NORTHWESTERN UNIVERSITY

Care to Share?

Investigating Mobility-on-Demand and other Shared Modes with Big Data and Surveys

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ABSTRACT

This dissertation is a culmination of work spanning several modes of travel, multiple datasets, and different contexts. Because the proliferation of new mobility services disrupted the transportation ecosystem, I aim to understand travel behavior and investigate how new and traditional modes intermingle. I focus my attention on Mobility-on-Demand which encompasses ridehailing services such as private ridehailing, ridesplitting, and microtransit. In the order listed, they represent an increasing degree of sharing; an increasing number of passengers will share the same vehicle at the same time. While each of them is distinct, there are interactions amongst them and other modes of travel. Therefore, this dissertation also examines the interactions of Mobility-on-Demand with other modes such as public transit, micromobility, and the private automobile.

At the start of this research endeavor, the City of Chicago made available a comprehensive and novel dataset of ridehailing trips. I deploy an unsupervised machine learning technique to uncover patterns of utilization. The clustering of trips reveals identifiable trip categories that reveal the spatio-temporal dynamics of ridehailing demand. Examples of clusters include trips servicing the Chicago airports, trips in the evening likely for recreational activities, and trips to avoid bad weather. After understanding trip types, I use an econometric approach to study the determinants of ridehailing demand with an emphasis on socio-spatial community area differences. During this task, I discover a divergent relationship between private ridehailing and ridesplitting based on community vulnerability. I find that more vulnerable communities, identified via a novel index, are correlated with higher ridesplitting demand whereas the opposite is true for more privileged communities. More vulnerable communities may be taking advantage of the tradeoffs that are in favor of ridesplitting, where sharing a vehicle with a stranger, losing privacy, and increasing travel time are compensated with lower fares. These studies use a

ridehailing trip dataset filled with millions of observations, yet these analyses cannot ascertain individual-level contexts and choices because the data does not include rider information such as gender, age, and income. Consequently, I turn to survey-based data to understand individual mode choice.

Microtransit is next in the evolution of ridehailing services. It begins to blur the lines between ridehailing and public transit by incorporating a mix of their attributes. For example, it represents an on-demand service and can operate as a curb-to-curb service. I design an efficient choice experiment with microtransit alternatives and accompany it with questions about respondent sociodemographics, attitudes, and current travel behavior. Using the respondents' current commute mode, the choice experiment seeks to observe the tradeoffs between travel time, cost, and novel features when choosing between the respondent's current mode and microtransit. By utilizing a discrete choice model that recognizes latent attitudes, I find not only differences between transit and car commuters when it comes to the effects of travel time and cost, but also differing effects of the COVID-19 pandemic: namely, that the pandemic increases the probability of choosing modes that are more private. This highlights the necessity of understanding the short-term impacts and long-term implications of COVID-19 on travel behavior.

To investigate the effects of the pandemic, I use survey-based data collected from Chicagoland transit users. Represented in the data are users of the Chicago Transit Authority, Metra, and Pace transit agencies with information on past transit ridership, COVID-19 ridership, priorities for transit investments, and intent to use transit after the pandemic. Also covered in this data is the respondents' travel behavior involving other modes, which connects to the Mobility-on-Demand theme of this research. I model their ridership status, their intent to return when all health concerns are alleviated, and the possibility of increased ridership with fare integration of multiple mobility services, which is a key feature of Mobility-as-a-Service. The model results indicate the importance of teleworking, the need to explore strategies that will bring back transit ridership equitably, and an opportunity for integrated transportation systems to attract ridership. What is clear from the pre-pandemic studies, microtransit, and transit ridership study is that Mobility-on-Demand plays an increasing role in the transport ecosystem.

After all this research, I synthesize the results to understand ridehailing utilization, determinants of demand, the effects of the pandemic, and transportation equity. With a broader perspective on Mobility-on-Demand, I provide policy recommendations and discuss avenues for future research.

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DEDICATION

In loving memory of Emelynda Malinay Soria

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
ACS	American Community Survey
API	Application Programming Interface
CBD	Central Business District
COVID-19	Coronavirus disease of 2019
CTA	Chicago Transit Authority
EFA	Exploratory Factor Analysis
ICLV	Integrated Choice and Latent Variable
ICT	Information and Communication Technology
IOS	Inclusion of Other in the Self
MaaS	Mobility-as-a-Service
MaaS-fare	Mobility-as-a-Service, Fare integration model
MoD	Mobility-on-Demand
MT-S	Microtransit Sedan
MT-V	Microtransit Van
RTA	Regional Transit Authority (of Chicago, IL and surrounding metropolitan area)
SC	Stated Choice
SDM	Spatial Durbin Model
SQ	Status Quo
SVI	Social Vulnerability Index
TAT	Transit Access Time
TNC	Transportation Network Company
VMT	Vehicle Miles Traveled

1 INTRODUCTION

Current urban transportation systems include public transit, on-demand, and shared forms of mobility which play a significant role in supporting the economic functioning and well-being of cities and their residents. Ongoing innovation in service models and delivery is reshaping how people engage with transportation, is shifting mobility patterns, and the competitive landscape between private and public modes. Among innovative smartphone app-based services exists ridehailing which connects drivers seeking compensation with riders through online booking, payment, and communication, and ridesplitting which is ridehailing with multiple parties being simultaneously consolidated into one vehicle (Shaheen & Cohen, 2018b). These services can complement transit and benefit both passengers and cities by improving accessibility while reducing transportation externalities such as air pollution and traffic congestion. Concurrently, there is increasing evidence from North American cities (New York, San Francisco, Chicago, Los Angeles, and Seattle) that ridehailing is a major contributor to traffic congestion (Erhardt et al., 2021; Graehler et al., 2019; Wu & MacKenzie, 2021) and may compete with mass transit (Yan et al., 2020). Measures like promoting ridepooling can help curb vehicle miles traveled (VMT), a negative impact of ridehailing. Yet, the effectiveness of ridesplitting in reducing congestion has come under scrutiny and depends on deadheading and pooling rates (Schaller, 2021).

Juxtaposed against the private automobile, modern forms of mobility are powered by advanced Information and Communication Technology (ICT) which offers new opportunities to improve transportation accessibility and mobility. Because these novel modes are characterized by their on-demand availability, their introduction to the transportation system has been disruptive. The most salient of these disruptors is ridehailing. It is an on-demand service facilitated by Transportation Network Companies (TNCs) which connect drivers-for-hire with riders through internet-based means, typically a smartphone application. Of the traditional modes, the most similar to ridehailing are taxis. While taxis are street-hailed and riders pay the driver directly, all transactions (whether they be informational or monetary) are handled by the TNCs through a smartphone application. Throughout the rest of this dissertation, I will refer to internet-based ridehailing systems as Mobility-on-Demand (MoD) which covers the evolving nature of TNC services. An example of this evolution is the leveraging of massive computational power in conjunction with advanced ICT where TNCs continue to expand their capabilities and provide services other than direct, door-to-door rides.

I will refer to the first iteration of ridehailing as private ridehailing or solo ridehailing (e.g. UberX). One such evolution is ridesplitting which pools several trip itineraries that share similar departure times and trajectories together into one for-hire vehicle. Another evolution of ridehailing is microtransit which blurs the lines between ridehailing and fixed-route transit by incorporating characteristics from both. Similar to ridehailing, microtransit is provided by TNCs that optimize routing and match riders and drivers. Similar to public transit, it pools several trips together into a vehicle typically larger than a passenger sedan. Microtransit can be flexible, with variations ranging from completely accommodating, door-to-door rides to fixed-route, curb-to-curb rides. In the early and middle 2010s, many lauded its benefits as tech-savvy users quickly adopted it.

MoD has the potential to contribute to a more efficient transportation system. Because a rider can access their destination with another person's vehicle, she can shed her car, relinquish space that would otherwise be used to park it, and avoid adding to roadway congestion. It can also act as a first-mile-last-mile mode to access public transportation and thereby complement mass transit. This benefit is further improved with ridesplitting which reduces the fleet size needed to serve demand. Proponents of microtransit see opportunities to replace low revenue public transit routes with on-demand vehicles which reduces operational costs. However, from their inception to the present day, the notion that these and other benefits have accrued or will ever accrue to a net positive impact is questionable. In other words, individuals who can access internet-powered modes have much to gain from these significant improvements in mobility and accessibility, but whether MoD contributes to an overall more efficient transportation system is heavily debated. Therefore, the motivation for this dissertation is to investigate ridehailing and other forms of shared mobility, patterns of their utilization, and attitudes that riders hold towards them so that their benefits and disadvantages are better understood.

The shifting travel behavior from familiar and traditional modes to modern offerings, included in the umbrella concept of Mobility-as-a-Service (MaaS), reveals the real benefits and disadvantages that ICT-powered mobility options can have on urban travel. Additionally, contextual factors such as the COVID-19 pandemic obfuscates rider behavior and motivations, calling for a careful investigation of their long-term impacts. By investigating these new modes, my goal is to push the boundaries of the state-of-the-art in transportation research by examining MoD from multiple angles. Specifically, this dissertation aims to answer the following four questions by completing the associated objectives.

1. How is ridehailing utilized?
    a. Use Chicago big data and clustering algorithms to identify trip types
    b. Investigate MoD and traditional mode relationships with surveys
2. What are the determinants of MoD demand?
    a. Regress ridehailing demand onto community-level variables

   b. Utilize a mode choice experiment to study the individual-level tradeoffs when microtransit is offered as a commute alternative

3. How did the COVID-19 pandemic affect short-term and long-term travel behavior towards public transit, MoD, and other shared modes?
   a. Study the short-term COVID-19 impacts on microtransit adoption
   b. Examine teleworking, shifting mode relationships, and opportunities for service integration to improve transportation accessibility
4. What are the societal and distributional impacts of innovative mobility services?
   a. Map the spread of ridehailing utilization in and between communities
   b. Research the link between community vulnerability and ridehailing
   c. Analyze how MoD can serve disproportionately impacted population segments in the pandemic recovery phase

Figure 1 summarizes where each question originated, which data are utilized to answer them, and the methods employed to uncover relationships within the data. My first question about ridehailing was about its utilization, then after I analyzed the data and investigated its implications, more questions emerged. However, each question could be answered across the multiple analyses. Hence the overlap of questions across several chapters. Data and methods also spanned across multiple chapters with the Chicago ridehailing trip database being analyzed in chapters three and four, and with discrete choice methods being used in chapters five and six.

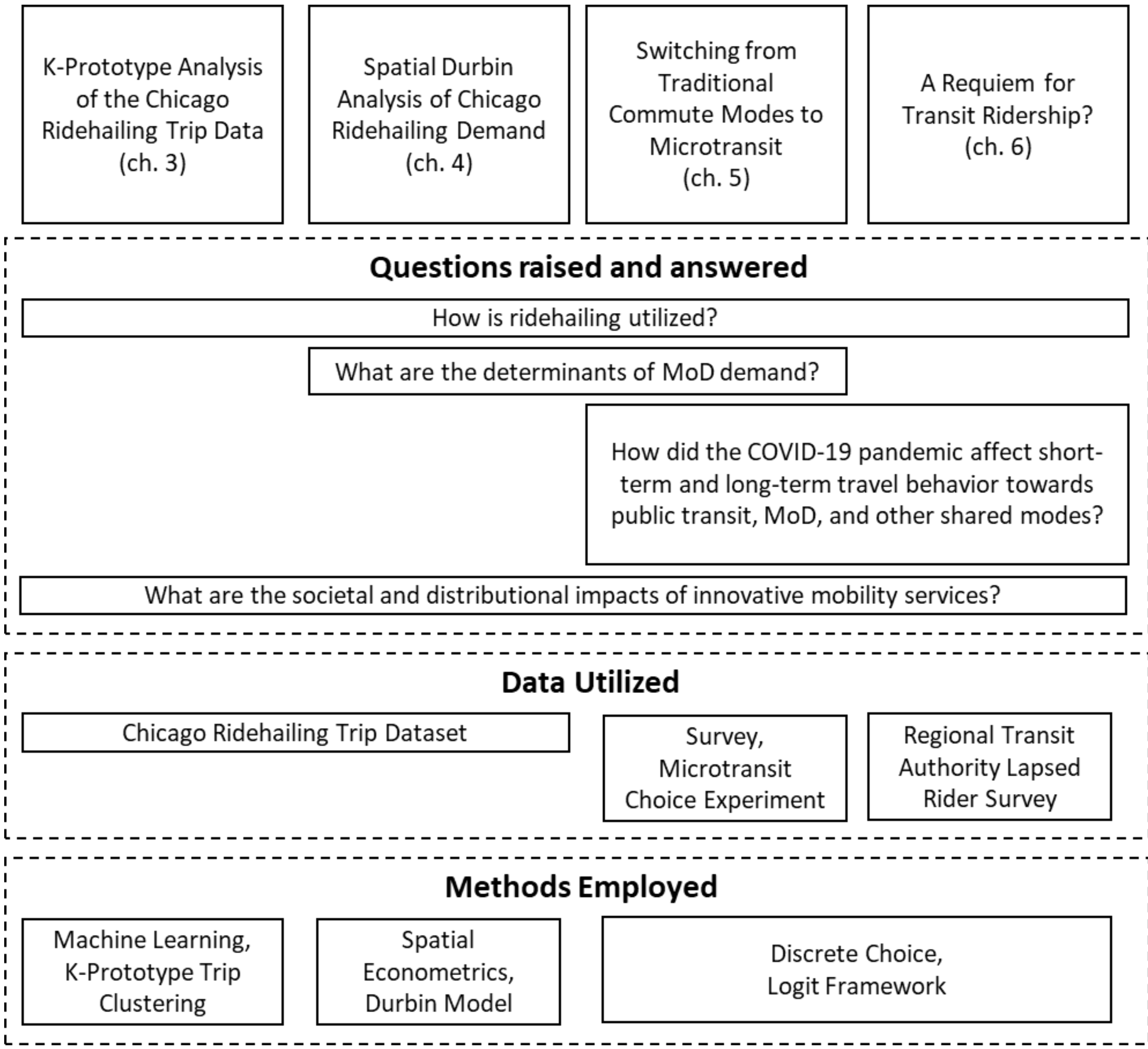

Figure 1 Summary of dissertation questions, data, and methods

This dissertation research began around the same time that the Chicago ridehailing trip dataset became publicly available in November of 2018. Early research in this area depended on survey-based data or trip data that only represented a fraction of total trips. Therefore, I started this research by investigating how ridehailing is utilized. Because this novel and large dataset had not yet been rigorously analyzed, the objective of chapter 3 is to use an unsupervised machine learning method, K-Prototypes, and identify distinct ridership patterns. Six prototypes (similar to clusters) are identified. When ridehailing data are supplemented with data on weather, transit performance, and taxi demand, it revealed that ridehailing is used to avoid bad weather and fill in the accessibility gap of traditional shared modes. However, one prototype (cluster) of trips that intrigued me is defined by nearly all rides being completed with ridesplitting rather than the private ride option. This inspired me to consider partitioning the data into private ridehailing and ridesplitting trips when analyzing community-based determinants of demand.

In chapter 4, I continue to use the Chicago ridehailing data to complete a spatial regression analysis that identifies determinants of demand. Because the data are aggregated to a spatial dimension and do not contain information about the riders, I supplement it with data that are similarly aggregated, including the American Community Survey (ACS) and transit data. I regress the average daily demand for private ridehailing and ridesplitting for each of the 77 Chicago community areas onto sociodemographic, transit accessibility, and other community-based variables. In line with the ridehailing literature and my expectations, results indicate that population and recreational activity density variables are positively correlated with the demand for private ridehailing and ridesplitting. The analysis also reveals significant contrasting effects of social vulnerability indicators, which correlate positively with ridesplitting and negatively with private ridehailing demand. This demonstrates that community areas with higher levels of underprivileged circumstances, such as living on below poverty level income and single parenthood, have a higher demand for ridesplitting but reduced demand for private ridehailing, hinting at different strategies for balancing the tradeoffs between mobility, accessibility, and privacy. Additionally, I find that higher rail transit access is associated with higher demand for both single and pooled ridership along with substantial indirect effects of one community’s transit accessibility affecting its neighbors. I continue to investigate the determinants of ridehailing demand by utilizing survey data, which seeks to understand individual level decision-making rather than relying on trip-level data that lacks information about the riders.

In addition to collecting data on individual-level determinants, I take part in designing a survey to study the decision-making of Israeli public transit and car commuters when offered novel microtransit options during the COVID-19 pandemic. In chapter 5, I investigate the tradeoffs between fare, walking time, waiting time, minimum advanced reservation time, and availability of shelter at designated boarding locations. Additionally, I analyze two latent constructs: attitudes toward sharing and risk-perceptions related to the pandemic arising from respondent experiences. Because ridehailing is not allowed in Israel at the time of survey distribution, it is an opportunity to investigate microtransit demand in a neutral country. I estimate Integrated Choice and Latent Variable (ICLV) models to compare the two commuter groups in terms of the likelihood of switching to microtransit, attribute tradeoffs, sharing preferences, and pandemic impacts. The results reveal high elasticities for travel time and COVID effects for car commuters compared to the relative insensitivity of transit commuters to the risk of COVID contraction. Moreover, for car commuters, those with strong sharing identities were more likely to be comfortable in situations where COVID contraction is higher and switch their commute mode to microtransit. Because the pandemic prolonged into multiple years and this survey captured behavior at the beginning of the pandemic, this dissertation also concentrates on investigating the pandemic's effect on shared mobility overall.

Specifically, I seek to understand the short- and long-term effects of the pandemic on public transit and identify opportunities to integrate new shared modes with traditional ones within this context. Chapter 6 covers this portion of the analysis where I obtain the data from a large survey of transit users (N = 5,648) in the jurisdiction of the Regional Transit Authority

(RTA) of Chicago, IL with variables concerning mode substitution, transit investment priorities from the user's perspective, and different types of transit services: Chicago Transit Authority (CTA) which operates bus and heavy rail services within the City of Chicago, Pace which is the region's suburban bus service, and Metra which is a commuter rail service with coverage spanning to the periphery of Chicagoland. With this data I analyze why transit users lapsed in ridership during the pandemic, who plans to eventually return to their status quo transit ridership levels, and opportunities to increase transit ridership by seamlessly integrating the fare structure of multiple shared modes together in a MaaS arrangement. While investigating this data, I observed the changing relationships between MoD, public transit, micromobility, and new employment dynamics that were caused by the pandemic. In summary, the results of modeling the decision to reduce ridership reveal that employment characteristics (e.g. income, telecommuting, employment status) and vehicle ownership had the highest impact, followed by race, user priority for sanitation of transit facilities and vehicles, and type of transit service utilized. Similar to what has been identified in the literature, racial minorities (i.e. Asian, Black, and Hispanic) are less likely to lapse in ridership than their white counterparts. However, a novel finding is that racial minorities who did lapse in ridership are less likely to return to previous ridership levels, which emphasizes the need for future research in these communities. Next, I investigate the opportunity for MaaS to increase ridership. I model the willingness to increase transit usage should MaaS be implemented and find that racial minorities, those who used on-demand modes to substitute transit or access it, and those who travel during off-peak times would use transit more. Altogether, the analysis of this survey data connects the observed effects of COVID on transit ridership with more hopeful and optimistic plans for the future.

Overall, this research covers many aspects of shared mobility by utilizing a wide array of datasets and methodologies. **Figure 2** summarizes the range of analyses and areas where future work can shed more light on modern mobility services. Analysis of large-scale datasets reveals distinct ridehailing trip categories and provides inspiration for the next project after it identifies ridesplitting trips as its own category (Chapter 3). While regressing the demand for private ridehailing and ridesplitting onto community-based variables, I discover that the sociodemographic profile of the communities correlates differently between these modes (Chapter 4). Specifically, communities with higher indicators of social vulnerability are positively correlated with higher ridesplitting demand and negatively correlated with private ridehailing demand. However, without knowing the characteristics or attitudes of the riders, not much can be gleaned from this finding about individual-level factors of demand for shared mobility. Because this demand was especially affected by the COVID-19 pandemic, I analyze survey-based data to understand individual-level tradeoffs between travelers' pre-pandemic commute modes and novel microtransit alternatives and the latent attitudes that affect mode choice in the pandemic context (Chapter 5). I also take this opportunity to see why transit riders lapsed in ridership during the pandemic, which rider-segments plan to return to transit, and who would use transit more with fare integration across several mobility services (Chapter 6). And at the core of the aforementioned research projects, I ask: what are the societal and distributional impacts implications of shared mobility? In the summary of my results (Chapter 7), I weave the results and implications from each chapter to gain a broader perspective of ridehailing utilization, demand determinants, the effects of the pandemic, and transport equity. At the end of the dissertation, I discuss limitations and future research.

This dissertation's purpose is to provide details of my research on new shared mobility with special attention given to MoD. In the next chapter, I review the state-of-the-art in MoD literature to explain the motivations behind choosing ridehailing and its relationship with other shared modes as my research topic. While much has been covered in the literature, there still remains gaps for more research. After the literature review, the next chapters focus on the specific background, data, methodology, results, and implications. At the end of this dissertation, I synthesize the results and provide a broader view of Mobility-on-Demand, changing relationships among several modes existing in the urban landscape, the current opportunities for shared mobility to continue to improve urban travel, and suggestions for future research.

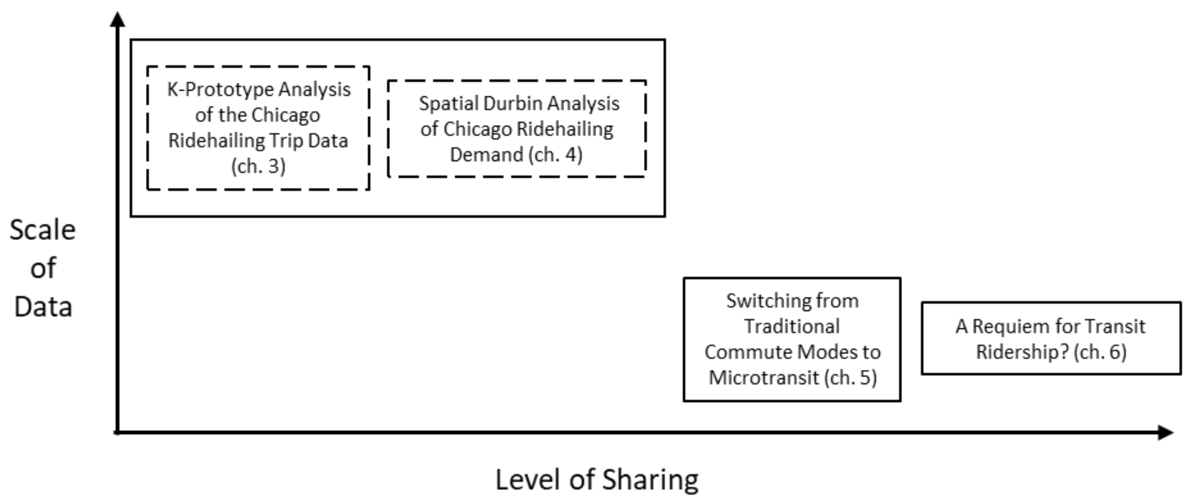

Figure 2 Range of research across the data and sharing dimensions

2 LITERATURE REVIEW

Since the early 2000s, numerous companies have disrupted existing transportation systems around the world with novel mobility services. Chief among them are Transportation Network Companies (TNCs) who brought ridehailing to the market. Their initial service offered reliable, affordable (relative to traditional taxis), on-demand, and door-to-door transportation that is requested (hailed), tracked, and paid by users through smartphone applications. Today, these services are known as Lyft Classic and UberX (Lyft, 2022; Uber, 2022). Over time, TNCs began introducing new services that blended advanced ICT capabilities with attributes from traditional shared mobility. For example, they began offering pooled rides (ridesplitting) and increased operational efficiency by embracing curb-to-curb services. This new generation of mobility services are poised to alter how cities fulfill their mission to offer people access to goods, services, and opportunities. Public agencies are currently compelled to react to new services and ensure that they contribute to serving the public good. Yet, intervening effectively is extremely challenging as there is currently no consensus on the impact, behavioral factors, and ideal role of new Mobility-on-Demand (MoD solutions. Supporters of ridehailing view it as an alternative to driving alone and as part of a suite of shared mobility options that serve previously unmet demand for fast, flexible, and convenient mobility in urban areas. On the other hand, critics suggest that ridehailing services compete with public transit, increase congestion during peak periods, and overall contribute to urban woes.

The proliferation of TNCs has produced a significant interest in the research community and a growing body of literature with search terms “transportation network company, ridehailing, and ridesourcing” producing more than 5,000 results from Google Scholar (Google Scholar, 2020). But, despite the strong policy relevance and a steady stream of research, there are gaps in our understanding of its impacts on equity, its usage, factors that contribute to its demand, and how the COVID-19 pandemic affects shared mobility as a whole. This chapter identifies the current state-of-the-art in MoD research and explains the motivations behind my research.

The rest of this chapter covers the following topics. First, the definitions of shared mobility, MoD, and the modes they encompass are provided. These definitions are provided to differentiate between similar modes which are often misused in the media. Next, I explore the state-of-the-art in MoD research. This research covers ridehailing utilization by understanding its adoption, its impact on roadway congestion, and how it competes with or complements traditional modes such as public transit. After exploring what has been observed, I will cover the literature on stated choice research. This section focuses on the literature which utilizes choice experiments to understand how respondents react to traditional travel attributes such as cost and travel time along with novel attributes (to ridehailing) such as walking distance to and availability of shelter at designated pickup locations. I will also cover the recent literature on the pandemic risk perceptions and their effects on shared mobility. Completing this chapter, I summarize the research and highlight how this dissertation endeavors to expand the state-of-the-art.

2.1 Definitions of Shared Mobility

Definitions of several types of shared mobility services and MoD are provided below to clarify the terminology used henceforth. They are sourced primarily from Shaheen and Cohen (2018b) with additional sourcing from Feigon and Murphy (2016) and the Federal Transit Authority (2022). Using these resources, I disambiguate traditional shared mobility, their ICT-enabled counterparts, and MoD which have been used interchangeably in the media (Huet, 2014; Weed, 2019).

Firstly, shared mobility is an umbrella term used to include several modes where vehicles are publicly accessible and used for a multitude of trip purposes. This term includes traditional public transit such as public transit buses and its variants, rail and its variants, ridesharing, carpooling, taxis, and other for-hire transportation services that were not established on an internet-based platform. Modern shared mobility includes modes that are powered by advanced ICT. Though not the main focus of this dissertation, it is important to note that bikeshare and e-scooters exist under the shared mobility umbrella. They are not analyzed individually in this thesis; however, they are included when MaaS is discussed. When mentioned individually, I will refer to these active shared modes as micromobility.

The critical difference between ridesharing and ridehailing is the purpose of the trip from the driver's perspective. Shaheen and Cohen (2018b) include this in their definition by clarifying that ridehailing drivers use the platform for compensation whereas ridesharing is used for several purposes other than as a source of income. Though ridesharing may be facilitated through smartphone applications like ridehailing, the purpose of ridesharing ranges from splitting tolls to accessing carpool lanes because the driver and passenger(s) share similar trajectories and the driver's trip is already planned. Ridehailing drivers provide services to earn an income. The first of the ridehailing modes that entered the market is private ridehailing which offers a door-to-door experience that exclusively serves a single party of travelers during the entirety of a trip (e.g. UberX and Lyft Classic). I will refer to this mode as private ridehailing. Also included from Shaheen and Cohen (2018b) are the definitions for ridesplitting and microtransit. Ridesplitting (e.g. UberPool) and microtransit (e.g. Via) are forms of ridehailing with nuances that also require clarification. Ridesplitting occurs when a passenger allows the trip to be shared with another party if this party shares a similar trajectory. It is an evolution of private ridehailing. Next along the sharing continuum is microtransit which is similar to ridesplitting. It has a large range of operation, offering completely flexible routing with door-to-door services, semi-fixed routing with curb-to-curb services, to fixed-route services with each offering being demand responsive. **Figure 3** illustrates the difference between door-to-door and curb-to-curb services. Passenger 1 (P1) and passenger 2 (P2) are traveling in a similar trajectory. Door-to-door microtransit will pick up P1 and P2 at their origins and drop them off directly at their final destinations. Instead, with curb-to-curb microtransit, P1 and P2 will walk to a designated pickup location, disembark the vehicle near their destination, and walk the rest of their trip. This opens the door for semi-fixed and fixed-route services which are more operationally efficient. The size of vehicles can also range from sedans to large-capacity vehicles that may require drivers to obtain commercial licenses. What differentiates ridesplitting and microtransit is microtransit's flexibility. Ridesplitting does not offer curb-to-curb services. Throughout this dissertation, I will use MoD to include private ridehailing, ridesplitting, and microtransit because these modes can be hailed on demand unlike micromobility which depends on the availability of a bike or scooter.

Importantly, with advanced ICT many of the modern shared mobility options can be bundled together. Mobility-as-a-Service (MaaS) exists to combine several personal mobility

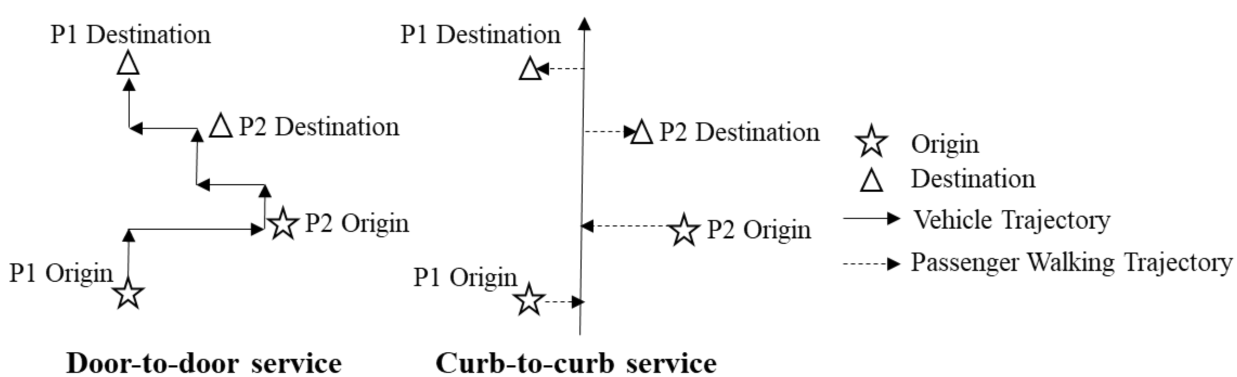

Figure 3 Comparing door-to-door and curb-to-curb Service Offerings

services from multiple providers through a single interface where all information and monetary transactions are handled (Smith & Hensher, 2020). This relies on cooperation from multiple TNCs and even public agencies to package and offer their services together.

With the definitions of shared mobility established, the next sections are dedicated to discussing the observed trends, survey-based analyses, the effects of the pandemic on shared mobility, identifying where the literature can be expanded, and the motivations for this dissertation.

2.2 Research on Ridehailing Utilization

2.2.1 Ridehailing adoption

The largest mobility-on-demand ridehailing provider, Uber, is present in 600 cities across 65 countries and has surpassed 10 billion rides worldwide (Iqbal, 2020). The ridehailing market is growing rapidly, especially in and around urban areas where it is primarily offered. A national survey conducted by Pew Research Center showed that in 2015, 15% of American adults have used ridehailing services, 51% were familiar with these services but have not used them, with the rest having not heard of them (Smith, 2016). Pew Research Center ran the survey again in 2018 and found that, in a mere 3 years, 36% of American adults have used ridehailing, 61% are familiar with it but have not used it, and only 3% are unaware of it (Jiang, 2019). Use appears to be concentrated in specific groups, with some authors suggesting the concept of supersharers which are users who routinely use MoD and multiple other shared mobility services (Feigon & Murphy, 2016).

National US surveys suggest that there are no significant differences in adoption across gender or race (Clewlow & Mishra, 2017; Smith, 2016). Evidence suggests that ridehailing use is higher in younger, well-educated, and higher income population segments (Alemi, Circella, Handy, et al., 2018; Clewlow & Mishra, 2017; Dias et al., 2017; Rayle et al., 2016; Wang et al., 2019). Additionally, surveys have shown that participation is linked to technology and mobile phone savviness (Lavieri & Bhat, 2019a). Because TNCs rely on ICT, those who are unbanked and without smartphones are unlikely to adopt ridehailing (Brown, 2019).

For the spatiotemporal profile of use the majority of ridehailing trips are undertaken during weekends (Yu & Peng, 2019), in the evening (Gehrke et al., 2019), and for leisure purposes (Rayle et al., 2016; Tirachini & del Río, 2019). It is broadly found that ridehailing demand is positively related to residential density (Dias et al., 2017; Conway et al., 2018; Yu & Peng, 2019; Li et al., 2019; and Goodspeed et al., 2019).

2.2.2 Ridehailing trends using empirical data

MoD research spans several countries and considers ridehailing's effect on existing transportation systems across several modes and contexts. At the end of this chapter, **Table 1** summarizes each of the studies in the order that they appear in the following subsections. It provides the author(s), where the data were collected, how the data were collected, methods, and a summary of the results.

2.2.2.1 Ridehailing and Traditional Taxis

The relationship between TNCs and taxis are the strongest in the literature with the consensus being that the market share for taxi shrinks once TNCs enter most markets. TNCs most resemble traditional taxi services as the difference between them hinges on ICT improvements and the use of personal vehicles that are typically not readily distinguishable in traffic like the traditional yellow cab.

While ridership numbers are not the focus of this study, Cramer and Krueger (2016) find stark differences between taxis and private ridehailing services, represented by UberX, in major

US markets. Their comparison is of utilization rates based on hours and miles driven with a passenger by the different services. Utilization rates for UberX were significantly higher in both measures. The higher utilization rates for UberX allow the platform operator to charge less per mile to passengers. The only market where utilization rates are identical between services is in New York City where the authors find that the higher density across the city aids taxis. Having a denser city makes it easier for riders to street hail a taxi. A major limitation of this study is that it does not examine the impact of ridehailing on the taxi industry. Instead, it is a comparison of the services and the advantages of ICT-enabled ride hailing over street hailing.

