route transit systems: An evaluation of traveler preferences in low-income communities. *Transportation Research Part A: Policy and Practice* 148: 481–495. DOI: https://doi.org/10.1016/j.tra.2021.03.019.

Young J (2015) Infrastructure: Mass Transit in 19th- and 20th-Century Urban America. In: *Oxford Research Encyclopedia of American History*. Oxford University Press. DOI: 10.1093/acrefore/9780199329175.013.28.

Young M and Farber S (2019) The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A: Policy and Practice* 119(December 2018). Elsevier: 383–392. DOI: 10.1016/j.tra.2018.11.018.

Zgheib N, Abou-Zeid M and Kaysi I (2020) Modeling demand for ridesourcing as feeder for high capacity mass transit systems with an application to the planned Beirut BRT. *Transportation Research Part A: Policy and Practice* 138: 70–91. DOI: https://doi.org/10.1016/j.tra.2020.05.019.

Zhou J (2019) Ride-sharing service planning based on smartcard data: An exploratory study. *Transport Policy* 79(April). Elsevier Ltd: 1–10. DOI: 10.1016/j.tranpol.2019.04.009.