Kim et al. (2018) explore the effect ridehailing has on taxis in New York City, New York. The authors use the number of daily taxi trips, average revenue per taxi driver, and occupancy rate of taxis from January 2009 to December 2015 as dependent variables in their regression models and find that the entrance of Uber did not decrease these measures. Rather, the entrance of Uber is statistically correlated with an increase in taxi trips and has no statistical effect on revenue per driver and occupancy rates. The authors include in their examination of Uber market entry the spatial distributions of taxi drop-offs and pickups over time to further explain their findings. They found that the once heavily concentrated drop-off and pickup zone in central Manhattan had eased following Uber's entry but increased in other parts of the city. The authors conclude that while their model does not find Uber affecting their model's dependent variables, the spatial dispersion shows that taxis reorganized themselves by serving different areas. Because they began serving other areas that were not frequented earlier, the new taxi strategies benefit consumers.

While the previous authors find that average revenue per taxi driver did not decrease in New York City, Berger et al. (2018) find differing results using data at the national level.

Utilizing a sample of taxi drivers obtained from the American Community Survey, the authors find that the labor supply did not change, but existing drivers' mean hourly earnings decreased. While controlling for these variables, the several models that the authors estimated conclude that the mean earnings of incumbent taxi drivers decreased 13% to 17%. On the effect of labor supply, the authors find that the model does not indicate a decrease in drivers but are not entirely convinced. The hesitation in this conclusion comes from the survey instruments' inability to longitudinally track drivers. The authors posit that their results do not explain the compositional change of the workforce as more productive taxi drivers could have left and thereby decrease the wages found in the previous result.

To complete an analysis of taxi ridership in the United States, Contreras and Paz (2018) research on taxi ridership in Las Vegas, Nevada is examined. The data employed in this study is for trips that either end or begin at McCarran International Airport from July 2010 to July 2016. Regressing ridehailing ridership on transit ridership reveals a statistically significant negative coefficient while controlling for transit ridership, average daily traffic counts, airport visitors, car rentals, average lodging costs, and population.

Taxi ridership globally also took a hit. Didi Chuxing, the equivalent of Uber and Lyft in China, similarly impacted taxi operations. Nie (2017) examines activity from 2,700 taxis in Shenzhen, China from 2013 to 2015. Utilizing GPS data from these taxis, the author developed four conclusions to explain the effect of ridehailing on Shenzhen's taxis. First, the taxis experienced a short disruption from ridehailing competition that began to stabilize in the later months of data. The author attributes the stabilization of taxi utilization to the availability of street-hailing for busy people and the navigational experience of taxi drivers. Secondly, taxis were still able to compete with ridehailing during peak commute times in high-density areas.

Thirdly, utilization rates were increased with the introduction of ridehailing. The productivity of taxis increased during off-peak hours by as much as 15%. Lastly, ridehailing worsens congestion but the author ensures that the 8% decrease in travel speed is mild when looking at the whole year.

Jiang and Zhang (2018) utilize taxi GPS data in November of 2012, 2014, and 2015 in Beijing, China. When comparing the average passenger trips per hour per day and average daily profit per taxi from 2012 to 2015, the authors find that they dropped 18.08% and 19.29%, respectively. Using the GPS data, the authors also found that taxis decreased the number of working hours and attribute it to competition and lower enthusiasm of drivers. Comparing more efficient to less efficient drivers, the efficient drivers tend to search locally, serve within inner Beijing, and complete their trips faster. Unlike in New York City, there was not a discernable increase in pickups outside of inner Beijing.

Dong et al. (2018) combine trip data from taxis and ridehailing also from Beijing. The datasets comprising approximately 50,000 taxi trips and 40,000 ridehailing trips from December 2015 to January 2016. Though the authors do not make any statement on ridership, they claim that their results show that ridehailing did not directly compete with taxis in Beijing. Rather than directly competing with taxis, the authors found that ridehailing filled a “spatial and temporal shortage” of taxis during peak travel hours. Another significant result is the number of trips per driver on workdays significantly varies across the services. During peak hours, taxi drivers completed about 7.8 trips per driver whereas ridehailing drivers completed 1.74 per driver. Given that this occurred during the same period this is evidence of lower vehicle utilization.

2.2.2.2 Ridehailing and Traffic

A chief concern related to the increasing adoption of ridehailing services is the increase in vehicle miles traveled. With a dearth of disaggregated ridehailing trip data, the studies examining its effect on traffic flows have developed indirect methods. Without detailed data, the total amount of Vehicle Miles Traveled (VMT) and congestion added by ridehailing is not fully known. Rather, these studies provide insights into the network effects using available data or by means of non-traditional methods of data collection.

Henao and Marshall (2018) collect data by conducting an intercept survey. The researchers would work as a driver for two ridehailing companies, Uber and Lyft, to distribute it. Their pseudo-experimental design resulted in data for 416 trips. The authors find that the addition of VMT to the roadway is significant. They conservatively estimate that ridehailing adds 40.8% of VMT from deadheading and the driver's commute home after finishing a driving shift. When accounting for deadheading, induced travel, and mode substitution, the estimated amount of VMT added to the system is 83.5%. The authors also estimate the occupancy of a trip to be 1.36 and when accounting for distance traveled it is 1.31 (not including the driver). This estimate drops down to 0.78 when considering deadheading which is lower than if the person drove themselves.

Nair et al. (2020) use 10 months of disaggregate data from 'Ride Austin' a local ridehailing initiative to study deadheading trips. The paper imputes deadheading related to the search for a new passenger by tracking the distance between the drop-off of one passenger to the pick-up of the next in different areas of Austin, TX which is relevant to predicting the local traffic flow impacts. What the authors find is that there is significant deadheading for trips originating in areas with low population density. After estimating expected deadheading distances during the afternoon peak commuting period, their results reveal deadheading of nearly 2 miles in the downtown core of Austin to greater than 11 miles in Traffic Analysis Zones 5 miles away from downtown.

A study looking at ridehailing's effect on traffic was completed by Li et al. (2016). In their study they use several measures to quantify the effect of ridehailing. Using data from the Urban Mobility Report, the authors use 2-stage least squares regression to find the effect of ridehailing entry into a market by utilizing several dependent variables. These variables are Travel Time Index, Commuter Stress Index, annual hours of total delay, annual hours of delay per auto commuter, annual congestion cost, annual congestion cost per auto commuter, annual excess fuel consumed due to congestion, and annual excess fuel per auto commuter. The results of their regression found that Uber entry improved nearly all dependent variables at a statistically significant level. The authors posit that Uber increases vehicle occupancy, reduces car ownership, shifts demand to different modes, changes demand around peak hours, and increase vehicle capacity utilization. Much like Henao and Marshall (2018), though, the lack of quality data stops the authors from testing these mechanisms directly.

Recent research, though, has used more comprehensive data and found nuances in the debate. Schaller (2021) combines several publicly available ridehailing trip datasets and accounts for mode substitution of non-auto modes for ridehailing. Focusing on Boston, Chicago, New York City, and San Francisco, the author estimates VMT increases ranging from 97% to 157%. He attributes much of this increased VMT to people switching from pooled modes such as public transit and ridesplitting to private options. In the same analysis, Schaller (2021) envisions a hypothetical scenario that leads to no changes in VMT from ridehailing. This scenario assumes that 85% of trips are pooled with most of the trips serving 3 passengers, that these pooled trips also only spend 20% of VMT with only 1 passenger (and not serving other passengers), and 70% of ridehailing mode substitution comes from auto or taxi trips. All very lofty goals.

Generally, researchers are increasingly finding nuance in their results. Dhanorkar and Burtch (2021) take a different approach from analyzing spatially aggregated data and instead utilizes traffic data collected from 9,000 vehicle detectors across California. Their results from a difference-in-difference analysis show that ridehailing does indeed increase congestion with the most significant effect occurring on the weekend, in areas with high population density, and areas with a dense network of local roads. Li et al. (2022) support these findings with their own difference-in-difference analysis. Their results also show increased traffic congestion in highly compact urban areas. Results from both research articles are intuitive as adding additional vehicles in areas with existing congestion concerns (e.g. dense urban areas) is likely to be more impactful than in areas with less congestion (e.g. around suburban sprawl).

2.2.2.3 Ridehailing and Public Transit

The chief concern of the relationship between ridehailing and public transit is that they are competitive rather than complementary. If ridehailing complements public transit, then transit ridership would increase because ridehailing would support a multi-modal lifestyle. If ridehailing and public transit compete, then the effect is two-fold. Firstly, public transit agencies would have less fare revenue and resort to cutting services. Secondly, given the reliance on public transit by captive users, this raises issues of transportation equity for transit dependent populations.

Hall et al. (2018) conclude in their study that Uber complements public transit systems. Their regression of Uber market entry into American Metropolitan Statistical Areas onto monthly transit ridership numbers from the National Transit Database from 2004 to 2015 finds that Uber is correlated with an increase in transit ridership. The authors estimate that for the average transit agency, Uber's presence increases ridership by 5% over two years. The authors explain that there is still significant heterogeneity in this effect as most of the increases in ridership occur in larger cities that have relatively smaller transit systems.

Nelson and Sadowsky (2019) have similar findings. Their study also utilizes not only the market entry of the first TNC but also the effects of the second TNC entering a market. Regressing market entry of TNCs onto monthly transit ridership at the urbanized area (UZA) from the Federal Transit Authority, the authors find that the entry of the first TNC increased ridership. During the time between the first TNC entering and the second, the authors posit that "just enough" drivers saw TNCs as an easier way to access and egress from public transit. When the second TNC was introduced, transit ridership decreased back to levels equal to or lower than what it was before the entry of the first company. The introduction of the second TNC caused price and nonprice competition, thus making it easier for travelers to decide to take the whole trip by TNC rather than to use it to access public transit.

The complementary nature of TNCs gains traction as another study supports this claim. Boisjoly et al. (2018) collect transit ridership data from 25 transit authorities from 2002 to 2015 using the National Transit Database and the Canadian Urban Transportation. Although the authors do not consider the presence of ridehailing as statistically significant in their regressions, they associate it with higher transit ridership because of changes in travel behavior across the population with the availability of Uber. By implementing policies that support multimodality and reducing auto ownership, ridehailing may increase transit ridership.

Babar and Burtch (2017) find different impacts on public transportation. With ridehailing being introduced to markets at different times, the researchers use cities without it as controls in a difference-in-difference framework. In this framework the authors pair transit agencies with ridehailing in their markets with agencies without it which showed similar trends in transit ridership. Unlike the previous studies in this section, they conclude that ridehailing reduces ridership for city buses but increases ridership for commuter rail and subway systems. This result adds a more nuanced approach to the conversation by distinguishing the transit modes and making a concerted effort to establish criteria for their controls. With evidence to show that transit is affected differently, the authors also find that transit agencies' quality of service before the introduction of ridehailing "attenuated and amplified" its competitive and complementary effects. That agencies with already high quality of service "benefit more (or suffer less)" with the introduction of ridehailing.

Erhardt et al. (2021) uses data scraped from the APIs of the two largest TNCs in San Francisco to study the ridehailing's impact on traffic in San Francisco, CA. The authors estimate a fixed-effects panel data regression model and their results reveal that the net effect of ridehailing is less transit ridership. After accounting for service changes and population growth, they find a 10% decline in transit ridership. Altogether, the results of these works of research show the need for continued research to further develop the literature's relationship between ridehailing and public transit.

2.3 The COVID-19 Pandemic and its Effects on MoD and Public Transit

2.3.1 MoD and the effects of COVID-19

In March of 2020, the World Health Organization declared that the rapid escalation of COVID-19 cases had resulted in a global pandemic (Xu & Li, 2020). The novel coronavirus had spread to 203 countries by this point, and as a result, numerous governments implemented mitigation strategies such as social distancing requirements in a variety of sectors (Lewnard &

Lo, 2020). The transportation industry, both public and private, was heavily impacted. Ridehailing saw an 80% decrease in ridership (Higgins & Olson, 2020). While ridehailing remained operational during the pandemic for essential travel, one of the first actions of TNCs was to halt ridepooling operations (e.g. UberPool and Lyft Line) (Bond, 2020).

As the pandemic evolved and lockdowns gradually eased, travel behavior is still impacted by the virus-related risk perceptions and contraction risk. Travelers will continue to evaluate the tradeoffs between the need to travel (e.g., to maintain livelihoods) and being exposed to COVID-19 in shared rides (Borowski et al., 2021; Rahimi et al., 2021). One negative long-term consequence is the persistent reluctance to use shared modes, rebounding in car travel, and an increase in car purchases (Hensher, 2020). Ongoing work is examining the perceptions and priorities of travelers in the uncertain COVID-19 era. Said et al. (2021) indicate there has been reduced intention to use pooled modes due to the pandemic. Another recent study found that approximately 41% of survey-takers would consider using ridehailing even if operators take extra precautions by providing masks, gloves, and sanitizing gel, whereas only 28% would be willing to pay more for the added protective measures (Awad-Núñez et al., 2021). The percentage of those willing to use public transit under the same conditions was similar. A Toronto survey found that 15% of respondents declared an intention never to use ridehailing again, and 21% would never use ridepooling (Loa et al., 2020). From the same report, approximately 30% of riders prefer to wait until the virus is no longer a threat as the earliest point in time when they would consider using ridehailing or pooling. In general, travelers are moving from public to private modes (Das et al., 2021).

2.3.2 Public transit and the effects of COVID-19

During the COVID-19 pandemic, transit ridership has been significantly disrupted. At its lowest, the total number of transit trips in the United States fell by 80% in April 2020 compared to April 2019 (National Transit Database, 2022). As a result, many public transport agencies made service cuts that disproportionately impacted low-income and otherwise vulnerable groups (Harris & Branion-Calles, 2021; Parker et al., 2021). A study of 40 major cities in the United States and Canada found that while local responses varied, almost all transit agencies made major service adjustments; however, Chicago is an outlier in this regard (DeWeese et al., 2020).

The Chicago Transit Authority (CTA) avoided making significant cuts, as they maintained that public transit is an essential service, particularly for healthcare workers and vulnerable groups (Chicago Transit Authority, 2020). Nonetheless, there were significant changes in traffic at 95% of transit stations in Chicago, with the city facing a 72.4% decrease in average ridership. This decline was steeper in areas with a greater proportion of white, educated, and high-income people, whereas ridership declined less in areas with more essential workers and a greater number of COVID-19 cases or deaths (Hu & Chen, 2021). This mirrors other work where teleworking friendly professions can abandon transit and work from home, which will be further discussed shortly.

2.3.3 Reasons behind reduced ridership

In general, the reduction in transit ridership was substantial and the reasons why riders used transit less are multifaceted. Causes of ridership decline include both motivations on the side of users and their behavior, and on the other side, operational and contextual changes occurring, often in response to the pandemic. In summary, the user motivations are driven by safety perceptions, while the closure of many activities during the pandemic, and the shift towards teleworking and away from in-office work accounts for the lapsed ridership. This subsection is divided into three parts, discussing the evolving demand, supply, and workplace expectations.

2.3.3.1 *Demand changes during the pandemic*

Safety perceptions of transit changed because the pandemic caused users to re-evaluate the tradeoffs and risks associated with riding with strangers. Several social distancing protocols were enacted by transit agencies. During the beginning of the pandemic, they added train cars to increase opportunities for distancing, taped off seats on buses and trains, added more physical barriers between riders, and reduced the capacity of vehicles (Gkiotsalitis & Cats, 2021; Kamga & Eickemeyer, 2021). Even with a plethora of strategies to mitigate health risks, perceptions of transit were affected. Shamshiripour et al. (2020) find that users perceived transit to have the highest risk followed by ridesplitting and ridehailing. During a particularly restrictive period of COVID lockdowns in Germany, risk perceptions were strong enough that some car-less households considered purchasing a vehicle (Eisenmann et al., 2021). Apprehension towards transit hygiene have since calmed after the initial stages of the pandemic, though passengers are still reluctant compared to pre-COVID times (Beck & Hensher, 2020). Because of this reluctance, there is a modal shift from transit to modes that better facilitate physical distancing such as using a private vehicle, especially for those with household vehicle access, and active modes which also include shared bikes and scooters (Abdullah et al., 2020; Das et al., 2021; He et al., 2022).

2.3.3.2 *Activity restrictions during the pandemic*

The pandemic caused restrictions on non-essential activities including eating at restaurants, night life, sporting events, and other large social gatherings (Center for Disease

Control, 2022). Activity restriction affects are seen across modes (Beck & Hensher, 2020; Parr et al., 2020). Fatmi et al. (2021) finds that out-of-home activities were reduced by 50% with higher income groups less likely to decrease. Indeed, the closure of non-essential activities also affected the ability to access essential activities. For example, the pivot from in-person schooling to remote schooling caused difficulties for women in particular because of the change in domestic responsibilities (He et al., 2022). In areas where transit agencies reduced service in response to lower demand, captive riders would lose nearly all accessibility to essential activities (He et al., 2022). For those who could, a major shift in activities outside of the home includes adopting work-from-home via advanced ICT.

2.3.3.3 *Remote work and telecommuting*

Teleworking is not new with this subject appearing several decades prior to the pandemic (Mokhtarian, 1991). The pandemic pushed several companies to allow their employees to work remotely. 30 to 50 percent of survey respondents indicated they moved towards teleworking and other remote activities such as shopping, learning, and accessing healthcare (Abdullah et al., 2020; Beck & Hensher, 2020; Mouratidis & Papagiannakis, 2021). Before the pandemic, researchers find that the choice and frequency of telecommuting are positively correlated with higher incomes, being well-educated, having children at home, and being white (Plaut, 2005; Popuri & Bhat, 2003). During the pandemic these factors remain the same with the opportunity to work from home predominately seen in high income, well-educated, and non-minority households (Barbour et al., 2021; Matson et al., 2021; Yasenov, 2020).

Research is ongoing on the connections between future work policies and travel patterns. One important aspect is the experience of workers, which is diverse (Martin et al., 2022; Tahlyan et al., 2022). Experience with remote work during the pandemic has led to increased preferences for hybrid work arrangements among employees (Venkataramani, 2021). The growing role of telework and hybrid work carries several implications for long-term travel behavior which will be discussed in the next section on the return to transit (Beck et al., 2020; Nayak & Pandit, 2021; Olde Kalter et al., 2021).

2.3.4 Literature on the return to transit

As COVID-19 restrictions loosen, the need to understand the immediate to long-term effects of the pandemic on transit ridership is clear. Gkiotsalitis and Cats (2021) review transit and COVID measures and finds great importance of the transition of ad-hoc (e.g. initial social distancing measures) to evidence-based transit planning which adapts to the current state-of-the-art in transit and COVID research. With a multitude of data to draw on, researchers look to a future without COVID-19 health-risks being the center of transit planning.

The hesitation among lapsed riders due to risk perceptions and ongoing working from home policies will make it difficult for public transit to return to pre-pandemic ridership levels (Rothengatter et al., 2021; Vickerman, 2021; Wang et al., 2021) finds that even a return to 100% capacity of transit services will not lead to a full return of riders due to behavioral inertia. Thombre and Agarwal (2021) suggest policies for short, medium, and long-term recovery and shift towards a more sustainable and resilient transport system. In the short-term, they suggest that transit agencies ought to re-establish trust with their constituents and expand services. In the medium term, they suggest incentivizing non-auto travel as the increased usage of private vehicles is likely to cause congestion. Shamshiripour et al. (2020) call for research to promote sustainable and safe non-auto travel to prevent car-dependency. In the long term, Thombre and Agarwal (2021) suggest infrastructure improvements to continue improving access by non-auto means (e.g. improve pedestrian and bicycle facilities and expand public transit infrastructure to areas where it did not exist). Beck and Hensher (2020) warn that decision-makers should think carefully about policies that would promote auto travel. Other long-term strategies involve monitoring the effects of teleworking as residential choice location choices are likely to change and there may be more time and work schedule flexibility (Beck & Hensher, 2020; Shamshiripour et al., 2020). Beck and Hensher (2020) also point out a “two speed economy” where some are successfully transitioning to working from home while others cannot. Transit agencies will need to evaluate their priorities carefully, taking into account equity and the tradeoffs between attracting choice riders who reduced their transit usage and improving services for captive riders who fill essential roles during the pandemic.

The silver lining to the pandemic is that it has opened opportunities for public transit both assisting in the post-pandemic recovery *and* strengthening its role in the urban transport system. Dai et al. (2021) explains the case for aggressive public transit fare policies that drastically reduce the cost to ride. Three Chinese cities implemented policies to bring riders back. One city attempted fare-free transit during peak hours and did not significantly impact ridership; however, ridership significantly increased when fare-free transit was offered during off-peak times. Hensher (2020) sees an opportunity for MaaS to further reduce car dependency. One possibility the author discusses, which our reality most reflects, is that pandemic forces several months of teleworking which brings new expectations for working from home which directly affects the demand for travel. In that scenario, private auto usage is reduced since there is a lower demand for commuting. With mobility investments for walking and cycling and overall greater support for multi-modality, MaaS can integrate several services together that better suit non-work travel.

2.4 Literature Take-aways and Motivations for Research

From the literature, the introduction of ridehailing and shared mobility in general has provided numerous opportunities for researchers to dissect their effects on the transportation system. My goal is to contribute to the literature by continuing to investigate who uses MoD, how it used, what factors contribute to its usage, how the COVID-19 pandemic affects it, and its relationship with other shared modes.

Many of the studies in this review consider sociodemographic variables and have consistent findings. Ridehailing is adopted mainly by the privileged who are defined as having higher incomes and more education. In general, this is also true for other forms of new forms of shared mobility such as bikesharing and scooter-sharing (Fishman, 2016; Lee et al., 2021). Within the context of the United States, many dependent on transit come from less-privileged backgrounds. Additionally, car ownership can be a financial burden to low-income families (Clifton, 2004; Klein & Smart, 2017). Therefore, there is a unique opportunity outlined by Hensher (2020) to promote shared mobility and see significant transportation benefits for the less-privileged. To understand how policies and strategies can maximize these benefits, there is a need to further investigate how shared mobility relates to disadvantaged communities and its opportunities in a post-pandemic scenario. Consequently, in this dissertation I answer the following question using results from each of the analyses - *what are the societal and distributional impacts of innovative mobility services?*

In the literature, many have studied the utilization of ridehailing across several continents and find a plethora of effects including, but not limited to, direct competition with traditional taxis, increased roadway congestion, and a complicated relationship with public transit. Because of the lack of available ridehailing trip data, though, few have been able to make concrete conclusions about ridehailing utilization patterns. Therefore, there is a gap in the literature about ridehailing utilization informed by large representative data. Because the City of Chicago began to provide comprehensive ridehailing data, I take this opportunity to examine that dataset rigorously. While researching this novel dataset, I ask – *how is ridehailing utilized?*

With the same Chicago ridehailing dataset, I also take this opportunity to examine the factors that affect ridehailing demand. While many have found relationships between sociodemographics and built environment factors contributing to demand, I consider a perspective adopted from health research and use the intersectionality of several sociodemographic indicators to define an index, which I regress on private ridehailing and ridesplitting demand. However, this research was completed at the community level. In other words, the trip data are aggregated to a spatial level representing Chicago communities rather and do not contain information about the individual riders. I dive deeper and utilize stated choice data to understand microtransit adoption as a commute mode and analyze the tradeoffs among traditional and novel mode attributes as well as the effects of latent attitudes. Therefore, there are three gaps in the literature that I investigate. First, the literature has not yet explored ridehailing demand as a function of community-based while considering spatial effects. Second, research that does investigate the demand for ridehailing using trip data do not disentangle the difference between private ridehailing and ridesplitting. And third, the evolution of ridehailing to accommodate a wide range of services demands the need to understand the effects of novel mode attributes that have yet to be widely implemented. In these endeavors, I answer the question: *what are the determinants of MoD demand?*

Lastly, the COVID-19 pandemic drastically affected the transportation system. MoD and public transit were hard hit with the literature showing significantly lower ridership. Among the reasons for this lower ridership is the transition to telecommuting and safety concerns. There is a gap in the research literature where researchers have yet to consider the factors that affect transit ridership during the pandemic recovery. Therefore, I investigate survey data collected throughout Chicagoland and the greater region to understand who reduced transit ridership, who will return once health concerns are alleviated, and how might MaaS increase transit ridership. During this study, I ask: *how did the COVID-19 pandemic affect short-term and long-term travel behavior towards public transit, MoD, and other shared modes?*

Table 1 Summary of research literature using empirical data to investigated Mobility-on-Demand

Author(s)	Location	Data collection	Focus	Methodology	Findings
Cramer and Krueger (2016)	USA	Publicly available data from public agencies and data request from Uber	Taxis	Comparison of Utilization rates	Uber utilization rates are higher than taxis in the case study cities except for New York City.
Kim et al. (2018)	New York City, USA	NYC Taxi trip data	Taxis	Regression	No evidence that number of taxi trips, revenue per driver, or occupancy rates changed since Uber entered the market. Rather, taxi drivers developed new strategies to reach status quo levels
Berger et al. (2018)	USA	ACS Sampling of Taxi Drivers	Taxis	Regression	Labor supply did not change but existing taxi driver's mean hourly earnings decreased
Contreras and Paz (2018)	Las Vegas, USA	Las Vegas Taxi Data	Taxis	Regression	Taxi ridership is down because of Uber entry
Nie (2017)	Shenzen, China	Taxi GPS data	Taxis	GPS tracking	There was a strong, temporary decline to taxi ridership after introduction of TNC services. Taxis still compete very well during peak periods due to heightened demand. TNCs lifted the capacity utilization of taxis.
Jiang and Zhang (2018)	Beijing, China	Taxi GPS data	Taxis	GPS tracking	Compared to 2012 taxi numbers, in 2015 avg. pax-delivery trip numbers per day per taxi dropped 180& and the avg. daily profit per taxi dropped 19%.
Dong et al. (2018)	Beijing, China	Taxi and ridehailing trip data	Taxis	GPS tracking	As the population of Beijing grew, the number of taxi drivers did not mirror the growth. Rather, ridehailing came about and relieved the increased demand, especially during peak travel times.
Henao and Marshall (2018)	Denver, CO, USA	Quasi-natural Experiment	Traffic Congestion	Statistical comparison	83.5% increase in VMT, 0.8 avg. occupancy of all rides, 34.1% substitution for transit or active modes
Nair et al. (2020)	Austin, TX, USA	Ridehailing trip data	Traffic Congestion	Statistical comparison	The farther away from the downtown core that a ridehailing trip is requested, there is more deadheading.
Li et al. (2016)	USA	Urban Mobility Report from TTI	Traffic Congestion	Regression	Entry of Uber in several markets correlates with lower traffic congestion indicators
Schaller (2021)	USA	Publicly available data from public agencies and data requests	Traffic Congestion	Meta-analysis	Increases in VMT are due to ridehailing users substituting public transit
Dhanorkar and Burtch (2021)	CA, USA	Vehicle congestion detectors	Traffic Congestion	Regression	Ridehailing caused more traffic on the weekend, areas with high population density, and areas with a dense network of local roads
Li et al. (2022)	USA	Vehicle congestion detectors	Traffic Congestion	Regression	Ridehailing caused increased traffic congestion in highly dense urban areas
Hall et al. (2018)	USA	Transit Ridership from Multiple Municipalities	Public Transit	Regression	After 2 years, TNC market entry is correlated with a 5% increase in transit ridership. TNCs complement transit because transit is still cheap enough for TNCs' role to be adding flexibility
Nelson and Sadowsky (2019)	USA	Transit ridership	Public Transit	Regression	The entry of the first ridehailing service in a market is correlated with higher public transit usage. The entry of the second service does not correlate with higher transit ridership. After entry of second service, over time transit ridership declines to pre-entry levels.

Boisjoly et al. (2018)	USA, Canada	NTD and CUTA data	Public Transit	Regression	The cause of declining transit ridership is decreasing vehicle revenue kilometers. The introduction of TNCs and bikeshare do not significantly impact model, but they are associated with higher transit ridership.
Babar and Burtch (2017)	USA	NTD	Public Transit	Regression	ridehailing has mixed effect on public transit use. ridehailing decreases ridership for city bus service but increases for commuter rail and subway
Erhardt et al. (2021)	San Francisco, CA, USA	API of TNCs	Public Transit	Regression	Ridehailing can be attributed to a 10% decline in transit ridership

3 K-PROTOTYPE ANALYSIS OF THE CHICAGO RIDEHAILING TRIP DATA[1]

3.1 Background

The proliferation of ridehailing services has been a disruptive force as it transforms the mobility landscape. This transformation has not been comprehensively studied as many TNCs are reluctant to make their data publicly available. Recent data-sharing agreements with the City of Chicago, IL enables researchers to examine the role of ridehailing in the transportation ecosystem using an abundance of temporal and spatial data on ridehailing trips. Several studies have characterized the adoption, frequency, and attitudes towards ridehailing (Alemi, Circella, Handy, et al., 2018; Alemi, Circella, Mokhtarian, et al., 2018; Circella et al., 2016; Dias et al., 2017), but few have used publicly available trip data at the scale and scope provided by the City of Chicago (Ghaffar et al., 2020) . In this chapter, I develop insights about ridehailing utilization, supplementing the trip dataset with information on weather, transit performance, and taxi demand.

Researchers have tried to develop a better understanding of ridehailing trips, but data is scarce. TNCs generally do not publicly share their data so there has been a dearth of empirical studies. Because the data is limited, Henao and Marshall (2018) went so far as to become TNC driver and collect trip information themselves. Other researchers have utilized congestion data obtained from traffic detection devices to infer the effect of ridehailing.

The current understanding of ridehailing travel is mostly informed by survey research. In the following I briefly summarize relevant ridehailing work and relate findings to the current

[1] Soria, J., Chen, Y., & Stathopoulos, A. (2020). K-prototypes segmentation analysis on large-scale ridesourcing trip data. Transportation Research Record, 2674(9), 383-394.

analysis of empirical large-scale data. Several studies delve into the trip purposes of ridehailing trips. Defined by its utilization of large capacity vehicles, microtransit (also known as demand-responsive transit, on-demand transit, or flexible transit) can serve as a tool to address public transit overcrowding and the first-last mile problem (Shaheen & Chan, 2016). It is mostly utilized to commute (Lewis & MacKenzie, 2017; Shaheen & Chan, 2016). Trips made by the more taxi-like TNCs are mostly for social/recreational trips (Henao & Marshall, 2018; Mahmoudifard et al., 2017; Rayle et al., 2014; Zhen, 2015). Trip purpose is not included in the current analysis due to the data anonymization. However, in future works spatial examination of locations of interest combined with other trip attributes can be used to infer trip types

The effects of TNCs on the transportation system is a core area of research. In particular, due to the similarity of the services, the impact on taxis has been widely studied. TNCs have significantly reduced the demand for traditional taxi services such that taxi drivers altered their strategies to remain profitable (Berger et al., 2018; Contreras & Paz, 2018; Dong et al., 2018; Jiang & Zhang, 2018; Kim et al., 2018; Nie, 2017). Schwieterman and Smith (2018) also find that TNCs are preferred over public transit especially when origin-destination pairs are not well served by transit. Further determinants of ridehailing use relate to the travel environment. Frei et al. (2017) found that weather affects TNC usage. Though their study focused on microtransit, TNC services may also be affected by adverse weather. Because

The main purpose of this chapter is to identify mobility patterns present in the trip data by grouping similar trips together. I utilize an unsupervised learning algorithm to examine the underlying relationships in the data. Due to the mixed data types (i.e. data containing both numeric and qualitative/categorical variables), a clustering algorithm must be chosen carefully. The unsupervised learning technique proposed in this paper is the K-Prototypes algorithm developed by Huang (1998). It is an extension of the K-Means algorithm that accepts categorical data. The results of this model are similar to K-Means algorithm as the output is a classification of the data into K number of prototypes, the equivalent of clusters.

3.2 Data

The following subsections describe the Chicago ridehailing data and supplementary data on weather, taxi demand, and transit performance. Because the ridehailing trip data are used extensively in other chapters and I would rather not waste the reader's time, I will explain in depth the trip dataset here and continue to refer to this section throughout the remainder of this thesis. A summary of the data used in this data are provided in **Table 2** and **Table 3**.

3.2.1 Chicago ridehailing trips

Considering the privacy of both drivers and riders, much of the data are censored to protect their identities. Mainly, the trips are spatiotemporally aggregated such that the origin-destination and trip departure times cannot be pinpointed and used to track the movement of either driver or rider. To mask the origin and destination, the data are aggregated, at the lowest level, to census tract level, and at the highest level to the community area. Additionally, the trip departure time are aggregated to 15-minute increments (e.g. 12:00PM to 12:15PM then 12:15PM to 12:30PM). Importantly, when a trip is the only trip within a 15-minute increment to occur in a census tract, then the census tract is censored and the community area is provided. In addition to censoring origin-destination pairs and departure times, the fare paid by riders is rounded to the nearest \$2.50 increment and tips are rounded to the nearest \$1.00 (if tipped through the smartphone application), though additional charges which include taxes, fees, and other surcharges are reported as is.

Also provided in this data are data on pooled modes. The data include information on if the trip is authorized to be shared. This includes trips made by ridesplitting and microtransit. Additionally, if the trip is matched to another itinerary, then the number of itineraries pooled into one trip are included. **Figure 4** shows how the data presents how the data count the number of trips pooled together. In Case 1, all trips are authorized to be pooled, however, none of their trips are pooled as indicated by the bars representing the parties not overlapping. In the data, there are 3 observations, each are authorized to be shared, but the number of trips pooled is only one for each observation. In Case 2, the parties overlap and the number of trips pooled together is equal to 3 for all 3 observations in the data. Although Party 1 and Party 3 do not overlap, there is a chain of 3 trip itineraries that were pooled into one vehicle. Unfortunately, the data does not provide information to identify which observations form a chain of trips.

The data used in this project is a partition of the entire available TNC trip data made available by the City of Chicago (City of Chicago, 2019). The trip data begins on November 1, 2018 and is updated monthly. For the purpose of obtaining lower optimization times and being able to match the equivalent transit travel times, the data is partitioned to weekdays in November 2018. Holidays are not included. Additionally, rather than analyzing the census tracts because

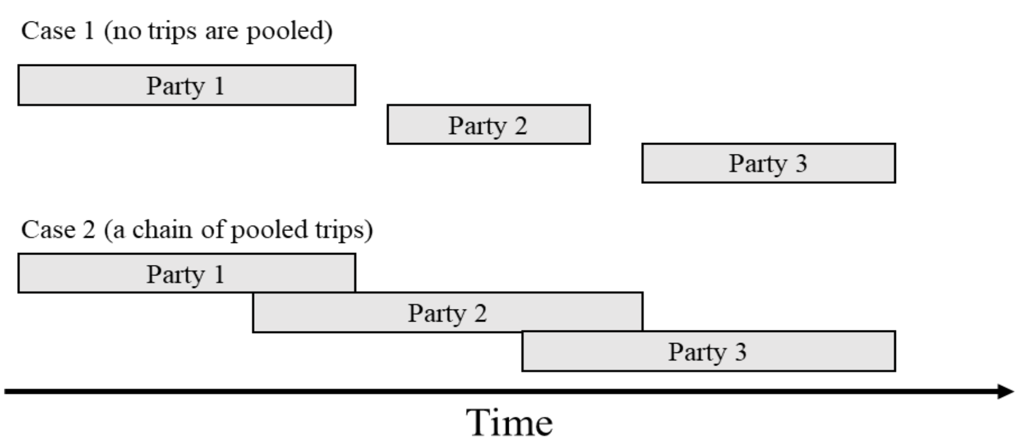

Figure 4 Trips authorized to be shared

there are missing data, I aggregate the origins and destinations to the community area level. This leaves a total of 3,085,070 trips in the analysis.

3.2.2 Weather

The weather data were collected from OpenWeatherMap specifically for the City of Chicago in November 2018 (Open Weather Map, 2019). The station collecting the data is located at O'Hare International Airport at the northwest tip of city limits. The data is at the hourly level and includes amount of rain and snow in the previous hour, qualitative description of the weather (such as raining, hazy, sunny, etc.), and temperature. To include weather with trip observations, I match the hour the weather data are collected and match it with the hour of trip departure. They are matched this way to estimate the current state of weather at the time of request.

There are a few weaknesses worth noting. First, the data are collected at O'Hare International Airport which is located approximately 16 miles away as the crow flies from the downtown core of Chicago. Therefore, the data may not be representative of the weather experienced at the beginning of the ride. Second, the weather may not be representative of the weather at the time of request. A ride may have been scheduled well before trip departure or the amount of deadheading may take long enough for the weather to change. Because trips where these weaknesses may apply are not identifiable, I will assume that there are enough trips that *are* representative of the data for these outliers to not impact the results significantly.

3.2.3 Taxi frequency

The data used are when taxi demand is at its highest point in 2014 (Y. Chen et al., 2018). This data is also collected and made publicly available by the City of Chicago. Like the ridehailing trip data described earlier, this data also similarly aggregates the data spatiotemporally. The departure time and origin-destination pairs are aggregated to 15-minute bins and census tracts, respectively. Origins and destinations that are outside of the city limits are also censored. Unlike the ridehailing data though, the taxi company, payment method, and unique identifiers for the drivers are provided for each trip.

To supplement the ridehailing data, the taxi demand between ridehailing census area origins and destinations are matched. The data are the monthly taxi trips between origin-destination pairs, which are referred to as Monthly Taxi Frequency later in the analysis. It is included to characterize and compare the spatial relationship of taxi usage by matching each ridehailing trip with the total taxi flow between the same origin and destination.

3.2.4 Transit performance

The supplementary transit travel times dataset was created for each unique origin-destination-time-day tuple. Transit travel time estimates were obtained using the Google Distance Matrix (Advanced) API by providing the census tract of origin, the census tract of destination, travel mode (transit), and departure time (Google, 2020). From the API, approximate transit travel times between origin-destination pairs are collected. Since the data were only collected from 6AM to 10PM, the TNC trips data are also restricted to these hours. The second piece of supplementary data are the monthly taxi trips between census tract origin-destination pairs.

Table 2 Descriptive statistics of ridehailing, transit, taxi, and weather data

Numerical Variable	Median	Mean (Standard Deviation)
Travel Time (minutes)	13.32	15.47 (9.98)
Distance (miles)	2.70	3.79 (3.19)
Total Fare ($)	10.00	11.24 (6.27)
Parties Joined in Trip	1	1.32 (0.77)
Humidity (%)	71.00	73.58 (11.89)
Wind Speed (mph)	3.00	3.82 (2.33)
Rain last hour (inches)	0.00	0.061 (0.26)
Minute after Midnight	930.00	887.5 (268.20)
Transit Travel Time (min)	17.95	21.10 (15.40)
Monthly Taxi Frequency	1004	14,976 (36,875.57)

Table 3 Community area characteristics of income, bar and tavern density, and transit access time

Community Area	Per Capita Income ($)	Bar and Tavern Density (per sq. mi)	Transit Access Time (min)
Chicago Average	32,534	4.78	19.75
Near North Side	91,948	32.66	13.00
Near West Side	50,394	10.51	10.57
West Town	54,429	11.86	11.03
Loop	77,722	46.84	9.53
Lincoln Park	73,965	13.43	12.94
Lake View	67,066	19.15	11.17
Midway	28,925	3.27	33.79
O'Hare	27,212	0.17	84.64

3.3 Methodology

The methodology used to examine patterns of ridehailing use in this project is an unsupervised learning technique called K-Prototypes. K-prototypes is similar to K-means since both aim to cluster several observations together according to their attributes. The advantage K-prototypes has in this situation is its ability to also accept categorical variables. More details on K-prototypes development can be found in Huang (1998).

The challenge of dealing with categorical variables has been considered for segmentation analysis. The problem is that the K-means algorithm relies on all variables to be numerical. Specifically, in the K-means algorithm for a continuous variable such as travel time, the distance between an observation's travel time and the proposed cluster's mean travel time is the key element for identifying clusters among observations. With a categorical variable such as vehicle type, the distance is no longer applicable. One strategy to include categorical variables in the K-means algorithm is to code each category as a dummy variable (0 or 1). The distance calculated by K-means algorithm for a categorical variable is then 0 or 1 because it was coded as a dummy variable, but this no longer makes sense. With the K-prototypes algorithm the mode of the category is used and a measure of a simple matching coefficient is used. The formulation from Huang (1998) of K-prototypes algorithm is summarized in the equations below.

The matching of observations to prototypes involves reducing the error or cost function. This cost function represents the distance between observation data and the assigned prototype center. **Equation 1** shows that the error, *E*, is the sum of distances from the prototype center. X_i are the attributes of trip *i*, Q_l is the center of prototype l, and y_{il} is a dummy variable that is equal to 0 when trip *i* is assigned to prototype l. It is then the sum of squared distances for n TNC trips across k number of prototypes. **Equation 2** breaks down $d(X_i, Q_l)$ into numerical and categorical components, where the first term is the squared numerical distance of attribute *j* of trip *i* from the center for attribute *j* of prototype l; the second term includes a term to determine the weight, γ_l, of the categorical variables to the total error *E*. The error of prototype l is then calculated in **Equation 3,** where E_l^c is further explained by **Equation 4**. C_j is the set of all unique values of categorical attribute *j*, and $p\left(c_j \in C_j \mid l\right)$ is then the probability of unique value q_j from set C_j being in prototype l.

$$E = \sum_{l=1}^{k}\sum_{i=1}^{n} y_{il} d(X_i, Q_l) \qquad \textbf{Equation 1}$$

$$d(X_i, Q_l) = \sum_{j=1}^{m_r}\left(x_{ij}^r - q_{lj}^r\right)^2 + \gamma_l \sum_{j=1}^{m_c} \delta\left(x_{ij}^c, q_{lj}^c\right) \qquad \textbf{Equation 2}$$

$$E_l = \sum_{i=1}^{n} y_{il} \sum_{j=1}^{m_r}\left(x_{ij}^r - q_{lj}^r\right)^2 + \gamma_l \sum_{i=1}^{n} y_{il} \sum_{j=1}^{m_c} \delta\left(x_{ij}^c, q_{lj}^c\right) = E_l^r + E_l^c \qquad \textbf{Equation 3}$$

$$E_l^c = \gamma_l \sum_{j=1}^{m_c} n_l \left(1 - p\left(q_{lj}^c \in C_j \middle| l\right)\right) \qquad \textbf{Equation 4}$$

The advantage of using K-Prototypes algorithm over other clustering algorithms is highlighted by **Equation 4**. A common way to code categorical variables for other data-driven methods is to use one-hot encoding. Using this method, the unique values of a category are coded as a dummy variable where they are equal to 1 when denoting the variable of interest and 0 otherwise. Algorithms using one-hot encoded data fail to recognize that these unique values belong to a categorical variable because categories are reduced to 0 or 1. The advantage of K-Prototype algorithm is then its recognition of these values being part of one categorical variable and using the probability of a unique value from a set C_j being in prototype l.

This model is implemented and tuned with the R programming language using the 'clustMixType' package (R Development Core Team, 2008; Szepannek & Aschenbruck, 2019). Using this package, the error is minimized and the weighting of the categorical error is optimized. Much like other clustering methods, the number of prototypes is a tunable parameter. The final tunable parameters are discussed in the results section.

3.4 Results

During the estimation phase, the K-prototype algorithm was tuned to select the optimal number of prototypes. This was determined by developing models including a number of prototypes ranging from 2 to 14 and calculating the total cost across all observations. The final number of prototypes chosen is 6 based on interpretability of segmentation variables and guidance from the plot which in **Figure 5** shows a clear "elbow" at 6 prototypes (Madhulatha, 2012). An elbow occurs when adding more clusters does not sufficiently improve the objective function. γ is the tradeoff between numerical cost and categorical cost optimized by the 'kproto' function in the 'clustMixType' package and is estimated to be 1.33 for all prototypes as per Equation 2 and Equation 4 (Szepannek & Aschenbruck, 2019). There is no intuitive meaning to this value except that it can be user-specified, and higher values mean that the categorical variables receive a higher weight. **Figure 6** shows how many observations belong in each prototype cluster. The clustering results are shown in **Table 4** along with mean values of explanatory attributes in each prototype.

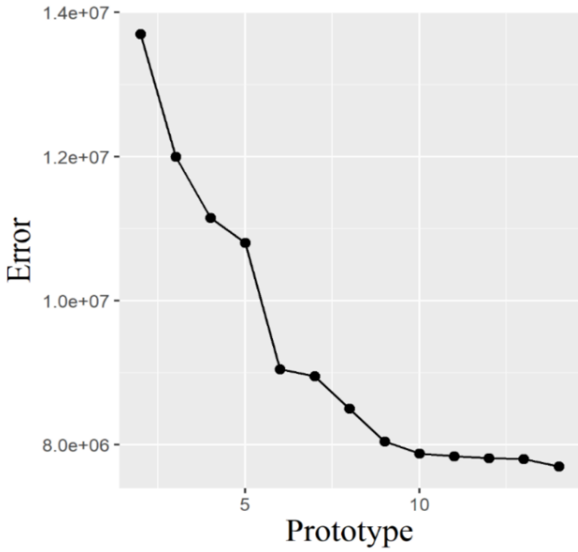

Figure 5 K-Prototype error, choosing K number of prototypes based on the elbow method

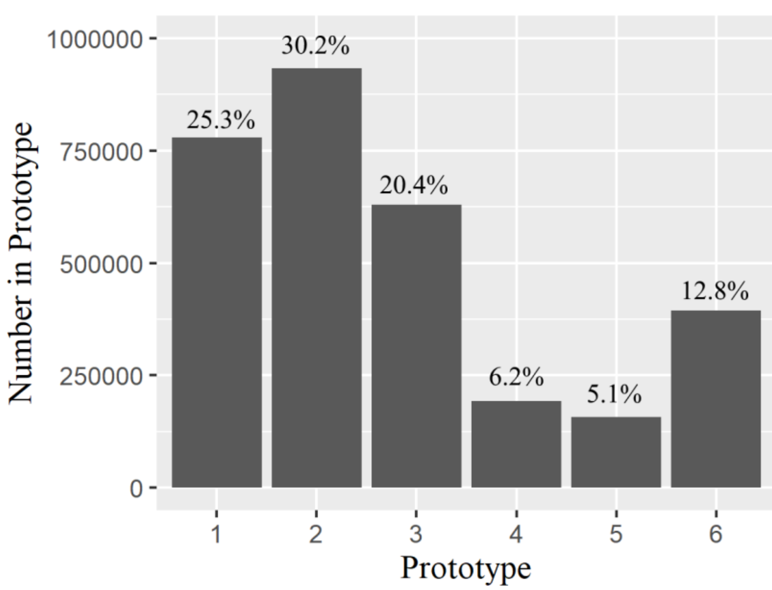

Figure 6 K-Prototype results, share of trips appearing in each prototype

An important observation related to variable selection in the presence of potential correlation needs to be made. In practice, transportation modelling often deals with concerns surrounding the correlation among time, distance and cost, either by interacting or dropping variables. Yet, ridehailing represents a special case due to the dynamic demand-responsive pricing that relaxes this typical correlation. While I cannot separate out instances of surge-pricing from this data I note that some interesting relationships are discovered when comparing prototypes. Notably, while the variables are correlated, *on average,* within the specific clusters the relationship reveal vast differences in per mile costs. **Table 5** and related discussion highlight these insights.

I now turn to summarize the contours of the six user clusters. On the whole, the analysis did not produce prototypes that were heavily differentiated by temperature or snow fall in the past hour. Yet weather effects were evident in the first segment of users (Prototype 1 or P1_weather). P1_weather is the second largest prototype and is characterized by its relatively low total fares and short travel times and distances. This short-distance travel, averaging 4 miles, is coupled with the strongest weather impacts observed, namely the presence of adverse weather seen with rain, humidity, and wind speed. The distinct nature of prototype 1 suggests the use of ridehailing for short distance travel to cope with adverse weather in the early part of the day.

Prototype 2 (P2_late-night) is the largest segment with 30.2 percent of users. While still representing shorter trips, it is distinct from P1 due to the trip timing in the evening (average is 1080 minutes after midnight or 6PM) and the lack of relationship to weather conditions. Observing **Table 6**, these trips are most heavily focused in the wealthy downtown and near north areas. Furthermore, **Table 6** illustrates that trips in this cluster originate from areas with the highest bar and tavern densities. This sizeable cluster suggests a strong tendency to use ridehailing for evening travel which is in line with findings from Lavieri and Bhat (2019a).

Prototype 3 (P3_solo-non-transit) has longer travel times which tend to be associated with longer distances (albeit not associated with airport travel) and higher total charges. This large user segment (20.4 % of usage) suggests some transit gap-filling capacity of ridehailing in Chicago whereas the origin-destination and time-matched potentially available transit trip would take 30% longer on average with transit travel-time taken as base. Notably, considering the fixed transit pricing of $2.25, the ridehailing trips were on average six times more costly. Trips in this prototype are also typically not shared and concentrated in wealthier areas. This finding mirrors observations by Schwieterman and Smith (2018) that ridehailing is used even in areas with a wealth of transit options, although my analysis suggests that transit speeds are relatively low (**Table 5**) a factor that is easily tracked by travelers using real-time smartphone navigation tools.

Prototype 4 (P4_airport) represents a small group of users with long travel times dominated by trips to and from the main airports O'Hare or Midway International Airports (**Table 6)**. This prototype also has trips where the origins and destinations are not served well by transit as seen with the average transit travel time being more than 70% longer. Along with poor transit connectivity, this cluster features relatively low taxi frequency. The low taxi frequency shows low demand for taxis between similar airport-based trips, likely because airport trips are relatively infrequent and can be completed by carpooling with known associates such as a family member or friend. These trips' fares are more expensive than in other prototypes, but relative to the cost of traditional taxis, are still affordable. Given that it is also more convenient to utilize ridehailing than to ask a family member to drive, the strong connection between airport travel and ridehailing is unsurprising. Taxi pickups at airports are declining and other revenue streams such as parking and rental cars are also negatively impacted (Bergal, 2017; Wadud, 2020). This prototype highlights the strong competitive position against both transit and taxi for airport access, albeit it does not account for the issue of waiting time that might change this assessment in particular considering departures from Chicago airport where TNCs have limited access.

Interestingly, prototype 5 (P5_transit-competitive) is a small cluster that stands out as representing the shortest trips and for being the only case where trips could have been served better by transit. Notably, the average transit travel times would be 12.44% lower than the observed TNC travel times. This is a stark contrast with other prototypes as **Table 5** shows that most other prototypes' transit travel times are at least 30% longer than the ridehailing equivalent ride. Most of these trips are in the Chicago Loop or just north of it where transit is highly concentrated in the core commercial area.

Table 4 K-Prototype attribute results and percentiles

Prototype	Travel Time (min)	Distance (miles)	Total Fare ($)	Parties Joining Trip**	Humidity (%)	Wind Speed (mph)**	Rain last hour (inches)**	Minute after Midnight	Transit Travel Time (min)	Monthly Taxi Frequency	Percent ridesplitting (%)
P1_weather (Percentile)	637.40* (36th)	2.16 (40th)	9.05 (41th)	1.07	**82.96 (79th)**	**4.32**	**0.15**	702.5 (37th)	844 (39th)	11695 (76th)	18.77
P2_late-night	600.9 (33rd)	2.07 (38th)	8.85 (41st)	1.07	66.07 (31st)	3.57	0.01	**1080 (72nd)**	804 (37th)	10031 (75th)	17.65
P3_solo-non-transit	1284.0 (78th)	5.74 (80th)	15.56 (85th)	1.04	72.29 (54th)	3.66	0.03	878 (45th)	**1838 (78th)**	**3558 (64th)**	**10.48**
P4_airport	**2014.0 (94th)**	**12.25 (97th)**	27.64 (97th)	1.17	75.09 (61st)	3.96	0.08	826.4 (40th)	**3392 (97th)**	**3840 (65th)**	16.58
P5_transit-competitive	572.2 (31st)	1.39 (21st)	8.40 (40th)	1.12	73.64 (56th)	3.70	0.05	815.9 (39th)	**501 (19th)**	**144687 (98th)**	13.76
P6_ridespli-tting	1320.0 (79th)	4.83 (74th)	7.43 (15th)	**3**	74.12 (59th)	3.66	0.05	870.7 (45th)	**1545 (69th)**	**5286 (68th)**	**100**

* **Bold** type indicates important feature
** Non-continuous variable with low range do not have percentiles included

Table 5 Prototype specific average costs and speed

Prototype	Average $ per Mile Traveled	Average $ per Minute Travel Time	Average Speed (mph)	% transit travel time above ridehailing equivalent trip*
All Trips	2.97	0.73	12.16	36.39
P1_weather	4.19	0.85	12.20	32.41
P2_late-night	4.28	0.88	12.40	33.80
P3_solo-non-transit	2.71	0.73	16.09	43.15
P4_airport	2.26	0.82	21.90	68.42
P5_transit_competitive	6.04	0.88	8.75	-12.44
P6_ridesplitting	1.54	0.34	13.17	17.05

* = (Transit Travel Time – Ridehailing Travel Time) / Ridehailing Travel Time

Table 6 Prominent prototype origins and destinations

	ORIGINS		DESTINATIONS	
Prototype	Community	% in Prototype	Prototype	% in Prototype
P1_weather	Near North Side	22.62	Near North Side	24.22
	Near West Side	13.63	Loop	15.40
	West Town	9.638	Near West Side	14.15
	Loop	9.537	West Town	5.280
	Lincoln Park	5.878	Lincoln Park	5.012
	Lake View	5.169	Lake View	4.561
P2_late-night	Near North Side	24.96	Near North Side	23.78
	Near West Side	12.84	Near West Side	13.16
	Loop	12.11	West Town	8.932
	West Town	7.502	Lincoln Park	8.162
	Lincoln Park	7.224	Loop	8.085
	Lake View	7.103	Lake View	7.664
P3_solo-non-transit	Near North Side	16.77	Loop	18.21
	Loop	10.47	Near North Side	12.07
	Lake View	9.795	Near West Side	11.25
	Near West Side	8.263	Lake View	7.916
	Lincoln Park	7.144	West Town	4.967
	West Town	6.115	Lincoln Park	4.723
P4_airport	**Midway***	**13.80**	**O'Hare**	**16.17**
	O'Hare	**9.523**	**Midway**	**15.08**
	Near North Side	7.606	Near North Side	9.966
	Loop	6.306	Loop	7.152
	Near West Side	5.624	Near West Side	6.974
	Lake View	4.607	Lake View	3.531
P5_transit-competitive	**Loop**	**45.57**	**Loop**	**54.35**
	Near North Side	**32.15**	**Near North Side**	**21.88**
	Near West Side	8.719	Near West Side	8.013
	Lake View	5.986	Lake View	5.982
	West Town	3.156	West Town	4.160
	Lincoln Park	2.688	Lincoln Park	3.112
P6_ridesplitting	Near West Side	13.81	Near North Side	14.90
	Near North Side	11.54	Near West Side	13.20
	Loop	10.60	Loop	13.18
	West Town	7.686	West Town	6.060
	Lake View	6.510	Lake View	6.058
	Lincoln Park	5.489	Lincoln Park	4.873

***Bold** type denotes important prototype features

Prototype 6 (P6_ridesplitting) with 12.8% of users is defined by representing nearly all shared authorized trips. This segment appears to reflect a more cost-conscious user group given that the ridehailing price per mile is the lowest, and the competition in terms of price and time is closer to the potentially available transit trip.

To further understand motivations of different users ***Table 5*** highlights the insights from comparing trade-offs within clusters, namely fare per mile, fare per minute, and average speed to the average reference of all ridehailing trips. ***Table 5*** shows that P1_weather, P2_late-night, and P5_transit-competitive prototypes have a more premium fare point with higher fare per mile and fare per minute than its counterparts. The results also show steep discounts for P6_ridesplitting as it has the lowest fare per mile and fare per minute. These results confirm the prototype interpretations as premiums are expected (through surge pricing or similar dynamics) for rides in bad weather, late at night when drivers may be few and potential-riders are unable to drive due to inebriation, and transit-competitive trips mostly occurring in the Loop community area which is the core commercial area. Discounts are also expected to appear with the ridesplitting prototype as reduced fares are expected with delays incurred by the detours when picking up a different party.

3.5 Discussion

The K-prototypes analysis is geared at finding relationships in the ridehailing data by grouping similar observations together. The merging of multiple datasets further enables the prototypes search to identify the main ridehailing profiles with regards to trip attributes (e.g. travel time, fare, origin and destinations, being private or shared), and competing mobility services (transit and taxi) along with weather conditions. This discussion section focuses on how the results relate to current research and can inform future research directions. Four areas of investigation are highlighted, centering on weather impacts, competition with transit and taxi, ridesplitting patterns and spatial distribution of ridehailing.

3.5.1 Weather-dependence

I find that while weather does not have a pervasive impact on ridehailing across clusters, it does strongly determine the choices in P1_weather highlighted by its higher average windspeed, humidity, and rainfall in the last hour. The identification of this prototype gives evidence that weather can have a significant impact on TNC usage for as many as 25% of trips. Taken together with results from Frei et al. (2017) demonstrating weather impacts in a micro-transit choice experiments, this illustrates the importance of including weather as an explanatory variable in future TNC analyses. Inclusion of weather-variables in TNC analyses can further explain the interactions between ridehailing and other modes. For example, weather was shown to impact active modes of transport, so including weather as an explanatory variable between the relationship of ridehailing and active mobility can inform their demand in the future (Saneinejad et al., 2012). This is especially useful for understanding how TNCs might relate to bikeshare as adverse weather has been shown to decrease its demand and contribute to increased ridership of other modes (Gebhart & Noland, 2014). find that ridehailing demand increases during adverse weather conditions and compared the supply of TNC drivers to taxis. Their results illustrate the benefit of TNCs – in particular its dynamic pricing – over taxis as a tool to increase the supply of drivers and meet consumer demand.

3.5.2 Mode-substitution with transit and taxi

The importance of understanding the relationship TNCs have with other modes is further highlighted by P4_airport and P5_transit-competitive prototypes. The airport prototype shows that airport trips are a major source of demand for ridehailing because it provides more effective service than current transit options for many users.

The transit-competitive prototype illustrates the competitive nature beyond travel time of TNCs. Though **Figure 6** shows that this is a smaller portion of the trips, representing only 5.1% of the data, this is still an interesting prototype because it emphasizes how TNCs offer several advantages that go beyond shorter travel times. As discussed by Lavieri and Bhat (2019a), this is troubling because ridehailing's relationship with transit is complex as solo rides do not necessarily substitute transit trips. With shorter transit travel times and some demand previously met effectively by taxis, there is a need to map out the difficult to measure variables such as comfort, safety, and convenience that must be considered in conjunction with travel time. These insights may be critical to understanding the differing user perspective towards solo and shared ridehailing.

The relationship between taxis and ridehailing is more straightforward as the services are more comparable. While the literature review section briefly discussed changes in the taxi industry, a thorough investigation of the interaction between these modes is completed by Nie (2017). Ridehailing is an attractive alternative to taxis, however, there still remains a role for taxis in the transportation system as they remain competitive in highly dense areas during peak commuting hours. The substitution of taxis for ridehailing also (though unintended) led to improved mobility equity in struggling communities as it is an option for those who do not possess bank accounts, credit cards, or smartphones (Young & Farber, 2019).

3.5.3 Ridesplitting patterns

Another major area of the literature is on the potential for TNCs to be a more efficient people mover than privately driven vehicles. The dynamic ridesharing literature examines the efficiency gains of ridesplitting over private modes (Alonso-Mora et al., 2017; Xue et al., 2018). Despite theoretical findings on the advantages of ridesplitting, there has been limited exploration of how this functions in real systems. A notable result from this work is the low share of split rides despite a relatively high share of riders indicating that they are willing to share their ride. For the complete dataset, 26.7% of all trips were authorized to be shared but of these only 68.5% were actually shared. That implies that only 18.3% of the overall rides were truly pooled, likely reflecting a lack of matching travel itineraries that were close enough in space and time for the matching to occur. The percentage of authorized shared trips of all prototypes except for P6_ridesplitting is well below the 26.7% figure.

When compared to the other prototypes, the ridesplitting prototype shows that pooled trip making can be seen as a separate profile of use. To further examine the patterns of ridesplitting, shows the number of trips by separate trip-makers within a pooled trip for each prototype. The ridesplitting prototype has a much higher share of pooled trips including more than 3 riders. However, this prototype only constitutes 12.8% of the data. With such a small share of trips being shared, decision-makers that support TNCs should consider strategies that increase the number of pooled trips.

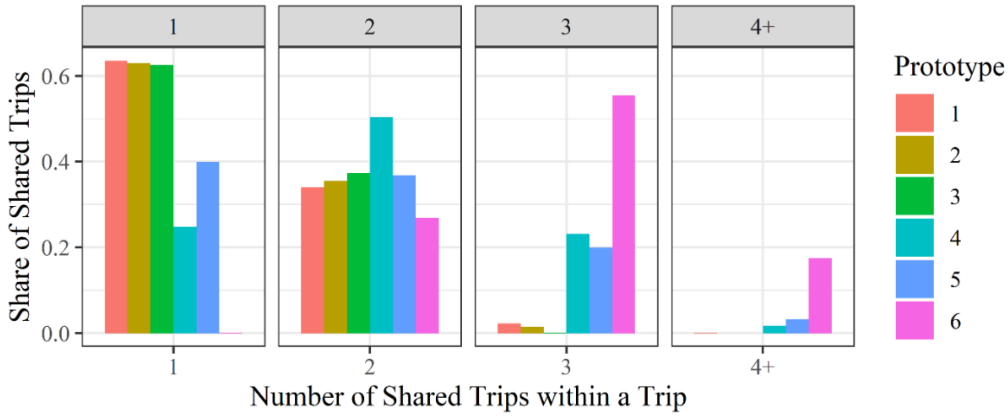

Figure 7 Number of travelers pooling a ride for actual shared trips

3.5.4 Spatial patterns of use

Lastly, I discuss the spatial distribution of travel. Notably, the majority of trips occur in or around the Chicago Loop or airports with standouts Near North Side and Near West Side where there are typically more residential units than in the Loop and overall higher density compared to the rest of the city. **Table 6** confirms that the top 6 origins and destinations hardly differ across prototypes. The strong concentration of flows is further illustrated in **Figure 8** that shows the location of the top O-D pairs distinguished by bold borders. These areas tend to have higher influx of visitors, along with more leisure landmarks such as restaurants and night clubs. The residents of these community areas tend to have higher average incomes and possess higher educational attainments than the average Chicagoan. These results are in line with findings from Clewlow and Mishra (2017) as those who are college-educated, younger, and living in denser areas are more likely to adopt ridehailing.

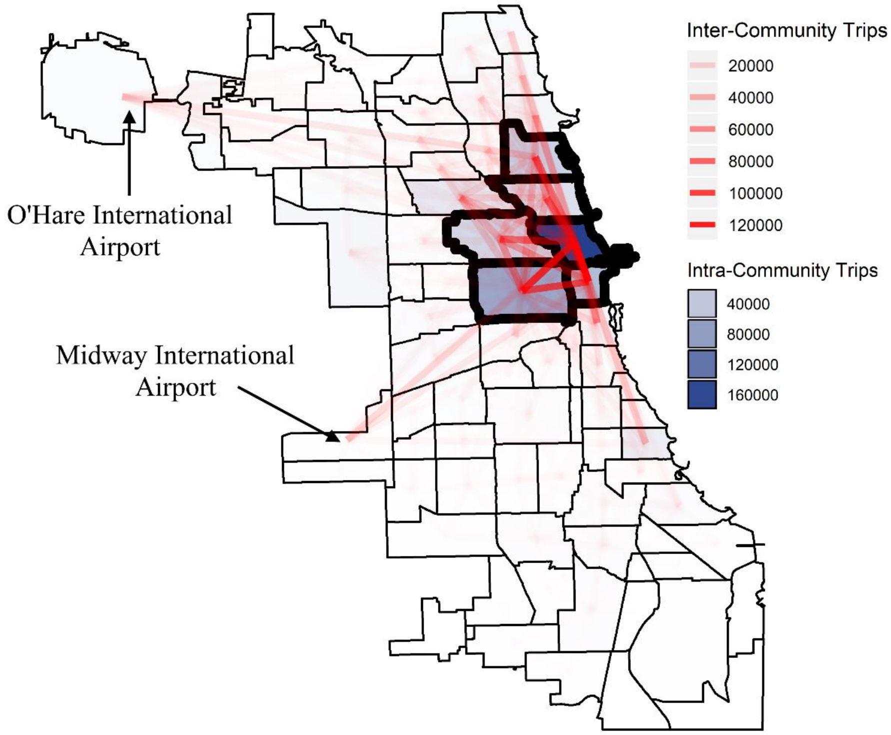

Figure 8 Ridehailing flows in the City of Chicago with bolded boundaries of prominent community areas

3.5.5 Policy implications

This study identified several patterns of ridehailing usage across Chicago that highlight the need for careful policy implementation. The discussion of policy implications will focus on modal interactions and ridesplitting due to the need for insights to guide ongoing efforts to tweak fares, promote partnerships and regulate ridehailing to better serve the comprehensive mobility needs of Chicago residents. The core questions that need to be explored relate to a) the challenge to provide effective service in areas with poor (or strong) transit options and b) to promote equity in hailing-access by understanding and promoting more affordable ride-splitting. Because ridehailing has been a disruptive innovation and lack of access to a comprehensive dataset on TNC activity, there is limited understanding regarding its relationship with other transport modes and the variation in ride-splitting adoption.

Much of the policy debate has focused on determining whether ridehailing is complementary or a substitute to other modes; this section discusses strategies that may facilitate synergy in the transport ecosystem.

3.5.5.1 Ridehailing and air-mobility accessibility

Given the identification of an airport prototype with strong connections to the core commercial areas of Chicago, one major policy trend has been to control ridehailing's effect on airport infrastructure. Examples of this include extra fees to ride into airports and curbside management of drop-offs and pickups. This prototype serves as evidence for continued development of policies that will better manage the relationship between airports and urban mobility including prominent use of ridehailing. With this prototype showing a strong connection between the commercial core of Chicago, policies should focus on connections that will appeal to business travelers. This remains a challenging area of research as new options including Vertical Urban Air Mobility is being tested in initiatives such as UberElevate with electric vertical takeoff and landing vehicles (Al Haddad et al., 2020; Kasliwal et al., 2019). This highlights the need to craft regulations and partnership arrangements such as security checkpoints and luggage drop-offs (Merkert & Beck, 2020). The rise of new services also highlights renewed equity and affordability concerns as they might give rise to further erosion of transit options.

3.5.5.2 Ridehailing and transit performance

Conversely, the airport prototype also suggests the need for policies to improve transit connections between downtown Chicago and the airports. The segmentation analysis revealed some intriguing patterns of competition. Ridehailing appears to be used by a small group of users even when transit is seemingly the better option (P5_transit-competitive 5.1%) and at the same time, a sizeable segment will turn to their mobility-apps in areas where transit is in abundant supply but time-performances is poor (P3_solo-non-transit 20.3%). This opens a debate about perception and motivations of users, communicating options to travelers and developing new partnerships.

With the transit-competitiveness prototype showing that there are real possibilities for transit to be faster than ridehailing, a practical policy effort is to improve the dissemination of transit information. Local transit agencies can develop Advanced Traveler Information Systems that highlight cases where transit is competitive to increase their ridership (Shaheen & Cohen, 2018a). Other strategies could be used in conjunction with MaaS in multi-modal systems to nudge riders towards transit. Studies have shown that travel behavior can be influenced using soft strategies (Gaker et al., 2010). These strategies such as making transit the default option or highlighting the broader benefits of supporting transit through patronage can be facilitated through navigation application. While this type of policy improves transit-competitiveness, ridehailing may still be dominant in many areas and promotion of sharing is vital in this situation.

3.5.5.3 More ridesplitting?

Promoting ridehailing naively may worsen traffic conditions, however, promoting shared rides to increase the demand for ridesplitting may be a reasonable solution. Policies that incentivize shared rides such as a tax that increases fees for exclusive rides could lead to higher demand for sharing and increased transit ridership (Zhu et al., 2020). The trade-off between delays and lower fares could be used to promote sharing and even increase mobility for disadvantaged groups where high fares turn them away. Policies providing travel support for unemployed and low-income residents via vouchers or further lowering fares increases travel and opportunities when other modes are not feasible. The ongoing debate in Chicago and cities around the US has focused on the lack of broader coverage, outside transit rich areas, of ridehailing. **Figure 8** highlights the lower share of rides occurring in and between historically underserved communities on the South and West sides of Chicago. Policies geared at promoting shared ridehailing between underserved areas is an opportunity to reduce Vehicle Miles Traveled and to support disadvantaged communities.

3.6 Conclusion

This study examines a unique TNC dataset from Chicago, IL by utilizing the unsupervised learning K-prototypes algorithm that accepts categorical data. The goal of this study is to identify patterns of TNC patronage regarding service attributes, weather, transit, taxis, characteristics of origins and destinations, and ridesplitting. The analysis revealed 6 distinct ridehailing user segments. The segments were identified in relation to adverse weather conditions, evening trips, longer trips, trips to the airport, trips that would be better served by transit, or trips that are pooled. The segments are discussed in the context of relative performance of ridehailing as well as examining the origin and destination of flows to better interpret the spatial and performance variation.

The identification of these distinct trip types shows where future research is warranted. The discussion in this study focuses on how future research should consider factors such as weather and other external factors when estimating the demand for TNCs and other modes, airport-based mobility options in the future, understanding why TNCs have competitive advantages besides faster travel times, and why more trips are not shared. The last point made in the discussion emphasizes how most of the trips are completed in and surrounding the CBD of Chicago. In summary, the concentration of trips in the downtown area where of mobility options and amenities are abundant, along with notable variation in performance of ridehailing across user clusters, prompt a deeper discussion of *where and for whom* ridehailing enables mobility.

The main limitations of this study come from the constraints of the merged data-sets. Firstly, the weather data is collected at only one location. Considering the size of Chicago and the location of the station, the data may not be representative of local weather. Secondly, the TNC, taxi, and transit data are aggregated at the Census tract level. This aggregation was needed to jointly analyze mode performance and supply but might lead to less precise findings about competing transit service. To increase the accuracy of these comparisons, more granular data is needed. Lastly, future analysis should expand the analysis to a longer panel of observations thereby capturing more variation in weather and other seasonal factors that determine demand for mobility.

4 A SPATIAL DURBIN ANALYSIS OF CHICAGO RIDEHAILING DEMAND[2]

4.1 Background

Mobility-on-Demand (MoD) was seen to offer more options to urban travelers, improve access to transit by providing first-last mile connections, increase vehicle occupancy via pooling, and offer on-demand flexibility for customers (Alonso-Mora et al., 2017; Shaheen & Cohen, 2018b). However, realization of these benefits has been questioned in recent studies (Diao et al., 2021). Empirical studies have shown that ridehailing tends to be used for recreational trips rather than transit last mile access, and leans towards substitution effects with transit (Alemi, Circella, Handy, et al., 2018; Tirachini & del Río, 2019). Additionally, several researchers find that surveyed ridehailing users are likely substituting active modes like walking and biking (Clewlow & Mishra, 2017; Rayle et al., 2016), and that ridehailing can generate induced demand (Rayle et al., 2016; Tirachini & Gomez-Lobo, 2020).

Research findings are also evolving to account for the constant service evolution of ridehailing. The creation of shared ridehailing service alternatives (also known as ridesplitting), such as UberPool, Lyft Line and Didi ExpressPool, match ride requests and give users a discount relative to the standard trip fare. These trips are authorized to be pooled and may possibly only serve one party when the demand is too low to efficiently match rides. In this paper I will refer to this service as ridesplitting, pooling, or pooled rides. I will also refer to the standard service (e.g. UberX and Lyft Classic) as private rides since this service is exclusive to one party (a party may consist of more than one rider). Though ridehailing has introduced a relatively more affordable

[2] Soria, J., & Stathopoulos, A. (2021). Investigating socio-spatial differences between solo ridehailing and pooled rides in diverse communities. *Journal of Transport Geography*, *95*, 103148.

alternative, ridehailing in general is mainly used by narrow population segments, and consistently producing low shares of ridesplitting (Lewis & MacKenzie, 2017; Li et al., 2019; Rayle et al., 2016).

To date there is limited understanding of how MoD demand is shaped by different community contexts and the degree to which private demand differs from ridesplitting (Soria et al., 2020). More commonly, these modes are not differentiated. In this paper I expand the literature on ridehailing demand by using spatial modelling to examine the socioeconomic community determinants. Specifically, I compare private and pooled trip-making patterns from a large-scale Chicago database to identify the unique determinants that encourage ridesplitting while controlling for spatial effects. The results of my analysis uncover new insights on how ridehailing ties in with community factors, the importance of accounting for spatial effects, and whether private and pooled rides serve distinct communities.

4.1.1 Potential for ridesplitting

Ridesplitting has the potential to reduce the number of passenger vehicles on the road assuming riders substitute personal or private vehicle travel when opting to share. Simulation work suggests TNC fleet sizes can be reduced with shared rides (Alonso-Mora et al., 2017). However, the share of pooling likely needs to be much higher than currently observed to unlock benefits. Rodier et al. (2016) suggests above 50%, while Fagnant and Kockelman (2018) estimate that pooled services need to account for 20–50% of the market-share. To date, little is known about the current demand for pooled rides nor the determinants of use. Basic statistics are uncertain but suggest a market-share of pooling between 6 and 35 % (California Air Resource Board, 2019; X. Chen et al., 2018; Chicago Metropolitan Agency for Planning, 2019a; Li et al., 2019; Lyft, 2018; Soria et al., 2020; Young et al., 2020). The estimated demand for pooling has been examined in stated preference work, finding that the addition of co-riders generates non-linear disutility in a shuttle setting and high sensitivity to time-cost trade-offs (Alonso-González, Cats, et al., 2020). In the context of a shared autonomous rides, Lavieri and Bhat (2019b) also suggest that the travel time/waiting time to cost trade-offs matter more than the perceived disutility of sharing a ride. In terms of mode-substitution, survey data from Hangzhou, China suggests that the biggest mode-shift of ridesplitting users would be to transit (bus and metro rail) (X. Chen et al., 2018).

Recently, a limited number of major ridehailing data-releases is supporting initial empirical analysis of pooling. Analysis of large-scale trip data suggests that private and pooled demand has different spatio-temporal patterns in Chengdu, China (Li et al., 2019). Ensemble machine learning highlights the importance of pricing and timing variables for ridesplitting demand in Hangzhou, China (Chen et al., 2017). Clustering analysis on Chicago ridehailing data reveals that pooled rides have distinct patterns, linked to affordability and local transit performance (Soria et al., 2020). These works shed light on the user trade-offs and aggregate demand patterns of ridesplitting. Yet I still know little about the hurdles to the increased adoption of pooled rides to reach the critical mass needed to unlock significant mobility benefits in terms of Vehicle Miles Traveled (VMT) reductions.

4.1.2 Spatial modeling of mobility impacts

There is ample evidence that transportation infrastructure is often associated with "broader" impacts via analysis of surrounding or neighboring spatial units (e.g. states, counties, Census Tracts). Yu et al. (2013) find that transport infrastructure capital (roadways, railways, water transport, and civil aviation) in China has a positive spillover effect on GDP across regions; Berechman et al. (2006) find strong spillover effects of highway capital investment in the US and, urban rail projects in the US have been tied to increased residential property values in surrounding areas (Chen et al., 1998; Diao, 2015). Similarly, other spillover effects such as increases in household income have been observed around urban rail stations in Denver, CO (Bardaka et al., 2018). Not all spillovers are positive, though. observe negative spillovers of nuisances such as noise associated with light rail transit. In practice, investments such as light rail construction, often comport both positive (accessibility) and negative (nuisance) effects spillover effects (Chen et al., 1998). In addition, the spatial distribution of new transportation infrastructure is often distributed unevenly with regard to race and socioeconomic status of residents. Hirsch et al. (2017) found that health-promoting infrastructure (parks, bicycle facilities, off-road trails, and public transportation) in four US cities was spatially clustered, and often associated with income and employment status of residents. In sum, spatial spillovers exist, and often play an important role in terms of equity and health disparities. Knowing the nature and degree of spillovers related to transportation investments has evident practical value by improving planning and accounting for the equity in distribution of spillover effects across areas (Cohen, 2010).

Little is known on the potential spatial aspects of ridehailing operations. This analysis is complicated by the spatio-temporal variation in on-demand services, limited data on both demand and supply, as well as continuous regulatory and service evolution. Research by Hughes and MacKenzie (2016) compared spatial variability in wait times for UberX throughout the Seattle region. Wait times increased in areas with higher average income and decreased in areas with greater population and employment density. Brown (2018) directly compared ridehailing and taxi performance for Los Angeles, California. She observed that ridehailing serves more diverse neighborhoods and have lower cancellation rates and waiting times than traditional taxis.

Other studies examine the competition between taxis and ridehailing by accounting for spatial differences. Kim et al. (2018) study the spatial effects TNCs have on New York City taxis where ridehailing's entry decreased taxi demand in one part of the city while increasing it in others. In other markets, ridehailing filled spatial and temporal gaps in taxi supply (Dong et al., 2018). Moreover, initial evidence from observed trip-data suggests robust spatial differences between private and pooled rides (Chen et al., 2017; Li et al., 2019; Soria et al., 2020). With limited analysis it is difficult to draw general conclusions about spatial variation in the demand and impact of ridehailing, though I note that the effects appear to be dynamic and tied to local community conditions. A deeper analysis of different spatial patterns that also account for socioeconomic conditions and land-use variables, is needed to understand ridesplitting and inform better policies to maximize their benefits for users across diverse urban environments.

4.1.3 Research objectives

On the whole, the diffusion of ridehailing appears to be related to existing socioeconomic and mobility advantage of users. Despite the significant growth in use, suggesting that 36% of U.S. adults have now tried ridehailing (Pew Research Center, 2018), adoption disparities persist, most notably between urban and rural communities, younger and older users, and income groups (Alemi, Circella, Handy, et al., 2018; Alonso-González, Cats, et al., 2020; Lavieri & Bhat, 2019a). While the adoption gaps among population segments is well established, the spatial gaps in use and service, including relationships to competing modes, are still unclear.

For both general ridehailing and ridesplitting analysis, most previous work typically uses an "aspatial" perspective, explaining usage patterns by accounting for characteristics within the spatial unit of analysis, but not controlling for spatial correlations nor investigating spillovers across neighborhoods. Ghaffar et al. (2020) and Dean and Kockelman (2021) consider similar socioeconomic, built environment, and transit accessibility variables with methods that consider spatial effects with Chicago ridehailing data. These studies use census tracts as the spatial unit of investigation. This research considers Chicago Community Areas as the spatial unit of investigation to include approximately 24% of the data that are missing due to trip origin censoring. The definition of Chicago Community Areas and information about trip origin censoring are provided in the Methods and Materials section.

I complement the existing research that considers spatial effects by considering a Spatial Durbin Model (SDM) (Dean & Kockelman, 2021; Ghaffar et al., 2020; Lavieri et al., 2018; Yu & Peng, 2019). Additionally, I investigate and compare determinants of demand for private and pooled ride demand in depth. Previous research does consider ridesplitting separately and finds that it is different from private rides based on average travel time and distance, time of day when it is most utilized, and general economic indicators such as gross domestic product and average house price (Li et al., 2019). To build upon this research, I account for socioeconomic, land-use, and rail access time variables to understand community dynamics of ridehailing adoption, including community level spillovers. Methodologically, I employ the SDM (Anselin, 2003). This approach enables us to investigate whether the intensity of ridehailing demand in a community area is associated with the features of the observed area, as well as of its neighbors. In this paper I focus on three research objectives that each make a contribution to understanding ridehailing demand determinants.

- *Q1:* What are the *spatial patterns of demand for private and pooled rides, and do they differ?* This research contributes to building fundamental insight from large-scale data on pooled demand distinctions. I further explain differences in Q2 and Q3.

- *Q2: What is the impact of socioeconomic conditions of communities on ridehailing demand (private and pooled)?* The specific contribution is to account for the bundled nature of socio-spatial privilege/vulnerability indicators and provide new insight on how pooling and private ridehailing relates to community vulnerability.
- *Q3: What is the demand-relationship between ridehailing (private and pooled) and transit accessibility?* This research contributes to more understanding of the still mixed findings of how ridehailing relates to transit.

My findings from the SDM analysis of Chicago ridehailing demand coupled with auxiliary data suggests uniformity in effects for land-use and density variables. Instead, private and pooled demand has nuanced and diverse effects when considering transit competition and social vulnerability impacts.

4.2 Data

4.2.1 Ridehailing trip data aggregation technique

The ridehailing trip data (plus metadata for spatial boundaries) are collected from the City of Chicago public data portal (City of Chicago, 2020). The data used in this analysis comes from the same database as the trip data used in the previous chapter. For the purpose of this study, I update the data to include trips after November 2018. It is processed and cleaned by removing observations with no origin or destination, fares of $0 and extremely high values (greater than $1,000), or 0 trip duration or miles recorded. The clean dataset used in this analysis comprises 127,598,605 ride records between November 2018 and December 2019. Approximately 25.5% of these trips were authorized to be shared, however, only 66.9% of these were truly shared, indicating that overall, 17% of all trips were truly pooled.

To preserve privacy, the Census tract info is censored if only one trip occurs in a 15-minute interval, and spatially aggregated up to the community area level. These types of trips account for nearly 24% of the data. Owing to this restriction, and the availability of auxiliary data, I opt to model ridehailing demand at the more aggregate spatial level of the 77 community areas defined by the city. These community areas were originally based on groups of neighborhoods and physical barriers (Owens, 2012). Using this spatial unit of analysis is also advantageous because the boundaries rarely change, unlike Census based spatial units.

The trip data were aggregated based on trip origins which are the most likely to reflect the socioeconomic origin of users, though I note that destination, or OD pairs could be used (Ni et al., 2018). I assume that the attributes of trip origins are the best descriptor of riders with Young et al. (2020) finding that 86.4% of trips were home-based. Owing to the varying sizes of community areas, the ridership data are normalized by the area of the communities (in square miles). Additionally, trip demand is heavily skewed towards the downtown areas. To account for this, a log transformation is applied. The dependent variable thereby represents long-term ridehailing intensity while controlling for community area and demand intensity variation.

4.2.2 Transit access time estimation

Studies have found that transit can play either a competing or complementary role with no consensus on which relationship is stronger (Babar & Burtch, 2017; Boisjoly et al., 2018; Hall et al., 2018; Nelson & Sadowsky, 2019; Young et al., 2020). To add to this discourse, I model the impact of transit accessibility on the intensity of ridehailing usage. The location of all Chicago Transit Authority and Metra public transit rail stations are collected from the public data portal (City of Chicago, 2020). The transit accessibility measure used in this study is akin to the Transit Access Time defined by Correa et al. (2017) where a hexagonal tessellation is overlaid on a map of the city. The edge of each cell is 1750 ft so that the theoretical walking time across is within the pedestrian access time defined by the Federal Highway Administration guidelines (Nabors et al., 2008). To determine average transit access time in each community area, the Google Maps API is used to determine the walking time from the center of a hexagon to the closest rail transit stop and averaged across the community area (Google, 2020). A similar approach was used to derive bus station density, but this measure was found to be insignificant in modeling.

4.2.3 Social Vulnerability Index derivation

Across cities, urban mobility systems naturally intersect with long-running challenges, including spatial mismatch, enduring racial residential segregation and economic inequality. For Chicago, it is known that economically depressed areas tend to be poorly served by transit (The Chicago Urban League, 2016). The local planning agency, CMAP has called for more research to examine the benefits and pitfalls of new mobility technologies, such as ridehailing, with regard to accessibility, affordable mobility, and quality of life in underserved communities (CMAP, 2018).

Moreover, work in the social sciences has established that numerous factors related to household structure, employment, income, wealth and racial status can make households more vulnerable to a lack of economic opportunity that is perpetuated as economic immobility (Sabol et al., 2020). Moreover, just like socio-demographic privilege, vulnerability comes in clusters, making it difficult to allocate the influence of separate factors (Smeeding, 2016). To date, existing ridehailing research has limited analysis to single socio-demographic factors, like race or income. In this paper I parse the simultaneous dimensions of socially vulnerable communities and how they correlate with the adoption of ridehailing services by developing a Social

Vulnerability Index (SVI). A similar index has been applied to examine the relationship between measures of deprivation and health outcomes (Butler et al., 2013). To determine the SVI I rely on data from the ACS 5-year estimates for the Census tracts, aggregated to the Chicago community area level (U.S. Census Bureau, 2019). A single factor Exploratory Factor Analysis (EFA) with a factor loading threshold of 0.30 and no rotations is used to obtain an SVI for each community area. The composition of the SVI is summarized in **Table 7**.

The index has intuitive results and high internal validity (Cronbach's α =0.91), suggesting strong links between household income and a number of vulnerability factors. The advantage of using an index is to enable a more holistic analysis that does not define hardship by looking at single factors such as racial or ethnic minority status. Instead, the validity of the proposed factor analysis affirms the strong correlations among vulnerability metrics, and the risk of spurious results should the items be included separately.

Beyond the SVI that captures economic vulnerability, my analysis controls for other relevant socio-demographics that have been tied to ridehailing demand in the literature: user age, household size, and population density (Clewlow & Mishra, 2017; Lavieri & Bhat, 2019a; Rayle et al., 2016). I collected this data from the ACS (U.S. Census Bureau, 2019).

Table 7 Social Vulnerability Index results

Item	Factor Loadings
Percent of population with poverty level income	0.989
Percent of households with single parent	0.873
Percent of population that are non-white	0.769
Percent of households with no vehicle	0.763
Percent of households renting for housing	0.744
Percent of working eligible that are unemployed	0.649
Cronbach's α	0.91

* Result from Exploratory Factor Analysis on ACS data, unrotated single-factor results

Ridehailing use is also associated with land-use mix (Ghaffar et al., 2020). I define a land-use mix index, following Ghaffar et al. (2020), and measure it at the community area level using data from CMAP (CMAP, 2018). This index was tested in my model specification but did not yield statistically significant results. Given the connection of ridehailing use to recreational and leisure travel (Soria et al 2020), I extract data on the location of restaurants and bars with active licenses during 2018 and 2019 (City of Chicago, 2020). This measure represents the impact of *third places*, namely the localities that are separate from home and work that generates a sense of community and contributes to urban vibrancy (Oldenburg & Brissett, 1982; Trentelman, 2009). The bar/restaurant variable is normalized by area.

Table 8 shows key socio-demographics, transit access, and ridehailing characteristics of major Chicago Districts (collection of community areas). I note that the areas with higher income (North and Central) tend to have better transit access (lower TAT) and more ridehailing pickups, but lower degrees of pooling, albeit with some variation across communities. **Figure** 9 maps the delimitations of these districts. **Table *9*** shows the summary statistics for all dependent and independent variables included in the final models. It shows that the model includes highly diverse communities with wide ranges of youth population, population density, bar and restaurant density, and TAT. Importantly, because the factor analysis only includes ACS data from Chicago, the SVI cannot be directly compared with other cities.

Table 8 Descriptive statistics of Spatial Durbin Modeling variables in Chicago districts

	Chicago	Far North	Far NW	North	Central	West	South	SW Side	Far SE	Far SW
Avg. Income Per Capita ($)	32,535	33,744	25,172	57,393	87,061	26,755	24,364	17,570	19,737	26,682
Avg. Income Per Household ($)	84,637	82,208	76,569	126,994	147,138	76,703	56,731	58,606	54,302	77,102
HS Degree only (% of pop)	23%	20%	28%	11%	6%	24%	23%	37%	30%	27%
Bachelor's or higher (%)	36%	45%	24%	66%	73%	31%	30%	11%	18%	26%
Commuting SOV (%)	53%	53%	67%	41%	32%	49%	46%	62%	63%	71%
Commuting Carpool (%)	8%	7%	11%	5%	4%	9%	8%	14%	9%	9%
Commuting Transit (%)	30%	32%	19%	45%	30%	31%	33%	20%	26%	19%
Commuting Active (%)	9%	7%	4%	9%	34%	11%	12%	4%	3%	1%
Avg. Rail Access Time (min)	24.1	38.9	21.9	13.3	11.0	14.7	12.5	24.7	31.0	22.1
Avg Daily TNC Pickups	263,192	27,030	7,763	53,727	77,952	57,390	18,833	11,371	5,619	3,507
Avg Daily Authorized Shared TNC Pickups	59,006	6,644	2,439	8,868	11,261	14,177	6,879	4,614	2,575	1,549
TNC Rides Authorized to be Pooled (%)	22%	19%	28%	17%	14%	24%	37%	35%	41%	37%
TNC Rides Truly Shared (%)	15%	12%	18%	12%	11%	18%	26%	23%	23%	22%
Share of Authorized Pooled Rides that are truly shared (%)	69%	65%	64%	73%	77%	72%	70%	65%	57%	58%

Table 9 Model variable summary statistics

Variable	Median	Mean	Standard Deviation
Dependent Variable: Log of Average Daily Private Trips per square mile	5.698	5.957	1.357
Dependent Variable: Log of Average Daily Shared Trips per square mile	5.316	5.196	1.119
Population 18yr to 34yr (%)	0.2530	0.2735	0.07741
Population Density (per sq. mile)	11,521	13,113	7,002
Mean Household Size	2.716	2.739	0.5407
Bar and Restaurant Density (per sq. mile)	35.559	58.058	73.76
Transit Access Time (minutes)	14.569	19.756	13.45
Social Vulnerability Index	-0.1683	0	0.9904

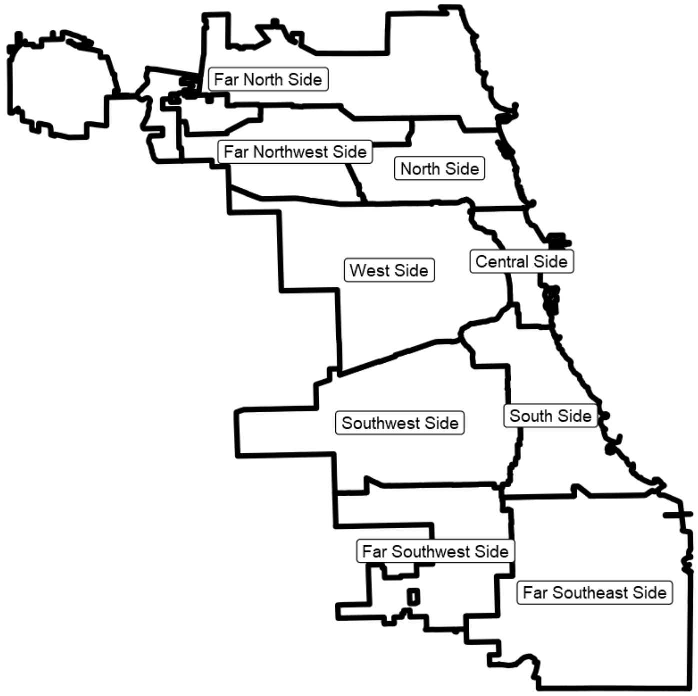

Figure 9 Chicago area district map

4.3 Methodology

Previous transportation research investigating ridehailing use has relied on representation of the context measuring only the "immediate spatial area", with limited investigation of factors occurring in surrounding areas. Importantly, while a portion of the impact is determined in the immediate spatial area, some effects are likely to spill over across communities. This spill-over is not directly tied to demand awareness. Instead, while it is unlikely that riders are directly aware of ridehailing demand in neighboring areas, the local and surrounding community conditions are likely to affect demand for ridehailing via waiting times and social effects. That is, local mobility praxis, driver pickup biases and strategies, and perceived attractiveness and viability of alternatives can all shape spatial (spillover) demand for ridehailing. To study this, I regress the intensity of both solo and pooled usage on a range of potential explanatory factors. I find evidence for a significant role of transit accessibility, SVI, along with four land-use/density variables, summarized in **Table *9***.

I apply spatial econometrics to account for spatial interactions (Manski, 1993). After verifying the presence of spatial autocorrelation, and using Moran's I and Lagrange Multiplier tests for model specification guidance, I specify a Spatial Durbin Model (SDM) to explore my three research questions (Anselin & Kelejian, 1997; Osland, 2010). The general SDM specification is summarized in **Equation 5.** Y is the response variable of community area ridehailing demand, ρ is a coefficient for the lagged effect representing the response variable in one community to other neighboring communities, and W is a weight matrix representing the spatial structure of community influences on the residuals. This first term, ρWY, measures the endogenous effect of ridehailing usage. The spatial weight matrix, W, is defined as a row-standardized matrix where each row represents the spatial unit of analysis, contiguous neighbors have an equal effect, with 0's along the diagonal. The row sum of the weights is equal to 1 for every spatial unit. The purpose of using the row-standardized weight matrix is two-fold. First, a row standardized matrix facilitates efficient maximum likelihood estimation of the SDM (LeSage & Pace, 2009). Secondly, the row normalization of W means that the effect of neighbors is averaged which is desirable when there is no a priori knowledge of neighbor influence. This W is used throughout the modeling to maintain comparability. X is a matrix of explanatory variables and β is the vector of corresponding coefficients. γ_l is the vector of spatial lag coefficients of the explanatory variables X_l. An extension of this model is the Spatial Durbin Error Model (SDEM) which considers the error term as a function of W.

Because SDM includes an endogenous term, the estimated coefficients are not representative of the impacts of the explanatory variables. To translate them into interpretable values, the coefficients are transformed. **Equation 6, Equation 7**, and **Equation 8** are used to obtain direct (immediate local effects), indirect (spillovers), and total impacts (the sum), respectively, to examine the impacts of the explanatory factors on both private and pooled ridehailing. These impacts are calculated for each explanatory variable, k, using the ρ estimated in **Equation 5.**

$$Y = \rho WY + X\beta + WX_l\gamma_l + \epsilon \qquad \textbf{Equation 5}$$

$$Direct = \frac{3-\rho^2}{3(1-\rho^2)}\beta_k + \frac{2\rho}{3(1-\rho^2)}\gamma_k \qquad \textbf{Equation 6}$$

$$Indirect = \frac{3\rho+\rho^2}{3(1-\rho^2)}\beta_k + \frac{3+\rho}{3(1-\rho^2)}\gamma_k \qquad \textbf{Equation 7}$$

$$Total = \frac{3+3\rho}{3(1-\rho^2)}(\beta_k + \gamma_k) \qquad \textbf{Equation 8}$$

4.4 Results

Before analyzing the model results, I explore the general patterns of demand for ridehailing along with ACS data. **Figure 10** depicts the percent of ridehailing rides that are private (a) and pooled (b), respectively. I also plot the SVI scores by community area in **Figure 11**. Comparing **Figure 10** and **Figure 11** suggests the community areas with higher SVI index (more vulnerable) tend to rely more on ride-pooling, as these maps have stronger spatial similarity. The trends are most evident with central and northern communities exhibiting lower rates of sharing and low SVI whereas western and southern community areas have higher rates of sharing with a higher SVI. Along with the statistics on ridesplitting shown in **Table 8,** this provides initial evidence that the spatial dynamics of private and pooled rides differ and have strong ties to socioeconomic vulnerability.

4.4.1 Spatial Durbin model specification

Given the strong differences in spatial patterns of private and pooled rides, I estimate separate models. The modeling starts with a bottom-up approach: estimating non-spatial linear regression models by OLS including all the theorized ridehailing demand drivers. Residual diagnostics and the Moran's I-test is used to detect spatial dependency. Both private rides (Moran's I = 0.30705, p-value = 0.001) and pooling (Moran's I = 0.37534, p-value = 0.001) gives evidence of spatial autocorrelation. Thereby I follow Elhorst (2010) combined approach using Lagrange multiplier (LM) and likelihood ratio testing. With the need to control for spatial effects apparent, the LM test is used to determine the need for spatial lag or spatial error controls. The spatial lag (statistic = 34.35, p-value < 0.001) and spatial error (statistic = 17.03, p-value < 0.001) model specifications indicate that either approach is potentially valid. However, with both tests significant, the SDM is favored over a potential SDEM because it is more robust (Osland, 2010). The estimation of the SDM was completed using the R programming language and spatialreg package (Bivand & Piras, 2015; R Development Core Team, 2008). Further comparison of SDM and SDEM likelihood ratio tests and inspection of spatial correlation confirms that the former provides more interpretable findings. **Table 10** and **Table 11** show the regression results and impacts, respectively. The following section discusses the interpretation of the findings followed by a deeper analysis of the three research questions.

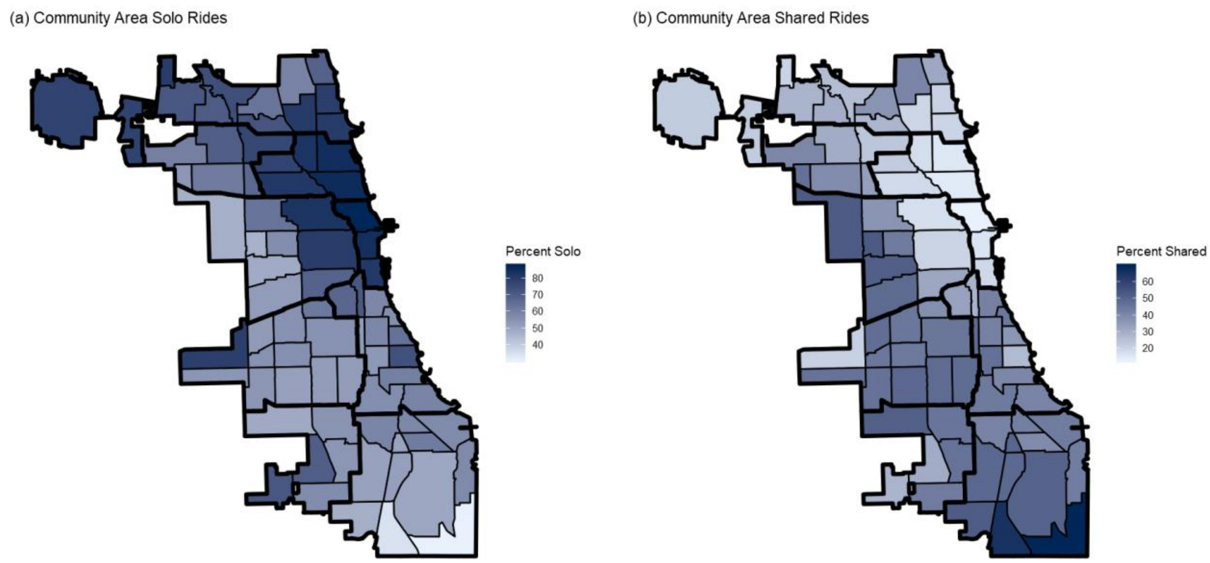

Figure 10 Community area percent use of private (a) and ridesplitting (b) map with bold borders depicting the boundaries of the Chicago sides from Figure 9

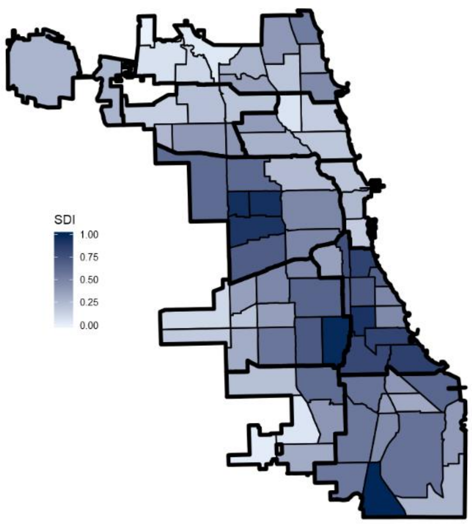

Figure 11 Social Vulnerability Index mapped by community area

Table 10 Spatial Durbin model estimation result[1]

	Private Rides		Authorized Ridesplitting Rides	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
(Intercept)	3.90***	5.87	2.37***	4.3
Population 18yr to 34yr (%)	4.03***	4.06	2.68**	3.26
Population Density (100,000s per mile)	3.57**	3.28	3.02***	3.47
Mean Household Size	-0.387***	-3.78	-0.163*	-1.98
Bar/Restaurant Density (1,000s per mile)	1.89^	1.88	1.17^	1.43
Transit Access Time (minutes)	0.00122	0.278	-0.00904*	-2.48
Social Vulnerability Index (score)	-0.124*	-2.38	0.146***	3.39
Lag (γ) for Transit Access Time (minutes)	-0.0411***	-4.32	-0.0201*	-2.52
ρ	0.369***		0.508***	
Nagelkerke Pseudo ρ^2	0.919		0.917	
AIC (OLS)	90.985 (105.97)		63.232 (91.301)	
Residual Autocorrelation	1.17		4.41*	
n. community areas	77		77	

[1] - Several variables were tested and found to be insignificant in both the Private and Authorized Pooled models were removed from the model specification. These were: bus stop density, percent of land area dedicated to parks, and mixed land-use

^ - p-value < 0.1; * p-value < 0.05; ** p-value <0.01; *** p-value <0.001

Table 11 Spatial impacts of explanatory variables from Spatial Durbin model results

	Private Rides			Authorized Ridesplitting Rides		
	Direct Impact	Indirect Impact	Total Impact	Direct Impact	Indirect Impact	Total Impact
Population 18yr to 34yr (%)	4.17	2.23**	6.40***	2.870	2.59**	5.457***
Population Density (100,000s per sq. mile)	3.69***	1.97**	5.66***	3.23***	2.91**	6.14***
Mean Household Size	-0.400^	-0.214**	-0.614***	-0.175^	-0.157^	-0.332*
Bar and Restaurant Density (1,000s per mile per mile)	1.95**	1.04	2.98^	1.25***	1.13	2.38
Transit Access Time (minutes)	-0.00237	-0.0608***	-0.0632***	-0.0124**	-0.0468***	-0.0592***
Social Vulnerability Index	-0.128*	-0.0685*	-0.196*	0.157*	0.141**	0.297***

^ - p-value < 0.1; * p-value < 0.05; ** p-value <0.01; *** p-value <0.001

4.4.2 Direct and indirect effects on ridehailing demand

Table 10 shows the SDM results with a spatial lag effect ρ evident for both private and pooled rides. The lagged γ coefficient for TAT is highly significant (p-value < 0.001). This suggests that in both ridehailing cases there is a need to account for spatial effects, including indirect impacts, most evident for transit accessibility. Both the private and pooled ride demand models produce a high goodness of fit with Nagelkerke pseudo ρ^2 (similar to r^2 in OLS) greater than 0.90 and AIC lower than equivalent OLS specifications, all suggesting the SDMs are valid and justified. There is evidence of residual spatial autocorrelation in the ridesplitting model, but the significance is low. Because these coefficients are not directly interpretable, the impacts of explanatory variables are calculated via the spatialreg package in R and summarized in **Table 11** in the form of direct, indirect and total effects as described in equation 2-4 (Bivand & Piras, 2015; R Development Core Team, 2008). That is, a change in the independent variables in a community area will not only lead to a change in the demand in the same community (direct effect), but also affect the ridehailing demand in other community areas (indirect effects, related to the off-diagonal elements in W).

There is evidence of six factors affecting the community area demand for ridehailing with some variability in terms of direct and indirect impacts. To gain more intuitive understanding of the effects, I use **Equation 9** to compute impact measures, where Δ_x is the change in variable x and I_x is the impact of variable x from **Table 11.** I thereby estimate changes in average daily requested rides. Interpreting the direct effects of population density, I find that an increase of 1000 in population density is associated with approximately 7,700 more private rides and 2,000 additional pooled rides per day in that community. Using the average population density from **Table *9*,** this translates to a 1% increase in population density being associated with a 0.49% and 0.42% increase in daily demand for private and pooled rides, respectively. These findings do not account for the spillover effects into other community areas. Turning to investigate transit rail accessibility, given the pronounced indirect effects, the spillovers are computed instead. For example, if a rail station were removed and a community area's average rail access time increases by 1 minute, then the sum of changes in neighboring community areas results in 12,000 fewer private rides and 2,700 fewer pooled rides. In terms of total (direct and indirect) impacts, on average, a 1% increase in TAT is associated with strong reduction in ridehailing requests (-1.24% for private; -1.16% for pooled).

$$\ln(r_2) - \ln(r_1) = \Delta_x I_x \ln\left(\frac{r_2}{r_1}\right) = \Delta_x I_x$$
$$\frac{r_2}{r_1} = \exp\,(\Delta_x I_x) \qquad \textbf{Equation 9}$$
$$r_2 = r_1 \exp\,(\Delta_x I_x)$$
$$r_2 - r_1 = \Delta_r = r_1(\exp(\Delta_x I_x) - 1)$$

4.4.3 Differences between private ridehailing and ridesplitting

My first goal is to investigate the spatial usage patterns of private versus pooled ridehailing. Before studying the model results, I examine the spatial distribution of Community area centroid Origin-Destination flows. Comparing **Figure 12** and **Figure 13** reveals stark differences in the user patterns with a greater spatial dispersion of ridesplitting compared to highly concentrated OD flows of private rides, illustrated by the red connectors concentrated in the downtown and airport corridors. Taken together, the mapping of ridehailing intensity (**Figure 10**) and flows (**Figure 12** and **Figure 13**) strongly suggests that ridership patterns are distinct. I turn to the model results in **Table 10** and **Table 11** to examine the causes for these differences formally. Both private and pooled ridehailing demand is higher in community areas with higher population density, more bars and restaurants, and higher share of young (18-34yr) population, with slightly stronger impact of each factor for private use. This leads to a first observation that urban vibrancy factors stimulate ridehailing demand more broadly, with uniform impact on private and pooled ride requests.

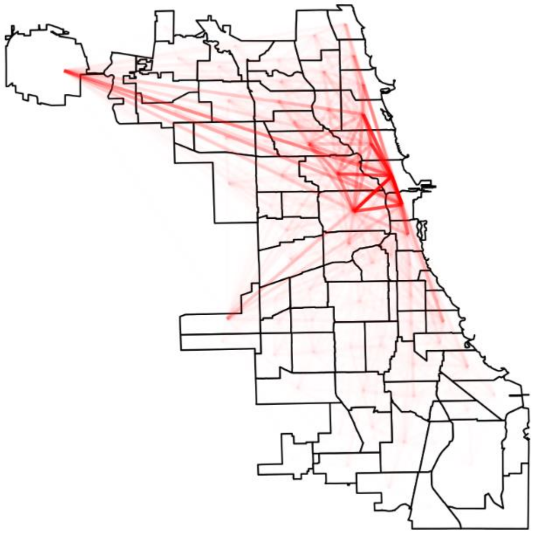

Figure 12 Intensity of OD flows of private ridehailing

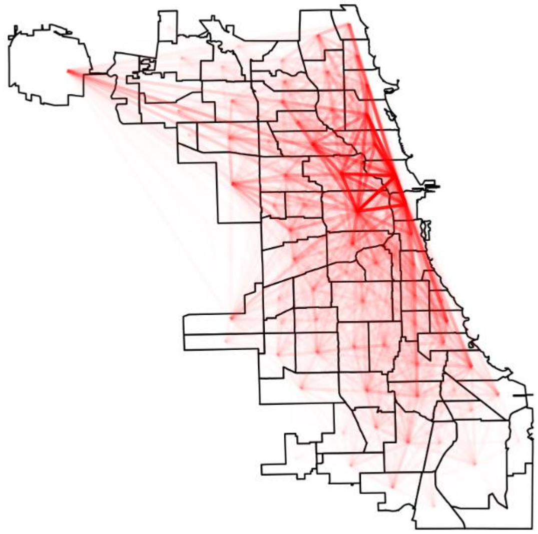

Figure 13 Intensity of OD flows of ridesplitting

This allows us to confirm established research findings on the key role played by urban density variables, and to extend those findings also to pooled ridehailing demand (Dias et al., 2019; Yu & Peng, 2019).

However, this leaves the question of explaining the prominent spatial differences for private and pooled hailing open. The SDM models reveal that the main source of the divergent spatial patterns are the social vulnerability and transit accessibility metrics, examined further in Sec. 3.5 and 3.6. Notably, the relative socioeconomic *vulnerability* of communities appears to be the main differentiator for pooled versus private ridehailing demand. This finding suggests an intriguing new connection between the evolving service portfolio of ridehailing operators and diverse socio-economic demand segments. That is, the small share of dynamic ridesplitting requests are disproportionally requested in areas of socioeconomic vulnerability, in contrast to the typically observed patterns of ridehailing demand established in the literature.

4.4.4 Social Vulnerability Index and spatial effects

The second research question centers on exploring the socioeconomic factors, and particularly the correlated socioeconomic vulnerability observed across Chicago. The SVI analysis and mapping confirm the correlated nature, as well as the spatial concentration of socioeconomic vulnerability indicators. The map in **Figure 11**, illustrates stronger vulnerability in the West, Southwest, South and Far Southeast districts (**Figure 9**) of Chicago.

The modelling confirms that concentrated vulnerability is associated with fewer private requests. This evidence supports the argument that (private) ridehailing is related to ridership privilege (Lewis & MacKenzie, 2017). This is because ridehailing, private rides in particular, is offered as a premium service and at a higher price than other available mobility options in the area. Yet, this correlation with privilege is not supported by the model results for pooling requests. This suggests an intriguing interpretation that ridesplitting plays a gap-filling role for households with lower income and limited access to a personal vehicle (Tirachini & del Río, 2019). It is worth noting that this higher demand occurs despite the higher price-point of ridehailing, even considering the discount for pooled rides. Considered jointly, I note that even after controlling for population and bar/restaurant density, the social and economic conditions in the community area still play an important role in shaping demand for ridehailing. A crucial question that arises from these results is the contradiction of a higher number of requests for sharing, occurring in the very areas where demand is generally low and matching multiple trip trajectories is challenging. This is also reflected in the **Table 8** statistics. The share of effectively matched trips (15%) is lower than the requested share of pooling (22%) with the rate of effective matching being highest in the wealthier central district and lowest in the far southeast district.

A second observation concerns the robust spillover effects for the SVI for shared rides. The negative indirect effect implies that vulnerability in adjacent community areas reinforces the direct demand effects. I attribute this indirect impact to the social nature of technology adoption (Alemi, Circella, Handy, et al., 2018; Alemi et al., 2019). For other shared mobility services like bikesharing, there is evidence of social/community factors driving adoption (Biehl et al., 2018; Manca et al., 2019). It is not clear that ridehailing embodies the same level of symbolism or spatial visibility that bikesharing does. Therefore, I propose as an area of future investigation to disentangle whether the observed spillover of socioeconomic conditions is due to supply effects (ridehailing drivers avoiding, or not opting in to offer pooled rides, in certain areas) or demand effects (local service/acceptability, social diffusion). For the latter case, I would specifically need to examine whether there are spatially bound social network effects leading to more use of pooled services, or whether the spatially correlated challenges of longer commutes and poorer mobility options (i.e. spatial mismatch) drive the needs for pooled ridehailing to fill gaps in underserved community areas.

4.4.5 Spatial effects and rail transit access

The third research question probes the relationship between ridehailing (private and pooled) and local rail transit accessibility measured via the TAT variable. The research is still divided regarding the substitutional (Clewlow & Mishra, 2017) or complementary (Boisjoly et al., 2018) relationship of ridehailing with transit. Moreover, research suggests systematic variation is likely according to the size of the city (Hall et al., 2018), locations within a city (Grahn et al., 2020), the number of TNC competitors in the market (Nelson & Sadowsky, 2019), and the transit option type and performance (Babar & Burtch, 2017). What is more, the existing research offers limited insight on the connection of pooled ridehailing and transit.

Looking at Chicago, there are factors suggesting both relationships are possible. The strong variability in wealth and service access across the city could suggest *complementarity* since users, particularly in underserved community areas, may opt to use ridehailing to fill gaps in transit accessibility (Alemi, Circella, Handy, et al., 2018), albeit with a need to consider the steep price differences (Hall et al., 2018). I would expect this to occur particularly for more affordable pooled rides. Instead, Chicago's expansive transit system with a high transit performance score (AllTransit, 2020) suggests that transit could remain *competitive* even in the presence of multiple TNC operators, as suggested by Babar and Burtch (2017). Finally, the loop-centered radial nature of Chicago's CTA rail system points to possible variation in effects according to the north-south corridor.

On the whole, my SDM model results suggest a significant positive correlation between ridehailing and rail accessibility. That is, in community areas where transit performs better (lower access times) the demand for ridehailing is also *higher*, in line with Correa et al. (2017) and Brown (2019). While this result is not surprising given the previous research using real trip data, the results are important because they can provide evidence of the separate effect of pooled rides. I expected that ridesplitting could have a more competitive demand relationship with rail transit, given the lower price-point and shared reliance on sharing. For example, Lewis and MacKenzie (2017) found that UberHOP, a ridesplitting service, predominantly drew riders form transit.

Instead, I find a significant direct demand effect only for pooled ridehailing, and no significant differences overall between private and pooled requests. Additionally, there is a strong spillover effects for TAT (**Table 11**), suggesting that transit accessibility in one community affects its neighbors. I attribute this to the spatial nature of transit systems where rail transit routes traverse several community areas.

In summary, in the central and northern areas of Chicago, excellent rail transit accessibility is correlated with higher demand for ridehailing. A possible explanation is that ridehailing competes more directly with driving than with transit, and the lower auto ownership and parking availability makes ridehailing more attractive precisely in the areas where transit also performs well, and vice versa. I do not conclude that the positive correlation confirms a complementary relationship over a competitive one between ridehailing and transit. This is because the analysis is based on spatially aggregated data rather than single trip data revealing replacement or complementary travel. Rather, I suggest that future research focus on collecting a representative dataset of transit and ridehailing users. This dataset should be at the individual level and capture mode substitution and induced travel.

On the whole, despite pooled rides serving a larger range of communities and more peripheral areas as discussed above, I cannot find any statistical evidence that pooling compensates for transit deserts. What is more, pooling seems to offer less gap-filling than private rides in areas where transit is poor, despite being more affordable. I speculate that ridesplitting might not be feasible or considered safe in transit-deserts.

4.5 Discussion

The findings suggest a number of implications for practice, ridehailing operators and researchers. On the public policy side, the finding that ridesplitting demand correlates with vulnerable socioeconomic living conditions measured by the SVI suggests that users in underserved community areas are benefitting from the convenience of an emerging mobility platform without paying the premium for private rides. In terms of policy, this points to a need for greater focus dedicated to the positive socioeconomic outcomes that TNCs can facilitate via pooled ridehailing. By promoting ridesplitting, there are not only potential benefits from reduced congestion but also from users in vulnerable community areas accessing more opportunities for employment and recreation. Thereby, public agencies ought to carefully differentiate ridehailing taxes and regulations according to the type of service model, along with user-segment and locations, to avoid reducing mobility and accessibility for underserved communities.

Concerning the operational and business perspective, an important challenge arises when considering the greater spatial spread of pooled ride requests. Notably, to maintain effective shared on-demand service operations it is necessary to match multiple requester trajectories in real time. However, with only one in five riders requesting sharing, and the requests being geographically dispersed, it is challenging to efficiently tie together trajectories. At the same time, on the side of riders, to maintain a growing customer base and loyalty to pooling, it is important to ensure service quality. Research suggests that riders likely care more about trip time/cost than sharing itself (Lavieri et al., 2017). Therefore, understanding user expectations, and the socio-spatial context is necessary to promote demand for pooled services, to in turn enable more stream-lined matching and unlock the critical mass of pooling. Given the benefits to vulnerable community areas, ridehailing operators and policy/mobility agencies have a strong motivation to work together to increase ridesplitting ridership.

On the research side there are three main take-aways. *First*, findings highlight the importance of studying contextual variables, such as socioeconomic measures, more carefully. This calls for more research to disentangle how different mobility service offerings from the ridehailing portfolio serves and affects different user segments and community areas. *Second*, ridehailing service model effects are not monolithic. Specifically, the results point to a difference in magnitude or even in direction of explanatory effects when looking at different ridehailing service models. *Third*, methodologically, this research uses a factor analysis-based index to study the overlapping factors of vulnerability that frequently affect communities. This helps overcome the underlying correlation between factors such as wealth, employment, and car-ownership, that jointly affect mobility decisions. An avenue for further work is to continue refining the indices that account for bundled factors to more accurately appraise the role of emerging mobility.

4.6 Conclusion

Innovative mobility services can be important tools to limit rising urban congestion and improve mobility for vulnerable populations. Yet, despite the significant growth in both the ridership and research on ridehailing in recent years, findings on disparities in use have persisted not just along demographic dimensions such as income, gender, race/ethnicity, but also geographically. There is still limited understanding of the diverse demand patterns and the impact of varied services offered by ridehailing operators (private, pooled, shuttles, curb-to-curb, etc). The goal of this study is to investigate the demand for ridehailing services, focusing on the distinct socio-spatial patterns of private requests versus ridesplitting. The analysis sheds light on how different emerging mobility services, with different sustainability, accessibility and equity implications, are used by diverse communities. I use a Spatial Durbin Model including measures of Social Vulnerability and Transit Accessibility applied to a publicly available dataset with 127 million ridehailing records from the City of Chicago. The results show that density and vibrancy variables related to concentration of restaurants, population and younger residents, have similar effects on the demand for private versus pooled rides. On the other hand, my analysis uncovers that pooling requests are geographically more dispersed and socially distinct from exclusive ridehailing use. With regard to the three research questions posed in this work there are several implications.

- For Q1 I uncover that ridesplitting is utilized among a broader range of community areas outside the central business district, thereby serving more diverse communities. Comparing the private and pooled ride determinants, I reveal that differences are mainly linked to community vulnerability. This suggests a novel connection between emerging mobility and vulnerability indicators where pooled services can serve entirely different needs and populations than what has been observed in the research focused on private ridehailing. This has two important implications. *One*, for the spatial modeling of ridehailing, vulnerability explain differences in demand, and also looms larger, that is, casts spillover effects across community areas. *Two*, the diffusion of pooling in underserved communities suggests an important socio-spatial dimension to consider in future work. Three, the more distributed demand pattern of pooled rides is tied to the sustainability of operations as critical demand-thresholds are harder to reach.
- For Q2 I develop an index that accounts for the bundled nature of socioeconomic vulnerability. The SVI represents the only flipped sign in my spatial model: higher vulnerability is associated with more ridesplitting, and less demand for private rides. Two implications arise. *One*, methodologically, there is value in using an index to account for overlapping factors that affect ridehailing demand. *Two*, a deeper analysis of the opportunity and barriers to accessing different ridehailing models is needed. Analyzing service attributes, socioeconomic circumstances and mobility context variables jointly is needed help understand which communities can access and benefit from pooling, and how it is used in practice.

- For Q3 I examined the impact of transit accessibility, finding that better rail transit access is correlated with more ridehailing pickups. The findings call for more investigation to clarify why ridesplitting demand, seemingly a closer transit substitute, surges in transit-rich areas, then tapers of more rapidly in transit-poor community areas.

I note some important *caveats* of this study. First, owing to data censoring I are unable to distinguish Uber, Lyft and Via rides, leaving the different character and promotional strategies as unknown factors in shaping demand for private versus pooled rides. Second, my trip data are not directly tied to rider sociodemographics. These are matched indirectly though the community area attributes and trip origin locations. Without precise rider data associated with each trip, it remains unknown whether the trips in high SVI areas, for example, are effectively requested by higher income trip-makers living in a vulnerable community. Third, the data do not include information on drivers search/driving patterns or on operator locational/pricing algorithms which could affect the choice to use ridehailing given that potential customers can view estimated waiting times and prices.

Future research should focus on further characterizing the differences between private and pooled demand patterns (such as focusing on other variables such as trip length, timing, and duration), and analyzing their complex relationship with transit (buses and rail). There are prospective benefits towards reducing (private) vehicle miles, and improving social outcomes, with increased use of pooling. Carefully designed stated and revealed preference/intercept surveys are needed to more fully capture the barriers to increased adoption of pooled rides.

Finally, with an eye to the future, while the ridehailing industry tends to spearhead new forms of ride-sharing, currently and in the near future, societal values around sharing are changing drastically. As the world contends with the ongoing COVID-19 pandemic, and in many cases suspension of pooled ridehailing services, it behooves researchers, policy-makers, and the ridehailing industry to investigate the perceived risks of vehicle sharing, and the tolerance for returning to various forms of shared mobility.

5 SWITCHING FROM TRADITIONAL COMMUTE MODES TO MICROTRANSIT: AN INTEGRATED CHOICE AND LATENT VARIABLE APPROACH[3]

5.1 Background

Building from previous chapters, it is evident that the Chicago ridehailing data cannot reveal individual behavior. With many of the concerns about ridehailing centering on its negative social and environmental impacts, it is important to understand new opportunities for ridehailing to pose less of a burden on urban transport networks. In response to these concerns, transit agencies and mobility startups have launched microtransit services—small-scale, on-demand transit fleets that can offer both fixed routes and schedules, as well as more flexible routes and on-demand scheduling (APTA, 2021). This new service model may produce environmental *and* rider benefits. It relies on Information and Communication Technology (ICT) to enable real-time service requests or coordination between riders and drivers for trip pooling. This coordination makes the transition from door-to-door to curb-to-curb (e.g. at transit stops) services easier to implement.

The shift to microtransit calls for research on user behavior, motivations, and acceptability to understand demand and its impacts. Beyond traditional transit attributes like travel time and fare, microtransit entails new attributes related to curb-to-curb routing, scheduling, and different sharing configurations. Pinpointing how customers evaluate these new service dimensions is critical for researchers and decision-makers to design new mobility

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[3] Soria, J., Etzioni, S., Shiftan, Y., Stathopoulos, A., & Ben-Elia, E. (2022). Microtransit adoption in the wake of the COVID-19 pandemic: evidence from a choice experiment with transit and car commuters. arXiv preprint arXiv:2204.01974.

platforms complementing existing transportation systems. Different mode experiences are also likely to lead to different service feature perceptions. An attribute such as expected walking time to the boarding location can be viewed as a disadvantage against the baseline of private car or ridehailing but is a familiar factor for transit users. Understanding how riders weigh microtransit attributes is key to designing and maintaining an efficient transportation service. Platform managers, either from the public or private sectors, can analyze this demand to optimize their fleet, attract patronage and minimize passenger delays. From the transportation system manager's perspective, knowledge of acceptability and attribute tradeoffs informs this mode's relationship to traditional commute options like personal vehicles and public transit, the outlook of public-private partnerships, and the need for additional infrastructure to support microtransit options (Shaheen et al., 2020).

Calderón and Miller (2020) highlight the range of service types within microtransit. This service model is positioned between current (typically single occupancy) ridehailing, and traditional fixed-route transit, owing to the promotion of pooling rides, walking to the curb to connect with optimal routes, and scheduling rides in advance of boarding time. In practical terms, I can characterize microtransit as a new form of ridehailing with transit-like attributes that aim to optimize trips collectively by minimizing vehicle miles traveled. I refer to **Figure 3** in chapter 2 to compare door-to-door ride-pooling with curb-to-curb microtransit. Fewer vehicles are needed to serve demand by pooling trips, thus reducing VMT (Fu & Chow, 2021). Providing curb-to-curb services where passengers walk to a designated boarding location and alight nearby their final destination reduces the amount of vehicle travel. In **Figure 3**, Party 1 (P1) and Party 2 (P2) can be served directly at their origins and destinations or meet the driver at a designated boarding location and alight nearby their destination. In the latter scheme, the vehicle travels less. Additionally, reserving a seat in a shared vehicle well ahead of boarding allows the operator time to pool trips optimally rather than relying on real-time driver-rider matching.

Research on van-based and other microtransit oriented ridehailing services is still limited. I can gain initial insight into the acceptance and behavior of shared rides by drawing on ridesplitting and related literature. Large fleets of shared-taxis have been shown in simulations to serve existing taxi demand without excessively long delays, not significantly reducing revenue, and importantly, mitigate VMT (Alonso-Mora et al., 2017; Martinez et al., 2015). However, achieving these outcomes requires a high market share of pooled trips, while VMT benefits can only be achieved with sufficiently large shared vehicles fleet sizes and passengers' demand (Rodier et al., 2016; Fagnant and Kockelman, 2018).

In reality, reported rates of ridesplitting are typically low and vary considerably. Empirical estimates range from 6-35% (California Air Resource Board, 2019; X. Chen et al., 2018; Chicago Metropolitan Agency for Planning, 2019b; Li et al., 2019; Lyft, 2018; Soria et al., 2020; Young et al., 2020). Lastly, there is much room to grow wider adoption of pooling as 94% of ridesplitting trips are made by 10% of riders (Brown, 2020).

Few empirical studies are available to evaluate microtransit in practice. The "Breng flex" pilot in the Netherlands stresses the risk of an excess shift of transit users towards microtransit in response to pricing differences (Alonso-González et al., 2018). A study of three U.S microtransit pilots concluded that implementation was fraught, and low ridership was a recurring problem (Westervelt et al., 2018). Additionally, an Uber-based microtransit service case study found that it did not attract single-occupant vehicle users and instead mainly drew users away from public transit (Lewis & MacKenzie, 2017). Similarly, pooling users are found to typically be multimodal already (Kostorz et al., 2021). Lastly, microtransit users may highly enjoy the service but be unwilling to pay higher fees. The Finnish pilot Kutsuplus found that substantial subsidies were needed for the program to be financially viable (Rissanen, 2016). In sum, for shared microtransit services to succeed in mitigating externalities, further research is needed to understand the tradeoffs travelers are willing to make to pool rides and optimal service implementation.

In addition to the still growing body of literature on microtransit, the COVID-19 pandemic and associated restrictive measures have drastically disrupted mobility systems worldwide—an additional layer of uncertainty to mobility demand analysis. Stay-at-home orders, move to telework, and other social distancing measures to prevent the spread of the coronavirus have led to steeply falling demand for mobility, especially public transit and shared vehicle mobility (Duarte, 2020; Higgins & Olson, 2020; Liu et al., 2020). Due to these changes and the lingering safety perceptions, the pandemic has likely heightened travelers' sensitivity to close physical interactions and consequently changed riders' priorities when trading off cost and comfort against health and safety. In 2021, as workers increasingly return to work, immunization rates increase, and people start commuting anew, the need for shared mobility services is growing. Notably, the need to understand the links between pandemic risk perceptions and mode preferences remains an urgent research priority (Hensher, 2020). Yet, I have limited insight into how people navigate the decisions of using different types of shared modes during the evolving pandemic (Shokouhyar et al., 2021).

This chapter aims to analyze commuting travelers' acceptability of novel microtransit commute options in the wake of the COVID-19 pandemic. I address three specific research questions: *First*, I analyze user acceptance of microtransit options, emphasizing several new microtransit-specific attributes. Specifically, I examine the factors that explain the shift from the status quo commute to microtransit travel and analyze attribute sensitivities and elasticities. *Second*, I explore the differences between current transit users and solo drivers. Given that microtransit combines on-demand rides and mass transit services' features, I expect differences based on current commute modes. *Third*, I assess the joint impact of COVID experiences and concerns along with shared mobility and intrinsic motivations for sharing to build a new understanding of how vehicle pooling and other novel attributes are perceived in the COVID-19 context. Thereby, the evolving perception and potential recovery of shared mobility and the trade-offs between traditional and novel mode attributes are further elucidated. Additionally, the examination of pandemic perceptions and sharing experience allows me to disentangle how different commuter groups view these novel services and attributes.

I use data from a Stated Choice (SC) survey conducted in Israel following the first COVID lockdown in May 2020. An efficient choice experiment (CE) pivoted design was administered as a web-based study. The CE scenarios present two microtransit alternatives using the respondents' status quo mode and their stated travel time and cost. The first is ridesplitting in a sedan-sized vehicle with a passenger capacity of 4 (not including the driver) which I will refer to as Microtransit Sedan (MT-S). This service has not been introduced in Israel so far due to regulatory limitations. The second is ridesplitting in a van-sized vehicle with a capacity of 10 passengers, which I will refer to as Microtransit Van (MT-V). This service is operated only on a limited scale—on a pilot basis in the main cities of Tel Aviv, Jerusalem, and Haifa and one rural area. Data about the respondents' sociodemographics, political views, COVID-19 attitudes, and sharing experiences is also collected. I employ an Integrated Choice and Latent Variable (ICLV) framework to examine the acceptance of these new commute options and the impact of user profiles, latent attributes of sharing motivations, and COVID perceptions.

The analysis reveals three key takeaways. (1) New mode attributes significantly affect the utility of the microtransit alternatives, with a notable aversion to walking and waiting among drivers. (2) Car and transit commuters have structural differences in attribute elasticities and the magnitude of latent variable effects. (3) For drivers evaluating microtransit, sharing experience and COVID Comfort play a key role in the decision-making. Overall, these results suggest that car commuters find out-of-vehicle travel and planning ahead highly unattractive. Transit users are much less affected by sharing and COVID constructs. The chapter also discusses the extent to which these results are due to captive transit users and the implications on their willingness to use microtransit modes for their commute.

5.2 Data

The data were collected after designing and distributing a SC survey in Tel Aviv, Israel. The survey was distributed to car and transit commuters throughout the metropolitan region which comprises nearly half of Israel's 9M population and includes the core city of Tel Aviv, the main business, culture, and high-tech hub. Tel Aviv also operates a small-scale microtransit pilot service known as Bubble-Dan, which operated before and during the pandemic (Bubble-Dan, 2021). A screening was applied to include only participants who commute at least three times a week with a commute duration of at least 10 minutes using only a personal vehicle or public transit. Data about current commute attributes, socio-demographics, past and expected future life events, latent attitudes, and choice experiments with microtransit alternatives were collected. Using the respondents' current commute attributes, I determine their commute mode, cost, and travel time for the reference alternative in the CE—referred to as the "Status Quo" (SQ).

Latent attitudes were measured using items based on respondent's sharing experience, schedule-keeping, environmental stances, and comfort with situations related to risks of COVID transmission. Sharing attitudes and COVID Comfort questions used in modeling are summarized in **Table 12**. The sharing-related items are drawn from previous research and modified to orient them around the sharing economy. The COVID-19 related items were created specifically for this survey. Each item uses a 5-point Likert scale that ranges from "Strongly Disagree" to "Strongly Agree" (Lehmann & Hulbert, 1972). In addition, I asked respondents to report the degree to which the COVID-19 pandemic had affected their lives. Respondents were asked to respond to this question by indicating "No Change, Little Change, Not Sure, "Big Change," or "Very Big Change." These questions were then used to identify latent variable effects on microtransit decision-making.

The experiment design and implementation was developed in sequential steps (**Figure 14**) following best practice guidance (Johnson et al., 2013; Kløjgaard et al., 2012). Step 1 covered attribute development, focusing on identification, selection, and presentation. Attribute selection was decided by identifying the attributes already studied in the research literature.

Table 13 summarizes relevant studies involving ridehailing and the attributes used in their choice scenarios. Important to note, studies emphasizing automated vehicles (where the ride may be driverless) are not included in this analysis as the perceptions of sharing attributes can be highly affected by the automation feature (Etzioni et al., 2021; Krueger et al., 2016). Additionally, I exclude portfolio-based Mobility as a Service studies where ridehailing (and related attributes) is a minor focus, for example Caiati et al. (2020).

Table 13 shows that each study covers different attributes and information provided to customers: Yan et al. (2018) provide survey-takers information about additional pickups; Frei et al. (2017) include headway for their flexible route, demand-responsive transit; Chavis and Gayah (2017) feature the availability of GPS tracking of vehicle for more traveler information; Al-

Ayyash et al. (2016) consider in-vehicle WiFi capabilities. In Alonso-González, van Oort, et al. (2020), the choice experiment included uncertainty for the waiting and in-vehicle times to determine Values of Time for individual and shared rides. Alonso-González, Cats, et al. (2020) then considered mode choice of flexible transit alternatives specifically. While Yan et al. (2019) and Al-Ayyash et al. (2016) focus on commuting as the trip purpose, Kang et al. (2021) consider multiple trip purposes including commuting, shopping, and leisure. On the whole, the most common attributes included in choice experiments other cost and in-vehicle travel time are the out-of-vehicle travel time and additional passengers sharing the ride. Following literature and industry report analysis, seven attributes were selected, representing two microtransit vehicle sizes. Further informal testing in step 2 led to a fractional factorial experiment with six scenarios (see more details in Soria et al. (2019)). Given Israel's limited familiarity with microtransit services, several auxiliary questions were designed to measure attribute acceptance cutoffs, importance, and choice certainty. In step 3, a full survey implemented in Qualtrics was administered to 301 pilot respondents.

Table 12 Sharing and COVID-19 comfort items with coding

Item	**Coding**	**Source**
I enjoy using sharing economy services	SI1_enjoy	Van der Heijden (2004)
I can see myself increasing my use of shared mobility in the future	SI2_increase	Bhattacherjee (2001)
I have never had a bad experience using sharing economy services	SI3_exp	Current study
Inclusion of Other in Self (IOS)	IOS	Adapted from Aron et al., (1992)
Given the current situation caused by the COVID-19 outbreak, I would feel comfortable engaging in the following activities:	-	Current study
Ridesharing with strangers	CC1_ride	
Eating out at a restaurant.	CC2_rest	
Going to the grocery store	CC3_grocery	

Table 13 Microtransit stated choice experiments in the research literature and their alternative attributes

Study	Travel time	Travel Cost	Waiting Time	Walking Time	Travel Time Uncertainty	GPS Tracking/Internet Services	Transfers	Headway	Additional Pickups	Time to find Parking	Level of Multitasking	Availability of Driver
Chavis and Gayah (2017)	x	x	x	x		x						
Frei et al. (2017)	x	x	x	x			x	x				
Yan et al. (2019)	x		x	x			x		x	x		
Al-Ayyash et al. (2016)	x	x	x									
Tarabay and Abou-Zeid (2019)	x	x				x						
Asgari and Jin (2020)	x	x									x	x
Alonso-González, Cats, et al. (2020)	x	x							x			
Alonso-González, van Oort, et al. (2020)	x	x	x	x	x		x					
Kang et al. (2021)	x	x							x			

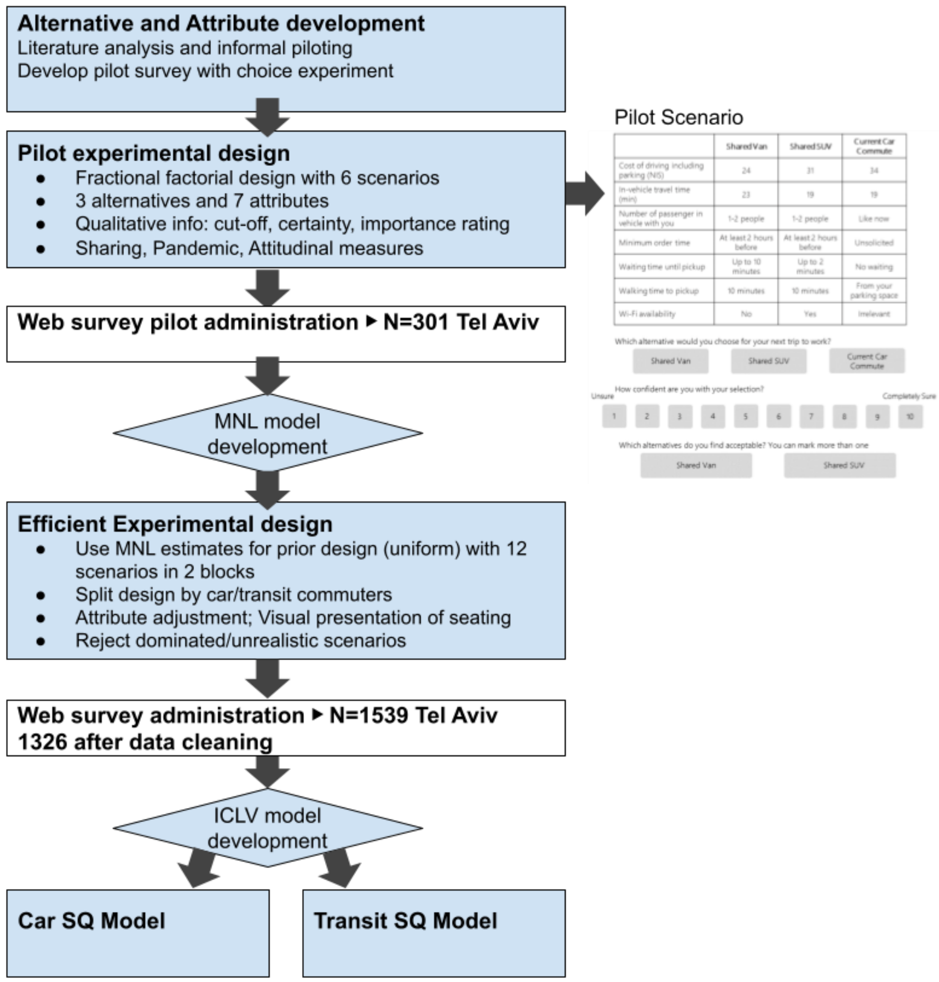

Figure 14 Steps in development of a microtransit discrete choice experiment

Results were analyzed in step 4 using discrete choice modeling, leading to the development of priors for an efficient experimental design in step 5 using Ngene (ChoiceMetrics, 2012). The resulting design included three alternatives: Status Quo (SQ, either car or public transit), Microtransit Sedan (MT-S), and Microtransit Van (MT-V). The pilot analysis led to broadening attribute ranges and providing a visual presentation for the seating variable. The travel time and travel cost attributes for current travel alternatives were pivoted off the reported (RP) levels to improve the realism of the experiment (Etzioni et al., 2020; Hensher & Rose, 2007; Train & Wilson, 2008). **Table 14** lists the mode attributes included in the final experiment along with the attribute levels. Graphics were presented in the choice experiment to reflect the number of additional passengers and which seats are available (**Figure 15**). The seating designation and vehicle seating configuration may also play a role in mode-sharing decisions (Etzioni et al., 2021). The respondents' current travel cost and time were defined using the following logic. If the typical commute mode is driving, the respondent provides further information about parking such as search time, if there is a reserved parking area, and if they pay for that parking. The travel costs are approximated for drivers by summing the daily parking fee and their travel distance in kilometers multiplied by two, using this information. In Israel, the value of 2 ILS per km is a gross estimate used by the public sector for reimbursing direct car use expenditures and is also

Table 14 Microtransit choice experiment alternative attribute levels

	Status Quo (fixed)	**Microtransit Sedan**	**Microtransit Van**
Cost (per day)	Current Cost	-10%/-20%/-30% (CAR)	-15%/-30%/-45% (CAR)
		+75%/+125%/+175% (PT)	+50%/+100%/+150% (PT)
Travel time	Current Door-to-door Time	-30%/ 0 / +30% (CAR)	0/+15%/+30% (CAR)
		-30%/ 0 / +30% (PT)	0/-15%/-30% (PT)
Number of occupants in a vehicle		1 person (driver)/ 2 people/ 4 people	1 person (driver)/ 5 people/ 8 people
Minimum Reservation Time Before Boarding		2hr/10 min/5 min before	2hr/10 min/5 min before
Waiting Time		2 min/up to 5 min/up to 10 min	2 min/up to 5 min/up to 10 min
Walking Time		No walking/Up to 5 min walk/Up to 10 min walk	No walking/Up to 5 min walk/Up to 10 min walk
Station amenity		Designated-shelter (yes/no)	Designated-shelter (yes/no)

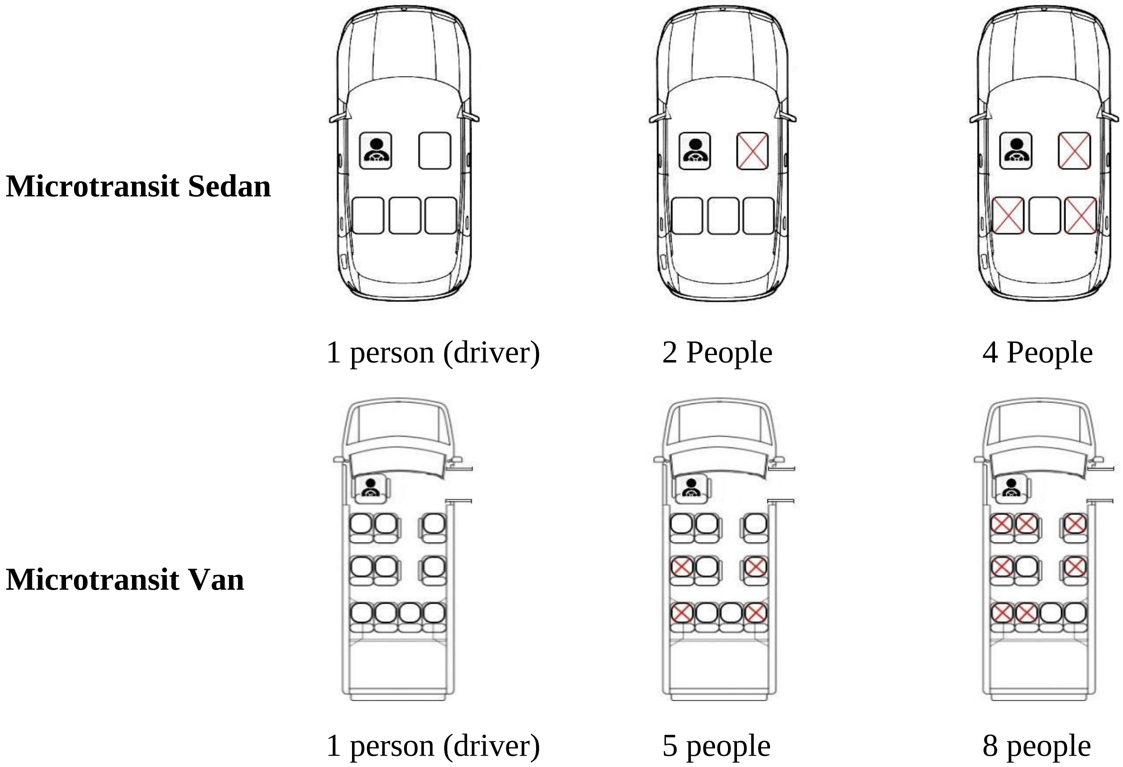

Figure 15 Depiction of additional passengers in microtransit choice experiment

the maximal value allowed by the Ministry of Transport regulations for determining direct cost-sharing in voluntary carpooling arrangements between driver and passengers. Travel time for car commuters is the sum of their stated commute time and parking search time. Travel cost corresponds to the single trip fare for transit commuters, and travel time is their current stated commute time. Because both car and transit commuters responded to this survey, the design was optimized for each commuter group separately.

The experiment is based on a D-efficient Bayesian design created using Ngene (ChoiceMetrics, 2012; Yu et al., 2011). The a priori coefficient values (Rose et al., 2008) were obtained using uniform distributions from the pilot survey (Soria et al., 2019). However, this pilot survey considered only car commuters; hence I assumed that the coefficient values for all attributes were equal across groups. Dominated and unrealistic alternatives were excluded using the Federov algorithm (ChoiceMetrics, 2012). These actions are put in place to ensure designs are plausible and realistic. For example, the transit fare was relatively low, so the fare for the microtransit alternatives was always greater than the transit one for transit commuters. In contrast, with car commuters, costs for MT-S and MT-V were always lower than the car cost. The design extracted 12 choice scenarios for each SQ mode; however, the scenarios were randomly assigned to two fixed sets of 6 scenarios to prevent respondent fatigue (Caussade et al., 2005). These sets are equally represented in the data of each respective commuter group.

In step 6, a web-based respondent panel was used to collect 1539 survey responses in May 2020. The data were cleaned by first removing responses that did not complete the choice experiment portion. To preserve data quality, responses that took less than 5 minutes or showed patterns of inattentiveness were removed. Because the average time it took to complete the survey was approximately 30 minutes, I treated 5 minutes as insufficient time to complete it earnestly. I considered inattentiveness when there was a pattern of always choosing the first option in a string of questions, selecting responses to attitudinal items inconsistently, or when indicating adversarial attitudes in the items. For the current analysis, current commute times greater than 90 minutes were removed to decrease heterogeneity and maintain a reasonable commuter service area for microtransit. After cleaning and subsetting the database, 1326 responses (86%) were retained, resulting in 7956 choice experiment observations. Of these 1326 responses, there were 879 (66%) car and 447 (34%) transit commuters.

Table 15 contains the descriptive statistics for the observed variables, COVID-19 impacts, and attitudes. For the respondents' current commutes, the largest difference between groups is the travel cost. Car commuters are also more likely to be married and male. The voter variable is a dummy variable denoting if the respondent voted in the 2020 legislative elections in

Israel, for which there is little difference between groups. On average, car commuters are likely to have more children. The Inclusion of Other in the Self (IOS) scale measures how close the respondent feels with strangers (Aron et al., 1992). In this study, I specifically asked respondents how close they feel to a stranger sharing a pooled vehicle. Overlapping circles are used to depict IOS, where the closer the respondent feels with the stranger in the vehicle, the more overlapped circles are seen in **Figure 16**. The pandemic has similarly impacted both groups. Lastly, they share nearly the same attitudes towards the sharing economy and COVID Comfort, with the most significant difference being the CC1_ride. Transit commuters are more comfortable sharing a ride with a stranger during the pandemic.

Table 15 Descriptive statistics of Integrated Choice and Latent Variable modeling variables

Variable	**All Commuters (std. deviation)**	**Car Commuters (std. deviation)**	**Transit Commuters (std. deviation)**
Current Commute			
Travel Cost (ILS)	35.31 (38.98)	50.34 (40.23)	5.78 (2.94)
Travel Time (minutes)	33.20 (15.75)	31.59 (14.71)	36.37 (17.18)
Individual Descriptors			
Married	55.81%	61.43%	44.74%
Gender is Male	50.45%	53.12%	45.19%
Voter	89.97%	89.30%	91.28%
Number of Children	1.27 (1.63)	1.45 (1.60)	0.90 (1.64)
COVID Impact			
No Impact	1.96%	1.37%	3.14%
Little Impact	32.81%	31.63%	35.12%
Big Impact	41.86%	42.54%	40.49%
Very Big Impact	12.67%	12.97%	12.08%
Not Sure	10.70%	11.49%	9.17%
Attitudes			
IOS (min = 1, max = 7)	2.75 (1.60)	2.80 (1.64)	2.67 (1.52)
SI1_enjoy	3.05 (1.08)	2.97 (1.08)	3.20 (1.06)
SI2_increase	3.17 (1.04)	3.12 (1.06)	3.27 (1.01)
SI3_exp	3.25 (1.04)	3.25 (1.04)	3.26 (1.05)
CC1_ride	2.27 (1.11)	2.10 (1.04)	2.59 (1.16)
CC2_rest	2.46 (0.83)	2.45 (0.81)	2.49 (0.85)
CC3_grocery	3.66 (0.96)	3.63 (0.96)	3.75 (0.95)
N	1326	879	447

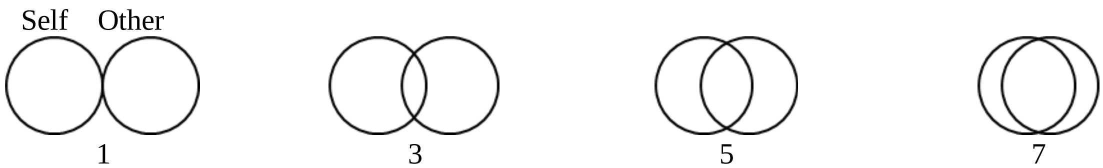

Figure 16 Inclusion of Other in the Self scale

5.3 Methodology

The purpose of this research was to identify the acceptability and tradeoffs among novel microtransit attributes and quantify the effect of latent variables on the decision-making process. Separate models were estimated using an Integrated Choice and Latent Variable (ICLV) model for the two commuter groups. The ICLV framework allows the choice and latent variable models to be estimated simultaneously (Abou-Zeid & Ben-Akiva, 2014; Bolduc & Alvarez-Daziano, 2010; Temme et al., 2008). **Figure 17** depicts the theorized relationship between the latent variables, mode attributes, utility of each mode, and, finally, mode choice. To estimate the ICLVs, I follow the guidelines from Walker (2001). From the guidelines, the first steps are to identify the choice model and structural equation model separately. Once this is completed, the models are jointly estimated.

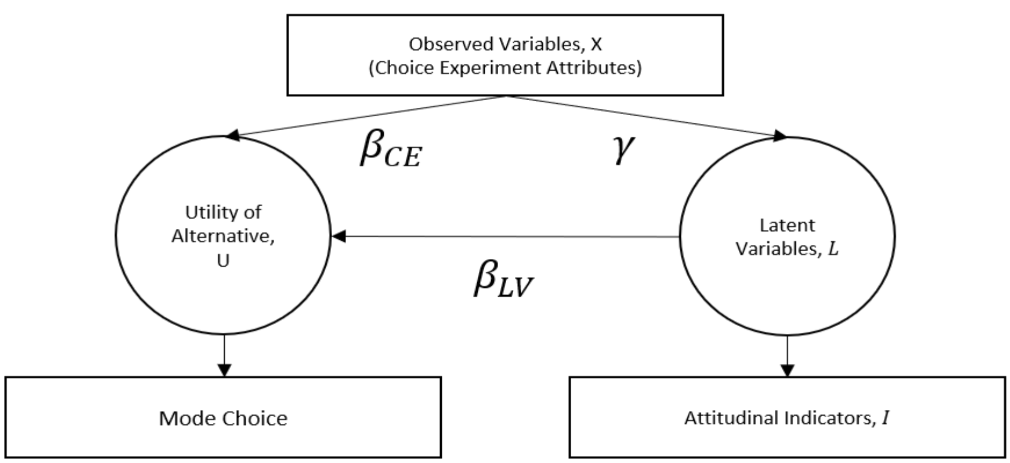

Figure 17 Integrated Choice and Latent Variable Framework

5.3.1 Discrete choice model

The first step of the guideline is to identify the utility specification of the choice model correctly. I completed this step by estimating a Multinomial Logistic Regression (MNL) for each commuter group with PandasBiogeme (Bierlaire, 2018). **Equation 10** and **Equation 11** describe the general utility specification. U_{in} is the latent utility of alternative I of observation n, X_{CE} is the matrix of explanatory variables from the choice experiment, L are the latent variables, β_{CE} and β_{LV} are the corresponding coefficients, and ϵ is the independently and identically distributed (IID) error term.

$$U_{in} = V_{in}(X, L; \beta) + \epsilon_{in} \qquad \textbf{Equation 10}$$

$$U_{in} = \beta_{CE}X_{CE} + \beta_{LV}L + \epsilon_{in} \qquad \textbf{Equation 11}$$

5.3.2 Structural equational model for attitudinal indicators

After identifying the mode choice model, the second step is to identify the latent variables. I estimated a Structural Equation Model (SEM) using the attitudinal items in the measurement component and explanatory variables including, socio-demographics, experience with sharing economy services, and the structural component's life impact and comfort related to COVID-19. **Equation 12** and **Equation 13** describe the measurement and structural components, respectively. The SEM's were first estimated using the R package psych, then confirmed again using PandasBiogeme (Bierlaire, 2018; Revelle, 2018). With both choice and latent variable models identified, the last step is to estimate the integrated models simultaneously.

Equation 12 (structural) and **Equation 13** (measurement) below describe the SEM. L is the latent variable, the intercept θ, observed variables X_{LV}, the corresponding estimated coefficients γ, and the error term, η, which is IID multivariate normally distributed. I is the response for the attitudinal items listed in **Table 12**. It is a function of α an intercept, λ the estimated coefficients, L a matrix of latent variables estimated from **Equation 13**, and ζ the IID multivariate normal error term. σ is a random variable to capture the random taste heterogeneity of the sample and is added to estimate numerically the likelihood described in the following subsection.

Several latent variables were estimated representing the respondents' attitudes towards Environmental Sustainability, Schedule Making, Pro-Sharing Economy, and COVID Comfort. Only the last two were consistently significant in at least one commute group, with a hierarchical relationship shown in **Table 12**. The latent variables were validated with the following metrics and threshold values: Comparative Fit Index (CFI) > 0.90, Root Mean Square Error of Approximation (RMSEA) < 0.06 and Standardized Root Mean Square Residual (SRMR) < 0.08 following recommendation in literature (Hooper et al., 2007; Hu & Bentler, 1999).

$$L = \theta + X_{LV}\gamma + \eta \qquad \textbf{Equation 12}$$

$$I = \alpha + \lambda L + \sigma + \zeta \qquad \textbf{Equation 13}$$

5.3.3 Integrated Choice and Latent Variable model

The models are estimated simultaneously by maximizing the joint log-likelihood of each component. **Equation 14** shows the joint likelihood. This integrand cannot be solved analytically, so it was estimated numerically with random variables, ϕ, in the latent variable model. $p(X, L; \beta)$ is the likelihood from the standard MNL. $f(L, X_{LV}; \gamma)$ is the likelihood from the structural component of the SEM and $g(I, L, \sigma; \lambda)$ is the likelihood of the measurement component.

$$Likelihood = \prod_{n=1}^{N} \int_{L} p(X, L; \beta) f(L, X_{LV}; \gamma) g(I, L, \phi; \lambda) dL$$ **Equation 14**

5.4 Results

Two ICLV models were estimated, one for car commuters and one for transit commuters, and the results are shown in **Table 16** and **Table 17**. The structure of the latent variables in the ICLVs is shown in **Figure 18**. Following extensive specification testing done individually, the models were similarly specified so that the results were as directly comparable as possible. Mode attributes were limited to the discrete choice portion of the ICLVs while attitudinal items and sociodemographic variables were limited to the latent variable models. Additionally, the latent variables were hypothesized to exist for both commuter groups and, subsequently, share the same scales. The final utility specifications are described in **Equation 15**, **Equation 16**, **Equation 17**, and **Equation 18**. **Equation 15** shows COVID Comfort in the utility specification for the car alternative. Two latent variables were identified and included in the final model because Pro-Sharing Economy was found to indirectly affect the utility of car through a structural relationship with COVID Comfort as shown in **Figure 18**.

$$\begin{aligned} V_{car} = \ & \beta_{Car} + \beta_{Car,Cost} CarCost + \beta_{Car,Time} CarTime \\ & + \beta_{CovidComfort} CovidComfort \end{aligned}$$ **Equation 15**

$$V_{PT} = \ \beta_{PT} + \beta_{PT,Cost} PTCost + \beta_{PT,Time} PTTime + \beta_{CovidComfort} CovidComfort$$ **Equation 16**

$$\begin{aligned} V_{MTS} = \ & \beta_{MTS} + \beta_{MTS,Cost} MTSCost + \beta_{MTS,Time} MTSTime \\ & + \beta_{MTS,Walk} MTSWalkTime + \beta_{MTS,Wait} MTSWaitTime \\ & + \beta_{MTS,MinRes} MTSMinResTime + \beta_{MTS,Passengers} MTSPassengers \\ & + \beta_{MTS,Shelter} MTSShelter \end{aligned}$$ **Equation 17**

$$\begin{aligned} V_{MTV} = \ & \beta_{MTV} + \beta_{MTV,Cost} MTVCost + \beta_{TV,Time} MTVTime \\ & + \beta_{MTV,Walk} MTVWalkTime + \beta_{MTV,Wait} MTVWaitTime \\ & + \beta_{TV,MinRes} MTVMinResTime + \beta_{MTV,Passengers} MTVPassengers \\ & + \beta_{MTV,Shelter} MTVShelter \end{aligned}$$ **Equation 18**

Table 16 Microtransit choice models results

	Car			Public Transit		
Coefficient	**Car (Std. Error)**	**MT-S (Std. Error)**	**MT-V (Std. Error)**	**Transit (Std. Error)**	**MT-S (Std. Error)**	**MT-V (Std. Error)**
Constant	0 - fixed	-4.31** (0.255)	-3.58** (0.272)	0 - fixed	-1.56** (0.263)	-1.67** (0.267)
Travel cost (ILS)	-0.00319** (0.000954)	[1]-0.0068** (0.00207)	[1]-0.00546* (0.00277)	-0.116** (-0.0341)	-0.0423** (0.0157)	-0.0683** (0.0174)
In-vehicle travel time (minutes)	-0.0494** (0.00509)	-0.0312** (0.00455)	-0.0364** (0.00444)	-0.0386** (0.00592)	-0.029** (0.00614)	-0.0248** (0.00675)
Walk time (minutes)	-	-0.0450** (0.0111)	-0.110** (0.0143)	-	NS	NS
Wait time (minutes)	-	-0.0306* (0.0143)	-0.0691** (0.0176)	-	NS	NS
Minimum reservation time before boarding (minutes)	-	-0.00140* (0.000680)	-0.00363** (0.00105)	-	-0.00348** (0.00131)	-0.0064** (0.00116)
Number of people in vehicle	-	NS	-0.0872** (0.0276)	-	-0.0978** (0.0381)	-0.0915** (0.0315)
Sheltered Boarding Location	-	NS	NS	-	NS	0.378** (0.104)
COVID Comfort	-1.34** (0.0969)	-	-	-0.14^ (0.0828)	-	-
n observations	5274			2682		
ρ^2	0.164			0.296		
Final Loglikelihood	-47665.05			-13590.62		

(NS) Not statistically significant at α = 0.1, not estimated in final model

(^) significant at α = 0.1

(*) significant at α = 0.05

(**) significant at α = 0.01

[1] Interacted with dummy variable for having commute time greater than 65 minutes, otherwise statistically insignificant

Table 17 Microtransit latent variable models results

Coefficient	Model	
	Car (Std. Error)	Transit (Std. Error)
COVID Comfort	-	-
CC1_ride	1 – fixed	1 – fixed
α_{CC1}	-	-
CC2_rest	0.496** (0.0323)	0.626** (0.0401)
α_{CC2}	1.41** (0.0696)	0.865** (0.106)
CC3_grocery	0.643** (0.0355)	0.649** (0.0425)
α_{CC3}	2.27** (0.0763)	2.07** (0.112)
θ_{CC}	1.02** (0.122)	2.46** (0.111)
Impact - Unsure	-0.572** (0.0976)	0.0887 (0.123)
Impact - No Change	0 – fixed	0 – fixed
Impact - Little Change	-0.539** (0.0939)	0.333** (0.111)
Impact - Big Change	-0.916** (0.0957)	0.0223 (0.112)
Impact - Very Big Change	-1.32** (0.102)	-0.383** (0.122)
Married	-0.138** (0.0220)	-
Male	-	0.186** (0.0389)
Number of Children	-	-0.0472** (0.0116)
σ_{CC}	0.113^ (0.0641)	0.628** (0.0259)
Pro-Sharing Economy	0.661** (0.0302)	-
SI1_enjoy	1 – fixed	-
α_{SI1}	-	-
SI2_increase	0.932** (0.0310)	-
α_{SI2}	-0.355** (0.0939)	-
SI3_exp	0.592** (0.0283)	-
α_{SI3}	1.49** (0.0856)	-
θ_{SI}	2.21** (0.0469)	-
Ridehailing App Experience	0.312** (0.0252)	-
Carpooling App Experience	0.292** (0.0249)	-
Carsharing App Experience	0.0301** (0.00621)	-
IOS	0.110** (0.00731)	-
Voter	0.201** (0.0371)	-
Male	0.112** (0.0230)	-
σ_{SI}	0.609** (0.0159)	-
$\chi^2/\,df$	2.67	2.47
CFI	0.923	0.939
RMSEA	0.044	0.055
SRMR	0.032	0.028

(-) Not applicable
(^) significant at α = 0.1
(*) significant at α = 0.05
(**) significant at α = 0.01

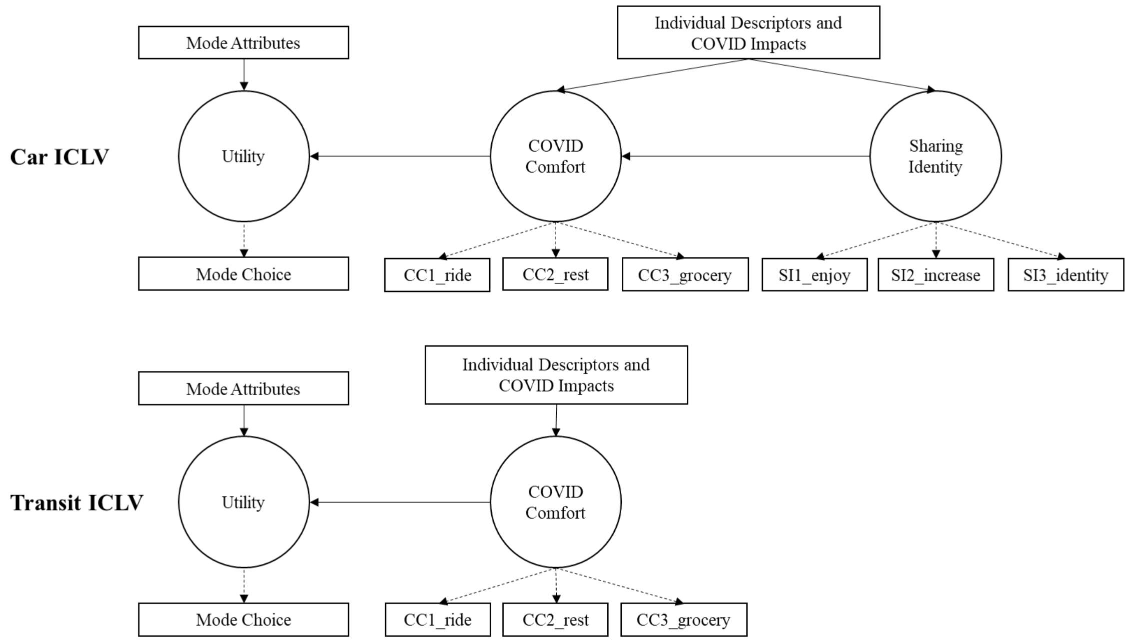

Figure 18 Structure of ICLV models for each commuter group

5.4.1 Microtransit Acceptance and Mode Attributes

All mode attributes for all alternatives were included in the discrete choice portion of the ICLV during model development. In the final estimations, statistically insignificant variables were not included. **Table 16** intercepts show an inherent attraction to the status quo modes. It was expected that transit commuters would find the on-demand sharing alternatives inherently more attractive than the status quo; however, the results show the opposite. When examining the attribute effects, all features have the expected sign, while I note several differences between the two commuter groups. The more traditional travel cost and travel time attributes are statistically significant for all alternatives in either commute group. Yet, I note that transit commuters have a higher sensitivity to cost and lower sensitivity to time than solo drivers, which is true also for microtransit options, suggesting that transit commuters transfer their preferences onto new options. Generic travel cost sensitivities for drivers were not significant, prompting us to interact with other variables to examine segmentation. Unlike other work suggesting marginally decreasing sensitivities (Daly, 2010), I find that only drivers with long commutes (greater than

65 minutes) are consistently sensitive to the cost attribute, with a higher sensitivity for the MT-S and MT-V. I speculate that the limited cost sensitivity is due to drivers' difficulty to perceive the largely hidden cost of driving and parking, coupled with an experimental design effect where prices for the microtransit alternatives were set to be lower than solo driving (Andor et al., 2020; Shoup, 2021).

The novel attributes were only included for the microtransit alternatives, and on the whole, I note that car commuters are sensitive to a more extensive range of microtransit attributes than transit commuters. This likely reflects the fundamental dissimilarity between driving and microtransit, which comports several unfamiliar attributes (Alemi, Circella, Mokhtarian, et al., 2018). Specifically, I note a major difference for time-related attributes of walk time to the curbside pickup location, and waiting time. Car commuters appear to have a strong aversion to walking and waiting, with a strong penalty for the van option. Instead, transit users are only sensitive to the in-vehicle travel time, with insignificant walking and waiting parameters, similar to the results from Frei et al. (2017). The last time-related attribute, minimum reservation time, is statistically significant for both alternatives, albeit with a lower magnitude than other time measures. Instead, a few features come into play only for the transit commuters. The number of additional passengers matters for both vehicle sizes in the transit model while only impacting the larger MT-V among drivers. Finally, the 'sheltered boarding' attribute is only significant for MT-V in the transit model. Additionally, car commuters are not sensitive to the number of additional passengers for MT-S, possibly stemming from this mode being a familiarly sized vehicle with relatively low capacity. Alonso-González, Cats, et al. (2020) also posit that perceptions of sharing reach a tipping point at four additional passengers since a vehicle larger than a regular car is needed. Finally, the presence of a sheltered boarding location is only statistically significant for MT-V.

In summary, transit users have likely interiorized the transit-like attributes of walking and waiting that are intrinsic to scheduled services. I note that transit users appear more sensitive than drivers to reservation time, shelter, and the number of other passengers, attributes that are more affected by the ICT-supported mobility platform and smaller vehicle sizes than experienced in current transit systems.

5.4.2 Latent Variable Effect

Overall, model fit for both latent variable models indicates good fit with CFI > 0.90, RMSEA < 0.06 and SRMR < 0.08 in both models (Hooper et al., 2007; Hu & Bentler, 1999). The most evident difference between car and transit commuters is in the latent variable portion of the ICLVs. The structure of the latent variables in the ICLV models is illustrated in **Figure 18**. As shown by estimates in **Table 16**, decision-making by car commuters was affected by both latent variables, namely: Pro-Sharing Economy and COVID Comfort, while transit users, surprisingly, were not motivated by these factors. COVID Comfort is designed to represent a respondent's comfort with different COVID-19 risk situations. As such, respondents' comfort in grocery stores, eating in restaurants, and sharing a vehicle with a stranger are used to identify this latent variable. The COVID Comfort parameter in **Table 16** shows a negative effect. That is, the more at ease respondents are with these situations, the more likely they are to accept trying the microtransit services. The structural component of this latent variable consists mostly of variables indicating the impact the pandemic has had on respondents' lives, measured by the Impact variable. The impacts are ordinal in nature; however, here, I chose to model the impact as a discrete categorical variable to facilitate separate modeling of the opt-out where respondents indicate their uncertainty. This decision proved to be useful as those who were uncertain of COVID impacts were found to be less comfortable with COVID than those who experienced "Little Change." Additionally, it was advantageous because the jump in effect from "No Change" to "Little Change" in the car commuter group resulted in a larger impact than the jump from other levels. I also considered the risk of transmission to significant others related to a respondent and found that married people are less comfortable with risky COVID situations. Transit commuters who had "Little Change" in their lives from COVID were more comfortable with it than those who had had impacts at other levels or were unsure about its impact. I also considered the risk of COVID transmission to loved ones and found that families with more children were less likely to be comfortable with COVID. Lastly, I found that men tended to be more comfortable with COVID-19 risk situations, which resonates with observations that men are less concerned about virus contraction and less likely to get vaccinated (Galasso et al., 2020; Lazarus et al., 2021)

Modeling also reveals that COVID Comfort is directly affected by the Pro-Sharing Economy construct (albeit only for drivers, as depicted in **Figure 18**). Because sharing in this context is of physical assets (including public areas), I hypothesized a structural relationship between these two latent variables. The positive sign implies that experience with sharing economy services — used to measure higher Pro-Sharing Economy — is underpinning higher comfort with sharing resources during COVID-19. There are two issues to note here. First, the hypothesized hierarchical causation suggests that sharing is an established trait that affects how respondents behave in the novel and temporary context of pandemic social distancing. In practice, it is likely that the evolving objective and subjective risks, as well as experience and fatigue from social distancing, will continue to shape willingness to ridesplit. Second, I expected

Pro-Sharing Economy to be a driving factor for transit users. Instead, I could find no evidence of this, affecting neither COVID Comfort nor likelihood to use microtransit directly. I speculate that the transit users I observe, especially during COVID-19, are not choice riders driven by shared ideals but rather by necessity. Like above, there are likely to be dynamic effects at play, connecting ridership to changing employment circumstances and COVID-19 risk levels. These issues warrant further research.

In addition to the sharing economy constructs, the IOS scale is used to measure sharing propensity. My study finds that the more closely a respondent identifies with other riders, the higher they score on Pro-Sharing Economy. Several personal characteristics are found to be related to sharing ideals. Being a voter in the latest election is positively correlated with sharing. I speculate that voters may have higher civic duty orientation related to higher sharing identities (Bolsen et al., 2014; Fowler, 2006). Lastly, men tend to have higher sharing identities, and I attribute this to women's perceptions of (lack of) safety, especially in situations where personal space cannot be guaranteed (Morales Sarriera et al., 2017; Polydoropoulou et al., 2021).

Finally, considering the limited specification for the transit sample, initial transit ICLV specifications included the Pro-Sharing Economy latent variable; however, it was not identified when the Structural Equation Model was estimated independently of the discrete choice model. Consequently, the only latent variable identified for transit commuters is COVID Comfort.

5.5 Discussion

5.5.1 Microtransit demand and curb-to-curb attribute elasticities

The curb-to-curb attributes involving out-of-vehicle travel time were only statistically significant in the car commuter ICLV. In contrast, transit commuters were unaffected by the walking and waiting time. I hypothesize that this may be since transit commuters already experience these attributes for their current commutes. Therefore, when trying to attract car commuters to microtransit to promote sustainability, attention must be paid to the effort needed to access the service in terms of expected walking and waiting time.

One strategy is to decrease waiting and walking times and to increase the minimum reservation time to facilitate better routing. To better explore such scenarios and the relative importance of microtransit attributes, I derive attribute elasticities. **Table 18** shows the elasticities at the mean of variables, which were calculated using **Equation 19** (Train, 2009). P_i is the probability of alternative i, $\beta_{x,i}$ is the coefficient of attribute x and alternative i, and x_i is the average of the explanatory variable. These elasticities reflect the percent change in demand for the alternative as a function of a unit percent change in the attribute. I note that most elasticities are inelastic, in the range of 4-76% change in demand for the Microtransit options. As expected from the model analysis, reservation time has a lower elasticity than in-vehicle, waiting, and walking time. In comparing the commuter groups, elasticities are in a comparable range for the sedan option, with a greater gap for the van microtransit option. Clearly, drivers are sensitive to more attributes and display significant aversion to access/walking time, while in-vehicle travel duration elasticity even exceeds unity for the van option.

Table 18 Elasticities and differences between commuter groups

Alternative	Variable	Elasticities: Car Commuters	Elasticities: Transit Commuters	Difference (Car-Transit)
Status Quo	Cost	-0.04	-0.30	0.26
Status Quo	TT	-0.41	-0.62	0.21
Status Quo	COVID	-0.94	-0.20	-0.74
Status Quo	Sharing (Indirect effect)	-0.83	NA	
MT-S	Cost	-0.59*	-0.39	-0.2
MT-S	TT	-0.77	-0.71	-0.06
MT-S	Reservation Time	-0.04	-0.07	0.03
MT-S	Wait	-0.13	NS	
MT-S	Walk	-0.13	NS	
MT-V	Cost	-0.49*	-0.62	0.13
MT-V	TT	-1.26	-0.64	-0.62
MT-V	Reservation Time	-0.12	-0.19	0.07
MT-V	Wait	-0.31	NS	
MT-V	Walk	-0.39	NS	

(*) Cost parameters are for car commuters with commutes > 65 minutes

$$E = (1 - P_i)\beta_{x,i}X_i \quad \textbf{Equation 19}$$

Operators can use these insights in several ways. Microtransit operators may unlock efficiency gains and reductions of passenger wait times by knowing the demand for rides well in advance. Indeed, the smaller elasticity suggests that increasing minimum reservation time would not be as consequential for the likelihood to opt for the microtransit alternatives as increasing walk and wait times. Thereby, the elasticity findings suggest an opportunity to extend reservation times to obtain more favorable walking and waiting performance as a means to attract drivers to the curb-to-curb mobility options. Similar to Alonso-González, Cats, et al. (2020), this reduction in travel time plays a prominent role in determining the likelihood of choosing microtransit. To further contextualize, Alonso-Mora et al. (2017) simulate scenarios with maximum waiting times of less than 7 minutes; however, this was in the highly-dense area of Manhattan, New York where high levels of demand and the road network topology allow this. Therefore, for success in less dense areas, a large vehicle fleet size is another strategy to reduce wait and walking times.

For transit commuters, much of the focus for microtransit operators will be on cost and travel time as these commuters did not exhibit significant sensitivity to waiting and walking times. One attribute that was only significant in a single instance was the sheltered boarding location. While this may be a prominent feature for public transit, it may not be a worthwhile investment in this context, where other curb-to-curb attributes play a greater role in shaping initial demand for microtransit.

5.5.2 Different perceptions for drivers and transit commuters: status quo effects

When considering the latent variables identified in the ICLVs, the lack of Pro-Sharing Economy in the transit commuter group is intriguing. It was expected that Pro-Sharing Economy would be identified in the transit group since this embodies shared mobility, yet my modeling did not support this. Additionally, COVID Comfort is only weakly significant ($0.10 < \text{p-value} < 0.05$). Taken together, the latent variable results suggest that the transit users in this sample are likely captive users (Etzioni et al., 2020). Indeed, the analysis of smartcard usage conducted before the pandemic shows that heavy users of transit in Israel are more likely to be regarded as captive with fewer mobility options—pupils, students, seniors, low income—while the modal split for the Tel Aviv metropolitan region is around 80/20 for car and transit respectively (Benenson et al., 2019; Etzioni et al., 2021).

Instead, both latent variables are strongly significant in the car ICLV. Because Pro-Sharing Economy is mainly determined by experience with sharing economy services like Uber and Airbnb, I hypothesized that knowledge and familiarity with these types of services would lower the risk perceptions related to COVID-19. What is more, operators have taken significant and public measures to increase patrons' safety, which may have contributed to indirectly shaping virus exposure concerns in the context of hypothetical microtransit alternatives. Therefore, unlike transit commuters, I do not conclude that car commuters are captive to their status quo. The elasticity of the COVID-19 comfort variable is much larger among car commuters. I interpret this strong effect to reflect greater adaptiveness of drivers in response to COVID-19. In contrast, those that rely on private vehicles have greater ease in adjusting ridership to reduce the risk of viral exposure.

5.6 Conclusion

Microtransit with rider pooling may generate mobility system benefits, with the most aspired being the VMT reductions provided enough trips are pooled. The demand for microtransit, especially with a curb-to-curb service offering, is not fully understood. It is challenging to promote the adoption of microtransit given that the service attributes lie at the halfway point between door-to-door on-demand mobility and scheduled transit. That means that current mode experiences are likely to shape the perception of attributes that constitute a departure from the status quo which is especially critical given the need for microtransit to attract not only transit users to ensure VMT and congestion reduction. In this study I developed a SC survey to identify how commuters perceive microtransit with its curb-to-curb attributes.

The survey included a choice experiment with two different designs for car and transit commuters. Utilizing a pivoted design with the status quo alternative, I identify how sensitive commuters are to a sedan (MT-S) and a van option (MT-V) and their curb-to-curb attributes such as walking and waiting times at a designated boarding location. Additionally, I included attributes that better represent scheduled transit services where advanced planning and amenities are key attributes. Specifically, I included novel attributes for minimum reservation time before boarding and a sheltered boarding location. The results reveal differences among commuter groups. While car commuters were sensitive to walking and waiting time, transit commuters were not. Minimum reservation time significantly affected the utility of the microtransit alternatives; however, the elasticities show that in- and out-of-vehicle travel time have larger effects. From these novel attributes, the sheltered boarding location had no significant effect on the utility of the shared modes except for MT-V for transit commuters.

This analysis took place after pandemic lockdown periods, and several questions were designed to measure COVID-19 risk and comfort to quantify the potential impacts. The latent variable portion of the ICLV reveals that COVID Comfort affects utility for car commuters but far less for transit commuters. Furthermore, the Pro-Sharing Economy latent variable was not identified for transit commuters, although public transit is defined by sharing. I take these results to interpret that car commuters are reliant on their cars while transit commuters are very likely captive. The latent variable results also show that COVID impacts have no significant effect on transit's utility, which shows that the risk perceptions across commuter groups are not uniform.

Based on these results, operators of pooled on-demand ride services must consider several strategies to attract riders. These strategies should also differ by commuter groups as they show major differences based on the ICLV models. When additional passengers add more coveted travel time, strategies for attracting car commuters should focus on the cost-fare tradeoffs. Strategies for transit commuters will have to focus on making their relatively more private modes worth the extra cost.

There are limitations to this study that should be noted. The sampling for this web-based survey may not represent the entire commuter population, especially digitally challenged citizens. Secondly, the survey and modeling were done separately for the commuter groups. The objective of this research was to identify differences between groups explicitly so two models were developed, though a single model my reveal other phenomena. The pandemic also introduces a limitation to this study as it presents rapidly evolving circumstances for the respondent to consider—what occurred following the 1^{st} lockdown is likely different after subsequent ones, the proliferation of new viral variants, and the rapid immunization campaign later on.

6 A REQUIEM FOR TRANSIT RIDERSHIP? WHO LEFT, WHO WILL RETURN, AND WHO WILL RIDE MORE

6.1 Background

Earlier chapters focused primarily on MoD whether it be private ridehailing, ridesplitting, or microtransit. Though without the ICT and real-time computing capabilities, public transit remains an essential component of urban transportation systems. This chapter examines the effects of COVID-19 on public transit, its evolving relationship with MoD and micromobility, and opportunities for them to work in tandem. Several researchers have studied the COVID effects on transit ridership at the aggregate level, understanding from a demand and operational perspective total ridership and revenue decline. There is still a dearth of understanding about the individual decision making that surround transit use variations during the pandemic, including the effects of novel work arrangements, safety attitudes, and sociodemographics. **Figure 19** compares national and Chicago transit ridership using data from the National Transit Database (2022). It illustrates percent ridership during COVID months compared to the same months in 2019, before the pandemic started. While there is growth in ridership, it is not yet at pre-COVID levels. Therefore, the goal of this chapter is to investigate public transit ridership decisions at the individual-level with the support of a comprehensive survey.

To achieve that goal, data from a survey conducted by the Regional Transit Authority (RTA) in the greater Chicago, IL metropolitan region is utilized. There are 3 objectives with this research. These are to analyze the factors relating to: (1) lapsed ridership during the pandemic, (2) the return to pre-pandemic transit usage assuming health risks from the COVID-19 virus has been alleviated, and (3) Mobility-as-a-Service's (MaaS's) potential to attract more ridership, specifically focusing on fare integration (MAAS-fare). To achieve these objectives, 3 separate models within the logistic regression framework are estimated independently. Though modeled independently, each model regresses the dependent variables on the same set of sociodemographic, travel behavior, and transit priority variables such that model results can be compared as closely as possible.

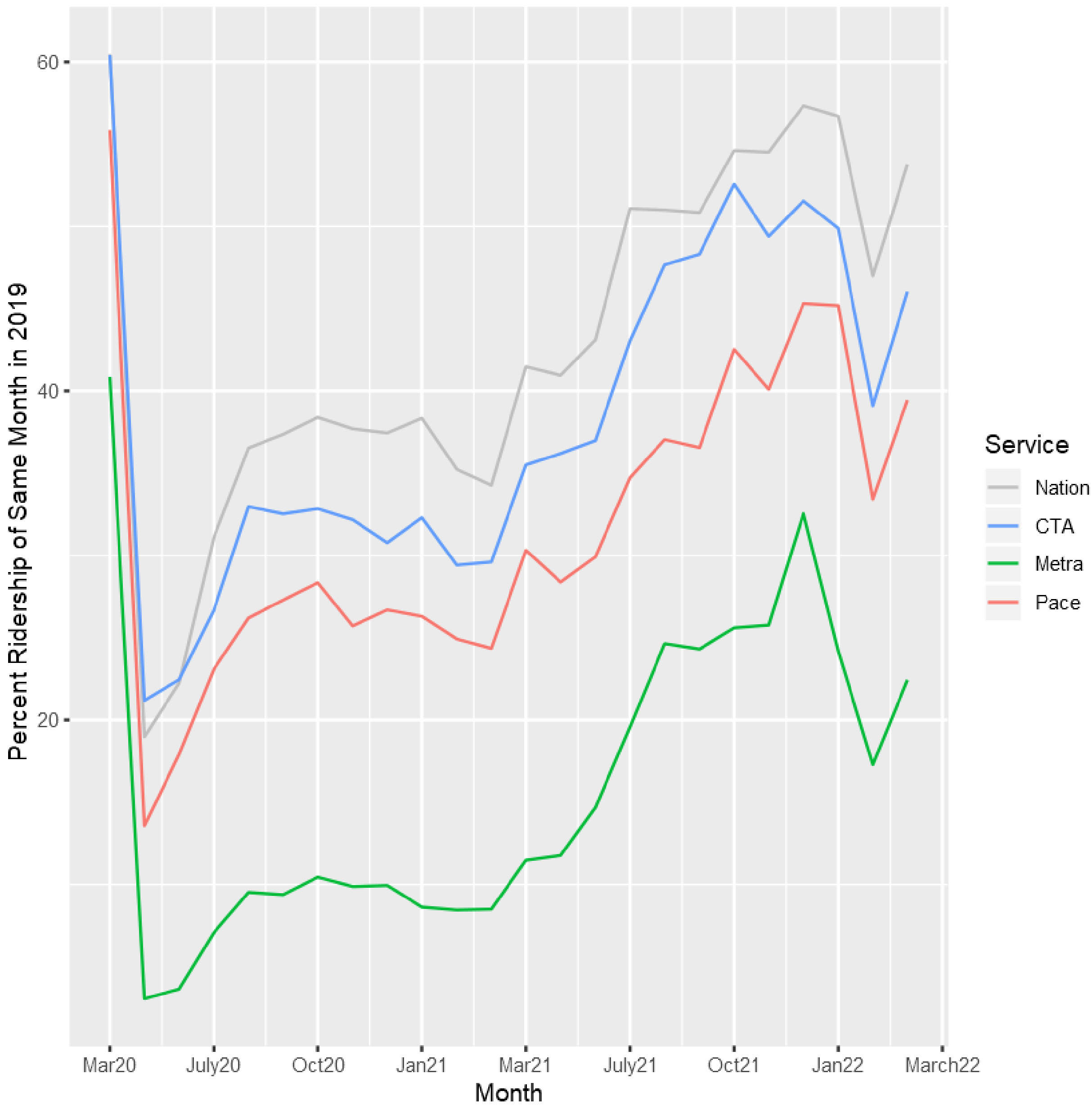

Figure 19 Transit ridership during COVID-19 across the nation and Chicago transit agencies

By completing this research, it fills a gap in the transportation literature by utilizing a large survey of transit users (N = 5,648) with variables concerning mode substitution, transit investment priorities from the user's perspective, and different types of transit services by three different operators: Chicago Transit Authority (CTA) which operates bus and heavy rail services within the City of Chicago, Pace which is the region's suburban bus service, Metra which is the commuter rail service with coverage spanning to the periphery of the region. The results from the lapsed ridership model reveal that employment characteristics and vehicle ownership had the highest impact, followed by race, user priority for sanitation of transit facilities and vehicles, and type of transit service utilized. From the "return" model, it is revealed that racial minorities (Asian, Black, and Hispanic) are not only more likely to lapse in ridership but also less likely to return to transit which emphasizes the need for future research in these communities. Lastly, racial minorities, those who used on-demand modes to substitute transit or access it, and those who travel during off-peak times are the most willing to increase their transit usage should fare integration be implemented.

6.2 Data

The data were collected by the RTA who graciously shared it with me. The survey was distributed in two waves. The first wave lasted from November 9, 2020 to December 4, 2020. The second wave lasted from January 19, 2021 to February 5, 2021. Sending emails to transit users listed in customer databases maintained by the transit agencies was the primary method of solicitation. The secondary strategy of distributing the survey was through social media and through the transit agencies' websites. Respondents were screened by collecting data on their revealed travel behavior as it relates to transit and COVID-19. To be included in the study, the respondent must have used CTA, Metra, or Pace services prior to March 2020 and live in the Chicagoland region or near the distant Metra stations in Wisconsin or Indiana.

The data were cleaned prior to being shared with the researchers and the process is outlined in RTA (2021). In summary, the data were cleaned of inconsistent responses and responses that were completed too quickly to be answered genuinely. In total, 5,648 observations are utilized in this research which represents 98% of all responses. All 5,648 observations were used in the lapsed ridership model. Some respondents did not respond to the attitudinal items that constitute the dependent variables in the remaining two models. Therefore, 5,518 observations were used in the ordered logit “Return to Transit” model, and 4,965 observations in the ordered logit “MaaS-fare” model. For more detailed information about the survey, I refer the readers to their report (RTA, 2021). The dependent variables obtained from the survey and their definitions are provided below. They are lapsed ridership status and two attitudinal questions with a Likert scale response about transit ridership when health concerns are alleviated.

- **LAPSED:** Lapsed ridership status – Uses a transit service less than one day per week during the pandemic but used it one day per week or more leading up to the pandemic
- **RETURN:** Return to Transit – Health Concerns Alleviated: I would return fully to transit as I used it before COVID-19
- **MaaS-fare**: Health Concerns Alleviated: I would consider riding transit more frequently if fare payments were seamless across transit, shared bikes, and ride services (e.g., Uber/Lyft)

The survey collected sociodemographic information such as age, income, ethnicity and race, and gender. It also collected data on employment characteristics such as sector, unemployment status, and teleworking frequency. In terms of travel behavior, respondents were asked about past travel behavior, which transit agencies they used, their access modes, and which modes substituted transit during the pandemic. An innovative section of the survey that is the basis for further modeling is the transit investment priority allocation.

An exploratory data analysis finds the high levels of multi-modality, investment priorities, low trip replacement, and a shift towards the automobile during the pandemic. **Figure 20** shows that 50.7% of respondents use more than one transit service with regularity. 16% of respondents use all three. Each respondent was presented with two investment allocation exercises. First, respondents were given a hypothetical $10 to allocate in any way they wished across pandemic related categories so long as the sum of their investment choices did not exceed their budget. The average budget allocation to the investment categories is shown with error bars representing the standard deviation in **Figure 21**. Respondents were given an additional hypothetical $10 to allocate in any way they wished across general transit investment categories. These investment categories along with the average budget allocation shown with error bars representing the standard deviation is shown in **Figure 22**. The investment allocation preference data, along with a number of explanatory variables were tested in the ridership models. **Figure 23** shows which modes are used to access transit. The CTA which operates within the core metropolitan city of Chicago is accessed primarily by active modes (79%) which is in stark contrast to the commuter rail service Metra where only 37% of respondents use personal active modes to access it. Private auto has the next largest share followed by ridehailing, shared active modes known as micromobility, taxi or shuttle, then other modes such as a moped. **Figure 24** shows that approximately 60% to 70% of respondents did not replace their transit trip. CTA trips had the lowest percentage with Metra and Pace trips not being replaced at a nearly equal rate. After considering only trips that were replaced, the modes that replaced transit are shown in

Figure 25. Approximately 80% to 90% of transit trips that were replaced were by the private auto followed by active modes, ridehailing or taxi, then other transit services. The definitions and descriptive statistics for all variables included in the modeling are provided in **Table 19**. With several of the explanatory variables defined, **Table 20** and **Table 21** shows the percent of the total budget allocation for each investment category across several dimensions including gender, race, lapsed ridership status, and by transit service. I include a heat map to show the rank of each investment with the highest priority (rank 1) having darker colors. This table will be further discussed in later sections.

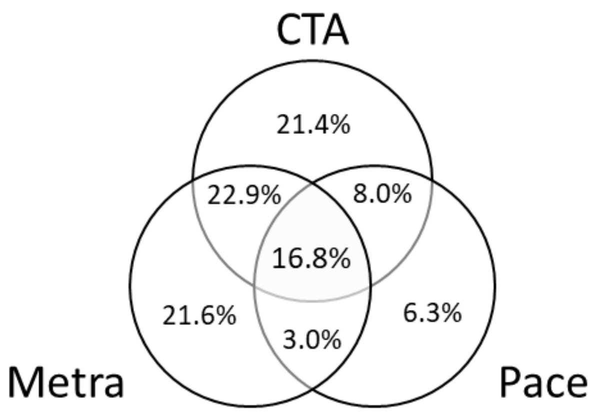

Figure 20 Share of users of each of the Chicago transit agencies

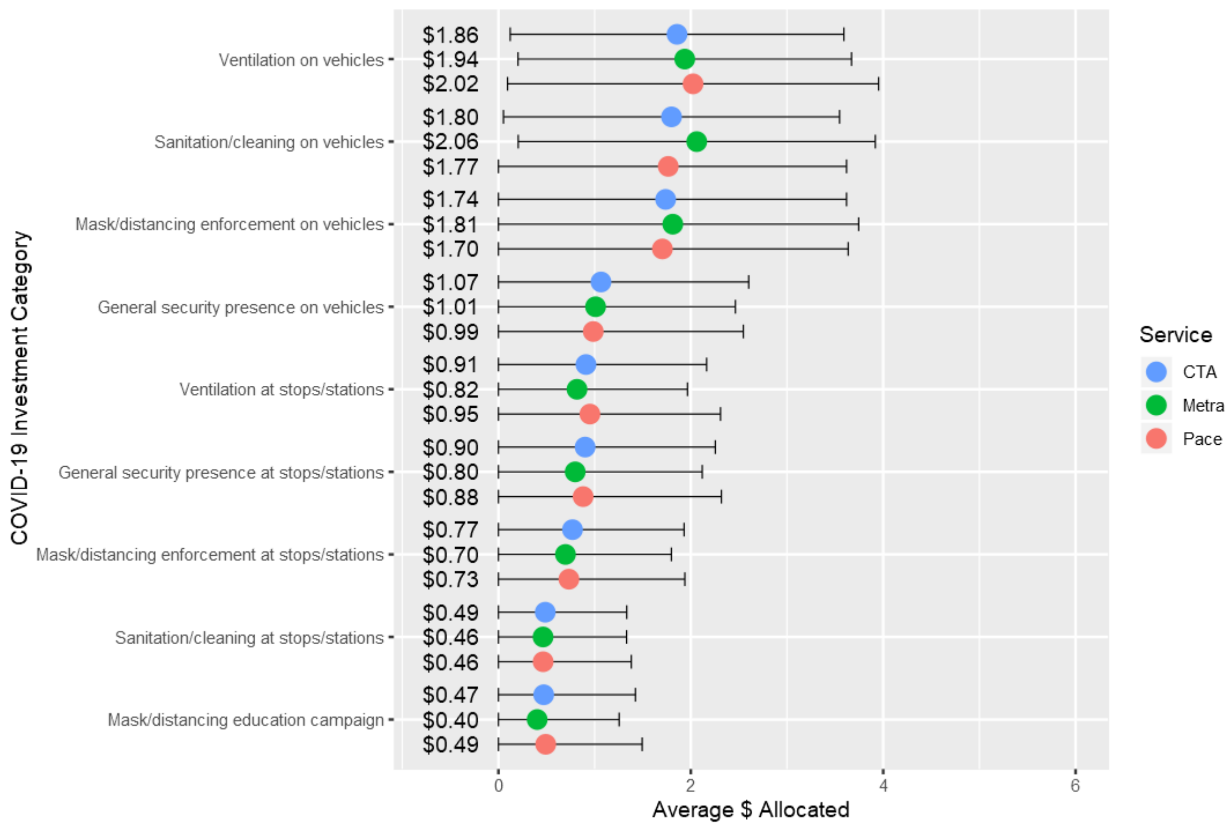

Figure 21 Average COVID-19 related public transit investment priorities by service out of a hypothetical $10 allocation (error bars show standard deviation)

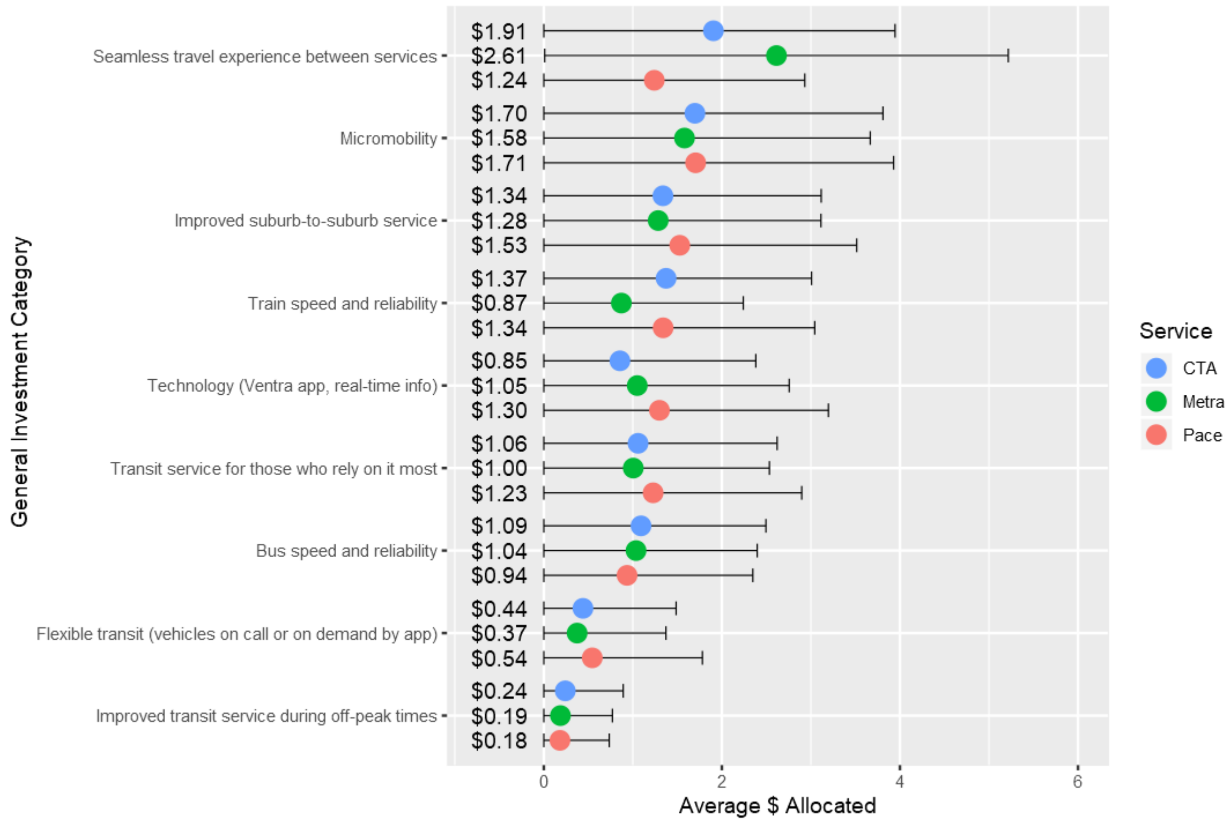

Figure 22 Average general transit investment priorities by service out of a hypothetical $10 allocation (error bars show standard deviation)

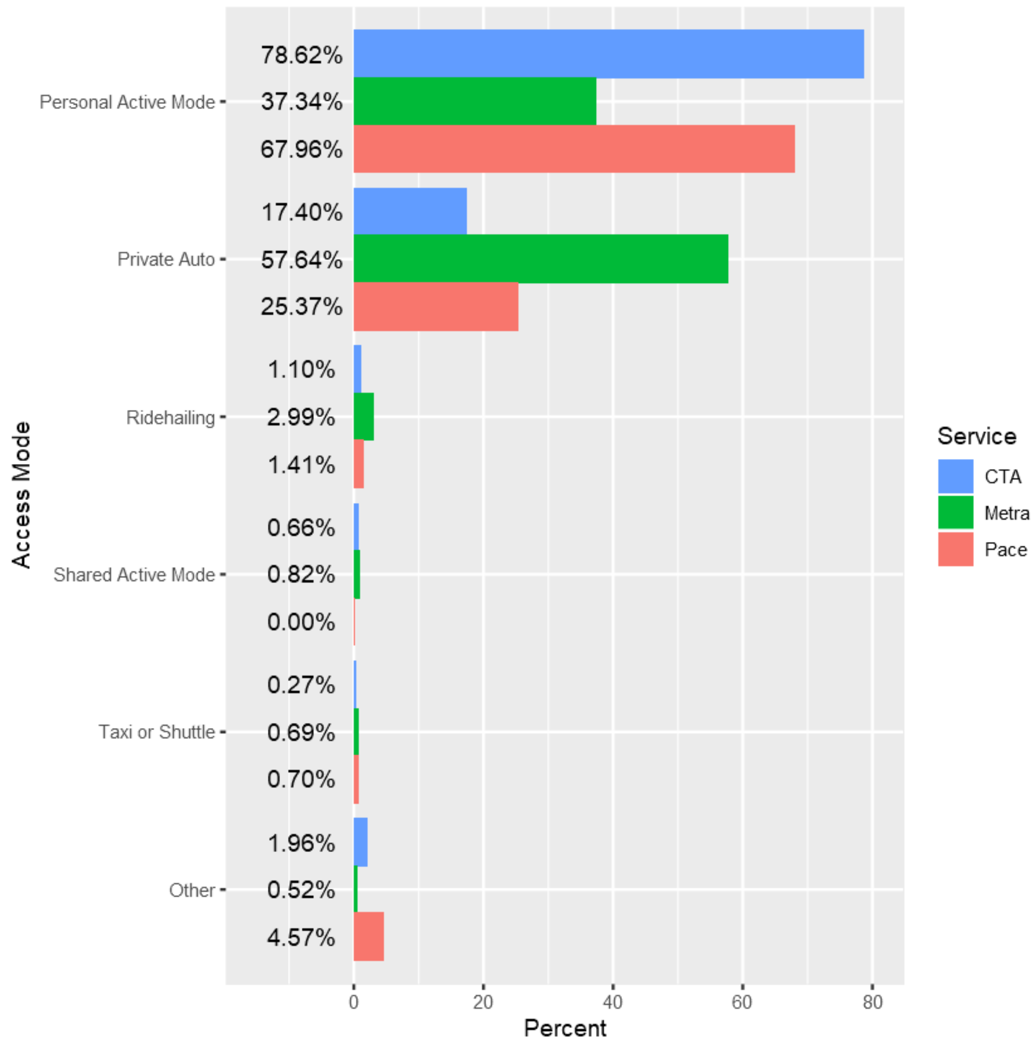

Figure 23 Percent of respondents indicating which access mode they used to reach public transit by service

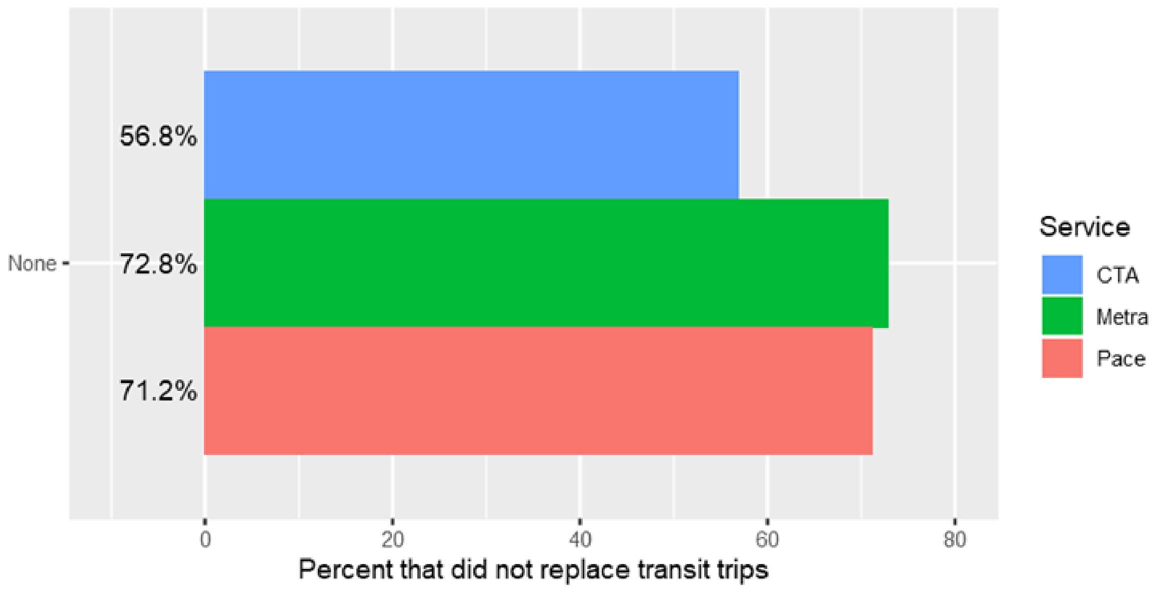

Figure 24 Percent of respondents that did not replace their transit trip

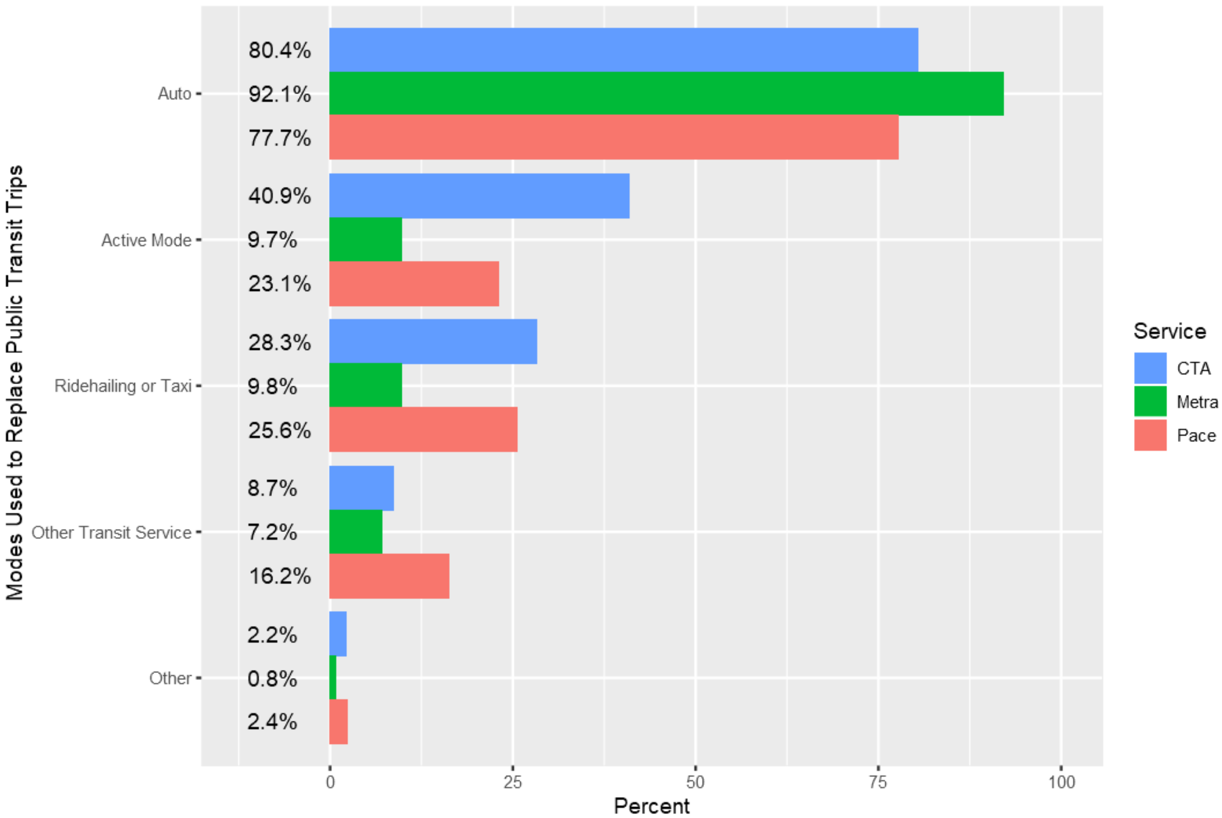

Figure 25 Percent of respondents indicating which modes they replaced transit with only if the trip was truly replaced

Table 19 Descriptive statistics of explanatory variables in RTA analysis

Variable	**Definition**	Count (%)
Female	Identifies as female	3182 (56.3%)
Non-female	Male, preferred not to express gender, or preferred to self-describe	2466 (43.7%)
Asian	Identifies as Asian, considered minority	315 (5.6%)
Black	Identifies as Black, considered minority	851 (15.1%)
Hispanic	Identifies as Hispanic, considered minority	567 (10.0%)
White	Identifies as White	3993 (70.7%)
Other Race or Ethnicity	Identifies as Native American, Middle Eastern or North African, or Native Hawaiian or Pacific Islander	160 (2.8%)
Younger than 35 (base 35 < Age < 64)		1251 (22.1%)
At or older than 65 (base 35 < Age < 64)		906 (16.0%)
Unemployed	Unemployed at the time of taking the survey Unemployed looking and unemployed not looking (retired, disabled, student)	1225 (21.7%)
Teleworking at least 4 days per week	In the past 7 days, on how many days have you worked from home (instead of traveling to work)? Is it at least 4 days per week?	2637 (46.7%)
Has HH Vehicle	Number of registered motor vehicles in the respondent's current household	4555 (80.6%)
CTA Bus User	Core city bus user (before or during the pandemic)	1358 (24.0%)
Pace (Bus) User	Suburban bus user (before or during the pandemic)	814 (14.4%)
Substituted Transit with TNC	During the pandemic, trips that were once completed with public transit were substituted with on-demand ride services	571 (10.1%)
Access Mode TNC	Used on-demand ride services to access transit	151 (2.7%)
Non-commute travel purposes only	Used transit only to access non-work or school activities	1590 (28.2%)

Table 20 COVID-19 transit investment priority rankings by different user segments

Investment	Everyone (rank)	Female (rank)	Non-female (rank)	Non-minority (rank)	Minority (rank)	Current Rider (rank)	Lapsed Rider (rank)	CTA Rider (rank)	Metra Rider (rank)	Pace Rider (rank)
Ventilation on vehicles	20% (1)	21% (1)	19% (1)	19% (2)	22% (1)	23% (1)	19% (2)	19% (1)	19% (2)	20% (1)
Sanitation/cleaning on vehicles	19% (2)	19% (2)	19% (2)	20% (1)	16% (2)	15% (3)	20% (1)	18% (2)	21% (1)	18% (2)
Mask/distancing enforcement on vehicles	18% (3)	18% (3)	17% (3)	19% (3)	15% (3)	16% (2)	18% (3)	17% (3)	18% (3)	17% (3)
General security presence on vehicles	10% (4)	10% (4)	10% (4)	11% (4)	9% (5)	11% (4)	10% (4)	11% (4)	10% (4)	10% (4)
Ventilation at stops/stations	9% (5)	9% (5)	9% (5)	7% (6)	11% (4)	10% (5)	8% (5)	9% (5)	8% (5)	10% (5)
General security presence at stops/stations	8% (6)	8% (6)	8% (6)	8% (5)	9% (6)	10% (6)	8% (6)	9% (6)	8% (6)	9% (6)
Mask/distancing enforcement at stops/stations	7% (7)	7% (7)	7% (7)	7% (7)	8% (7)	7% (7)	7% (7)	8% (7)	7% (7)	7% (7)
Sanitation/cleaning at stops/stations	5% (8)	5% (8)	5% (9)	5% (8)	5% (9)	4% (9)	5% (8)	5% (8)	5% (8)	5% (9)
Mask/distancing education campaign	4% (9)	4% (9)	5% (8)	4% (9)	5% (8)	5% (8)	4% (9)	5% (9)	4% (9)	5% (8)
Sum	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 21 General transit investment priority rankings by different user segments

Investment	Everyone (rank)	Female (rank)	Non-female (rank)	Non-minority (rank)	Minority (rank)	Current Rider (rank)	Lapsed Rider (rank)	CTA Rider (rank)	Metra Rider (rank)	Pace Rider (rank)
Seamless travel experience between CTA, Metra, and Pace	22% (1)	21% (1)	24% (1)	25% (1)	16% (2)	18% (1)	23% (1)	19% (1)	26% (1)	12% (5)
Other shared mobility options (Divvy, scooters, etc.)	17% (2)	19% (2)	14% (2)	17% (2)	17% (1)	17% (2)	17% (2)	17% (2)	16% (2)	17% (1)
Improved suburb-to-suburb transit service	13% (3)	14% (3)	13% (3)	13% (3)	15% (3)	17% (3)	12% (3)	13% (4)	13% (3)	15% (2)
Bus speed and reliability	11% (4)	11% (4)	11% (4)	11% (4)	11% (5)	10% (5)	11% (5)	11% (5)	10% (4)	9% (7)
Transit service for those who rely on it most	11% (5)	11% (5)	11% (5)	10% (6)	14% (4)	13% (4)	11% (4)	14% (3)	9% (7)	13% (4)
Train speed and reliability	10% (6)	10% (6)	10% (6)	10% (5)	9% (7)	10% (6)	10% (6)	9% (7)	10% (6)	13% (3)
Technology (Ventra app, real-time info)	9% (7)	9% (7)	10% (7)	9% (7)	10% (6)	9% (7)	10% (7)	11% (6)	10% (5)	12% (6)
Flexible transit (vehicles on call or on demand by app)	4% (8)	5% (8)	4% (8)	4% (8)	6% (8)	4% (8)	4% (8)	4% (8)	4% (8)	5% (8)
Improved transit service during off-peak times	3% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)
Sum	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

6.3 Methodology

Three models are estimated. The first model is a binary logit model using lapsed ridership status as the dependent variable. The second and third models are ordered logit models which analyze attitudes towards the return to transit and fare integration, defined as a 5-level ordered variable from "Strongly Disagree" to "Strongly Agree." Each model was estimated using PandasBiogeme (Bierlaire, 2018).

6.3.1 Binary Logit Model of Lapsed Ridership Status

The first model investigates the main determinants of the changed ridership status (lapsed versus non-lapsed) via thorough testing of variables relating to personal characteristics such as sociodemographics, employment, remote work status, transportation behavior, and transit investment priorities. Based on those explanatory variables, a latent measure of utility is estimated for each alternative and the probability of each respondent being either lapsed or non-lapsed is assigned. Because the probability of being lapsed or non-lapsed depends on differences in utility, the utility specification for the two alternatives can be simplified according to **Equation 20** where the utility for being non-lapsed, $U_{nonlapsed}$, is fixed to 0. The utility for lapsed ridership status, U_{lapsed}, includes all explanatory variables as shown in **Equation 21** where **X** is a matrix of explanatory variables, **β** is a matrix of estimated coefficients, and **ϵ** is an independent and identically distributed Gumbel(0,1) error term. The general form of the logit probability is described by **Equation 22**. By fixing the non-lapsed alternative utility to 0, the probability of being lapsed can be described with **Equation 23**. The coefficients, **β**, are estimated by maximizing the log-likelihood which is defined by **Equation 24**.

$$U_{nonlapsed} = \mathbf{0}$$ **Equation 20**

$$U_{lapsed} = \boldsymbol{X\beta} + \boldsymbol{\epsilon}$$ **Equation 21**

$$P(y_i) = \frac{\exp(U_i)}{\sum \exp\,(U_n)}$$ **Equation 22**

$$P(lapse) = \frac{1}{1 + \exp(-U_{lapsed})}$$ **Equation 23**

$$LL(\beta) = \sum\sum(y_{ni} \ln\big(P(lapse)\big)$$ **Equation 24**

6.3.2 Ordered Logit model of returning to transit and fare integration

The ordered responses from attitudinal statements on transit ridership after health concerns are alleviated range from “Strongly Disagree” to “Strongly Agree.” Given the ordered nature of the question, modeling is based on the Ordered Logit, also known as the proportional odds model (Train, 2009). An interpretation of the Ordered Logit is to generalize the decision problem into several binary logits where the latent utility score in **Equation 25**, U_{OL}, is also a function of the matrix of explanatory variables **X**, the estimated coefficients $\boldsymbol{\beta}$, and the error term $\boldsymbol{\epsilon}$ which is independently and identically distributed Logistic(0,1) **Equation 26**. shows which ordered response is associated with the latent utility score where k_1 to k_4 are the estimated threshold parameters.

$$U_{OL} = X\beta + \epsilon \qquad \textbf{Equation 25}$$

$$y_i = \begin{cases} \text{Strongly Disagree,} & U_{OL} \leq k_1 \\ \text{Disagree,} & k_1 < U_{OL} \leq k_2 \\ \text{Neutral,} & k_2 < U_{OL} \leq k_3 \\ \text{Agree,} & k_3 < U_{OL} \leq k_4 \\ \text{Strongly Agree,} & k_4 < U_{OL} \end{cases} \qquad \textbf{Equation 26}$$

The probability of the respondent indicating that they "Strongly Disagree" with a statement is shown in **Equation 27**. Continuing from **Equation 27**, the probability of the respondent indicating that they "Disagree" can be described with **Equation 28**. The probabilities of other responses being chosen can be obtained similarly. The proportional odds assumption inherent in the model implies that in **Equation 28**, the coefficients $\boldsymbol{\beta}$ are equal across the components. This implies that the effect of explanatory variables **X** has an equal effect in each of the categorical responses in **Equation 26**. To test this assumption a Brant test is employed (Brant, 1990).

$$\begin{aligned} &\text{P(Strongly Disagree)} = P(U_{OL} \leq k_1) \\ &= P(XB + \epsilon \leq k_1) \\ &= P(\epsilon \leq k_1 - X\beta) \\ &= \frac{\exp\,(k_1 - X\beta)}{1 + \exp\,(k_1 - X\beta)} \\ &= \frac{1}{1 + \exp(X\beta - k_1)} \end{aligned} \qquad \textbf{Equation 27}$$

$$\begin{aligned} &\text{P(Disagree)} = P(k_1 < U_{OL} \leq k_2) \\ &= P(k_1 < X\beta + \epsilon \leq k_2) \\ &= P(k_1 - X\beta < \epsilon \leq k_2 - X\beta) \\ &= P(\epsilon \leq k_2 - X\beta) - P(\epsilon < k_1 - X\beta) \\ &= \frac{\exp\,(k_2 - X\beta)}{1 + \exp\,(k_2 - X\beta)} - \frac{\exp\,(k_1 - X\beta)}{1 + \exp\,(k_1 - X\beta)} \end{aligned} \qquad \textbf{Equation 28}$$

6.4 Results

Response frequencies for each dependent variable are shown in **Table 22**. **Figure 26** visualizes the responses by each service. Most respondents lapsed in ridership at the time of the study, 80% of respondents stated they would return to transit, and 38% agree that they would use transit more with MaaS-fare. Across the different services, lapsed ridership, the intent to return, and intent to use transit more with fare integration is consistent. The results for binary logit model and the two ordered logit models are shown in **Table 23.** Using the Brant test, the ordered logit models each satisfy the proportional odds assumption (Brant, 1990). Each model is estimated using as many common variables so that comparisons between models are more straightforward.

Table 22 Response frequency for RTA analysis dependent variables

Lapsed Rider	Count (%)	Response	Return to Transit (%)	MaaS-fare (%)
No	1234 (22%)	"Strongly Agree"	3101 (55%)	955 (17%)
Yes	4414 (78%)	"Somewhat Agree"	1390 (25%)	1165 (21%)
Total	5648	"Neutral"	438 (8%)	1864 (33%)
		"Somewhat disagree"	372 (7%)	498 (9%)
		"Strongly Disagree"	217 (4%)	483 (9%)
		"Don't Know or Not Applicable"	130 (1%)	683 (11%)
		Total	5648	5648

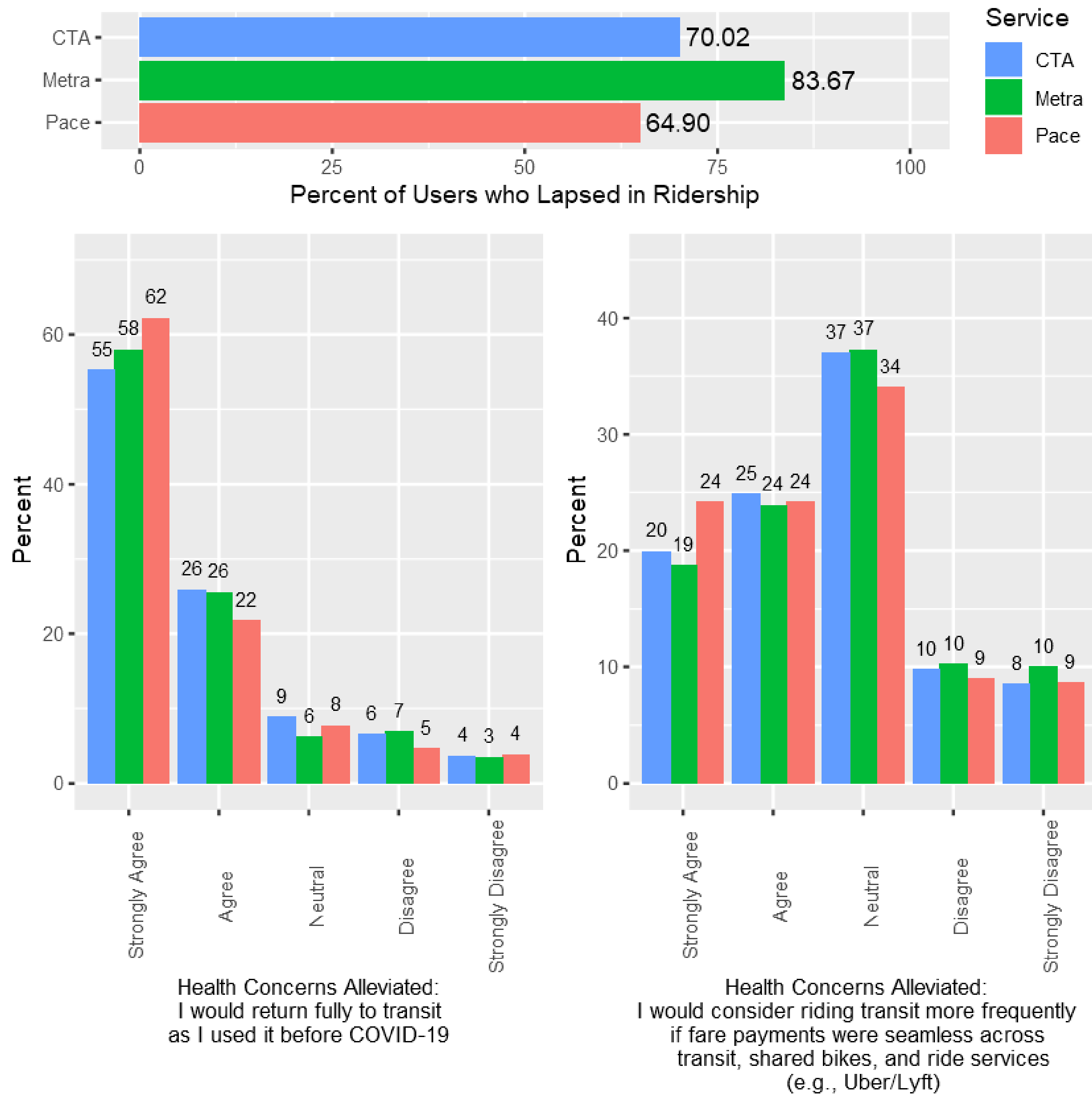

Figure 26 Lapsed ridership, return to transit, and MaaS-fare responses by service

Table 23 RTA logit model coefficients

Coefficient Names	LAPSED RIDER (Binary Logit) Model 1	RETURN (Ordered Logit) Model 2	MaaS-fare (Ordered Logit) Model 3
PERSONAL DESCRIPTORS	Value (t-stat)	Value (t-stat)	Value (t-stat)
Constant (Lapsed)	-1.07 (7.11)	-	-
Female	0.202 (2.67)	-0.157 (2.93)	-0.201 (3.82)
Asian	-0.504 (3.37)	-0.381 (3.42)	0.414 (3.64)
Black	-0.584 (6.00)	-0.547 (7.24)	-
Hispanic	-0.631 (5.63)	-0.395 (4.50)	0.397 (4.55)
Younger than 35 (base 35 < Age < 64)	-	-0.241 (3.62)	0.181 (2.78)
At or older than 65 (base 35 < Age < 64)	0.396 (3.62)	0.267 (3.48)	-
Income ($10,000s)	0.0317 (4.81)	-	-0.150 (4.05)
Unemployed	1.03 (10.6)	-	-
Teleworking at least 4 days per week	1.98 (20.8)	-	-
TRANSPORTATION			
Has HH Vehicle	0.959 (10.3)	-	-
CTA Bus User	-0.267 (3.16)	0.209 (3.23)	-
Pace (Bus) User	-0.432 (4.62)	0.401 (5.02)	0.217 (2.84)
Substituted Transit with TNC	-	-	0.33 (3.85)
Access Mode TNC	-	-	0.51 (3.29)
Non-commute travel purposes only	0.602 (7.00)	0.148 (2.48)	0.199 (3.36)
INVESTMENT PRIORITIES			
Sanitation	0.0839 (4.5)	-	-
Shared Mobility	-	0.118 (2.21)	-
Transit for those who rely on it most	-	-	0.19 (10.6)
Improve off-peak service	-	-	0.211 (4.75)
THRESHOLDS			
Tau_1	-	-3.21 (34.3)	-2.02 (22.2)
Delta2	-	1.08 (19.1)	0.842 (23.0)
Delta3	-	0.659 (21.5)	1.77 (48.5)
Delta4	-	1.26 (40.5)	1.2 (37.0)
FIT STATISTICS			
Sample size (n)	5648	5518	4965
Initial Loglikelihood	-3914.895	-21207.14	-12338.51
Final Loglikelihood	-2324.28	-6438.101	-7204.744
ρ^2	0.406	0.696	0.416
AIC	4676.561	12904.2	14439.49
BIC	4769.508	12996.82	14537.14

Sociodemographic variables are highly significant in each model. Gender, race/ethnicity, and age appear in all models. Interesting observations can be made by comparing sociodemographic effects across models. For example, female respondents are more likely to lapse in ridership, and are also less likely to return to transit in the future, even with pandemic concerns alleviated and in combination with MaaS upgrade to encompass fare integration. Non-white respondents are less likely to lapse to begin with, though looking to the future they are less likely to return to transit than white respondents. Future research should consider analyzing the attitudes towards transit in these communities as minority choice riders run a risk of not returning to transit. An interesting nuance is that, Asian and Hispanic respondents were more likely to use transit more with fare integration compared to Black and White respondents.

Income appears in the lapsed ridership and MaaS-fare model where higher incomes are associated with increased probability of being lapsed but lower likelihood to use transit more with fare integration. Employment characteristics only appear in the lapsed ridership model. In line with expectations, unemployment status and teleworking at least 4 days per week increase the probability of lapsing. The decision to model teleworking as a dummy variable using at least 4 days per week as the threshold was not arbitrary. During the model building process, using any threshold below 4 days per week was statistically insignificant. Additionally, Model 1 outperforms an alternative model where telework is included as a count variable (AIC = 4698, BIC = 4791). This suggests that there is a strong threshold effect observed for workers that telework 4 or more days per week.

Several transportation related variables are also included in each model. Access to a household vehicle affects ridership abandonment status, however, does not appear to affect intentions to return or not. Some instructive differences are observed for different transit services: Bus users were less likely to lapse in ridership overall, are more likely to return to transit as they used it before, and specifically Pace bus users are more likely to state they would use transit more with MaaS-fare availability. Riders who substituted transit with MoD or used it to access transit also are more likely to indicate they would ride transit more with fare integration. Interestingly, a trip purpose variable that appears in all models is a dummy variable representing users who only use transit for non-commute purposes. This user segment is more likely to lapse but more likely to return and use transit more with MaaS-fare.

The investment allocation preference variables show the impact of different service priorities on rider behavior and intentions. While most of the budget allocation measures were not significant in the modeling, three reveal valuable insights. Prioritizing sanitation correlated with a higher probability of lapsing, likely related to heightened concerns during the pandemic. Prioritizing improvements to shared mobility (e.g. e-scooters and bikeshare) correlated with increased intent to return to transit. More equity-oriented concerns, namely prioritizing transit improvements for those who need it most and during off-peak hours was associated with being more likely to increase use of transit if combined with MaaS-fare.

While it is clear to see which variables affect each dependent variable, the coefficients themselves do not speak to the likelihood of each respondent lapsing in ridership, returning to transit, or utilizing transit more with MaaS-fare availability. Therefore, the odds ratios of explanatory variables are reported in **Table 24** along with each variable's impact ranked. The odds ratios represent the likelihood of being a lapsed rider in the lapsed rider model, and it represents the likelihood of agreeing with the attitudinal statements in the other two models. These results are highlighted in the next section.

Table 24 Odds ratios of RTA choice model results

Coefficient Names	LAPSED RIDER (BINARY)		RETURN (ORDERED)		MaaS-fare (ORDERED)	
	Model 1		Model 2		Model 3	
PERSONAL DESCRIPTORS	Odds Ratio (Inverse)*	Rank **	Odds Ratio (Inverse)*	Rank **	Odds Ratio (Inverse)*	Rank **
Female	1.22	11	0.854 (1.17)	8	0.818 (1.22)	7
Asian (base White)	0.604 (1.66)	7	0.683 (1.46)	4	1.51	2
Black (base White)	0.558 (1.79)	6	0.579 (1.72)	1	-	-
Hispanic (base White)	0.532 (1.88)	4	0.674 (1.48)	3	1.49	3
Younger than 35 (base 35 < Age < 64)	-	-	0.786 (1.27)	6	1.20	10
At or older than 65 (base 35 < Age < 64)	1.49	9	1.31	5	-	
Income ($10,000s)	1.03	13	-	-	0.985 (1.02)	11
Unemployed	2.80	2	-	-	-	-
Teleworking at least 4 days per week	7.24	1	-	-	-	-
TRAVEL BEHAVIOR						
Has HH Vehicle	2.61	3	-		-	-
CTA Bus User	0.766 (1.31)	10	1.23	7	-	-
Pace (Bus) User	0.650 (1.54)	8	1.49	2	1.24	5
Substituted Transit with TNC	-	-	-	-	1.39	4
Access Mode TNC	-	-	-	-	1.67	1
Non-commute travel purposes only	1.83	5	1.16	9	1.22	8
INVESTMENTS						
Sanitation	1.08	12	-	-	-	-
Shared Mobility	-	-	1.13	10	-	-
Transit for those who rely on it most	-	-	-	-	1.21	9
Improve off-peak service	-	-	-	-	1.23	6

* An inverse of the original odds ratio is provided when it is less than 0

** Ranking is based on absolute impact, therefore the inverse of an odds ratio which is less than 1 is used for comparison

6.5 Discussion and Transit Strategy Implications

6.5.1 Top Community-informed Transit Investments

Before discussing the implications from the model results, the earlier data exploration informs us about users' priorities for transit investments. From **Table 20** and **Table 21**, the percentage of money allocated to the different investment priorities after summing the total amount along with their rankings across the user segments is fairly consistent. The top pandemic investment priorities for all user segments are to directly reduce the health risks on vehicles. Ventilation, sanitation, and mask/distancing enforcement on vehicles are the top priorities by a large margin. These categories garnered between 15% to 23% of the total budget allocation while the other 6 categories ranged between 4% and 11% across all user segments. Though investments at stations and stops garnered some support, investing in and advertising clean vehicles can be an important tool to attract ridership. For nearly all user segments, general security presence on vehicles is the next priority which further emphasizes the need to have a safe riding environment during travel.

The top priority from general investments is seamless travel across the different transit services and agencies. With transfer penalties having a high value, it is expected that this is one of the top priorities (Lee & Vuchic Vukan, 2005). While faster buses and trains has some support, reducing the penalties associated with inefficient transfers could increase the attractiveness of transit more than the equivalent time savings from improving vehicle speeds. The next two investment priorities have a common theme. Transit users prioritized investments into micromobility. These mobility options could be used to access transit or to replace a trip. The third highest priority is improved suburb-to-suburb services. Both of these investment priorities focus on accessibility. However, these improvements should coincide with the necessary policies that can increase the likelihood of success. Examples of support for micromobility is the installation of protected bike lanes, which is shown to increase bike lane ridership (Karpinski, 2021). Micromobility can also aid with improving suburb-to-suburb services by being strategically placed in areas for customers to access public transit. Though, a better strategy may be to focus bicycle infrastructure and build protected bikeways between suburbs. **Figure 23** shows that micromobility is hardly used as an access mode to transit. If not to access transit, micromobility can be used as an alternative to it. Although this may not increase transit ridership, micromobility and supporting investments still contribute to reducing auto-dependency.

6.5.2 Key Contextual Factors to Consider

Employment variables had the highest impact on lapsed ridership status with teleworking at least 4 days per week and unemployment status having odds ratios of 7.24 and 2.80, respectively. This suggests that those who teleworked a majority of the week are 7.24 times as likely to be lapsed riders than those who do not. Similarly, those who are unemployed are 2.80 times as likely to be lapsed riders than employed respondents. These results were expected as transit ridership during the pandemic depended on employers' teleworking policies and whether there was even a need for a commute trip given that jobs relating to non-essential activities were heavily impacted by pandemic restrictions.

Outside of employment, trip purpose appeared significant in all three models. Respondents who used transit for only non-commuting purposes likely lapsed in ridership due to the lack of recreational activities. The two other models suggest that these users, though, are likely to return and use transit more with MaaS focused on fare integration. The loosening of restrictions on recreational activities will likely cause more trip making and should be closely monitored.

While employment characteristics and the loosening of restrictions on recreational activities are not within the control of transit agencies, the importance of agencies to be prepared for increased demand is clear. DeWeese et al. (2020) find that several agencies chose to reduce their services which leaves them vulnerable to missing out on ridership when demand increases.

One strategy that could prepare agencies is to increase their employment. The return to transit and maintaining ridership may depend on the level of service that an agency can provide. This is motivation for agencies to consider increasing their labor pool. Mack et al. (2021) found that 30% of urban transit employees could not work because of the pandemic. In Chicago worker shortages caused service disruptions that led to significant delays for users (Freishtat, 2021).

In addition to the contextual factors and their own labor pool, transit agencies can consider other avenues to increase ridership. The next subsections discuss the model results for race and ethnicity, the potential for fare integration to attract more ridership, and strategies transit agencies may consider to prepare for in the future when COVID-19 no longer poses a significant health concern.

6.5.3 On an Equitable Return

The model results on lapsed ridership and the intent to return to transit show a concerning result for gender. Women are more likely to lapse in ridership and less likely to return to pre-pandemic ridership levels. They are also likely to not have access to a household vehicle because of gendered household car use dynamics where women are less likely to use the household vehicle to complete tasks (Palm et al., 2021). Therefore, women are particularly vulnerable to reduced access to public transportation.

Also of importance are the race and ethnicity results. These factors appear in all models and are all highly impactful as well. As a group they are the second most impactful factor compared to the employment characteristics with minority riders being less likely than their counterparts to lapse in ridership. This result reflects the high representation of minorities holding essential jobs (Wilder, 2021). However, race and ethnicity are the most impactful variable in the return model which indicates that even if abandonment is lower, minorities are less likely to return to transit as they used it before. I hypothesize that the disproportionate impact of COVID on minority communities within Chicago plays a major role in the decision not to return (Pierce et al., 2021). With higher rates of infection in these communities, minority transit users may consider the risk of infection too high to consider sharing a bus or train with others. Indeed, **Table 20** does show that the top priorities among minority riders are ventilation, sanitation, and mask/distancing enforcement on vehicles. In addition to risk perceptions, there may be another issue which compound this surprising finding that Asian, Black, and Hispanic users are less likely to return to transit.

With the substitution of transit for ridehailing being correlated with crime (Meredith-Karam et al., 2021), an increased general security presence around transit infrastructure can create a safer environment that attracts lapsed riders, especially in minority communities where crime rates are higher. Increased security may also help transit be an attractive mode for women as perceptions of safety are important (Lubitow et al., 2017). Though, security measures must be taken carefully so that policing does not become discriminatory (Carter & Johnson, 2021). Beyond increasing security, transit agencies can also improve the level of service in these communities, though with equity being the focal point of any strategy's implementation.

Improving access to jobs for minority and low-income communities by responding to the spatial mismatch of people and employment centers could spur ridership, especially for low-income workers who live outside of the inner city (Liu & Kwan, 2020). For women in particular, investigating the relationship between household responsibilities and travel and could lead to opportunities to reduce their transportation vulnerability (Scheiner & Holz-Rau, 2017). This further emphasizes the need to understand the dynamics surrounding teleworking, labor, and household dynamics as cities transition out of restrictive measures. Strategies which emphasize transit-oriented development ought to consider strong community engagement to ensure equitable outcomes (Lubitow et al., 2017; Lung-Amam et al., 2019). Increased security presence and continued development of transit services improves access and are ongoing efforts by many agencies. One effort that transit agencies may consider is to accelerate fare integration with private services such as micromobility, ridehailing, and carsharing.

6.6 Conclusion

In this chapter I examine the determinants contributing to transit commuters reducing their ridership during the COVID-19 pandemic, returning to transit once health concerns are alleviated, and increasing ridership should MaaS with fare integration be implemented. Three models are estimated to understand how these details contribute to their transit ridership decisions. The **first** model focuses on understanding the factors leading to reduced transit ridership during the pandemic. The strongest factors which lead to ridership cessation are teleworking a majority of the work week, being unemployed, and household car ownership levels. The **second** model considers the potential return to pre-pandemic transit ridership levels. It showed the concerning impact of race and ethnicity on the reduced likelihood of returning. Though being a minority is not in itself a reason to shift away from transit, this highlights a need to understand how transit is perceived in these communities and how to best serve them with an attractive alternative to private auto ownership and use. This model also highlights that bus users are more likely to return than train riders and that age does play a role with younger commuters being less likely to return. The **third** model analyzes the factors leading to increased transit ridership should the fare system across several shared modes be integrated. The model shows that transit riders who use ridehailing are likely to increase their usage, pointing to an opportunity for ridehailing and public transit to complement each other for multimodal lifestyles.

Interestingly, race and ethnicity play a role here and show the reverse outcome seen in the second model, namely that Asian and Hispanic transit riders are more likely to increase their ridership. The third model also reveals how transit investment priorities reveal the relationship between MaaS and accessibility, where those who prioritize off-peak services are likely to use transit more with fare integration.

With these models, I also provide avenues for future research and policy recommendations. For future research, an equitable public transit system depends on understanding the unique needs in minority communities. It behooves researchers and service providers to understand how transit can attract these customers during the pandemic recovery. Additionally, the importance of telecommuting is seen here and confirmed in other studies. This shift towards normalizing telecommuting highlights the need to investigate long-term residential and mode choices. On the policy side, the transit investment priorities shed light on what riders would like to see. Among several population segments, improved coordination between CTA, Metra, and Pace services was the consensus top priority. The next top priority is more shared mobility options, specifically bikeshare, scooters, and carsharing. The third top priority is improved suburb-to-suburb services. These last two priorities focus on transit accessibility where shared mobility can be used to fill the gap for fixed-route transit and suburb-to-suburb services increase accessibility in the Chicago radial system.

7 CONCLUSION

7.1 Summary of Dissertation Research

This dissertation explores shared mobility across several dimensions to answer the following four questions:

1. How is ridehailing utilized?
2. What are the determinants of MoD demand?
3. How did the COVID-19 pandemic affect short-term and long-term travel behavior towards public transit, MoD, and other shared modes?
4. What are the societal and distributional impacts of innovative mobility services?

I began this research when the Chicago ridehailing trip data first became available at the end of 2018. Earlier research relied on surveys or a small sample of trips to understand ridehailing utilization. Because of the novelty of the data, I aimed to also understand the general trends of ridehailing and supplement the literature with evidence from empirical data. I completed a K-Prototypes analysis to cluster similar trips together. In total, 6 types of trips were identified. What appeared are several categories that mirror what has been found in survey-based studies. Ridehailing is being used in the evening in areas known to have bustling nightlife, to access the airport, avoid bad weather, and replace public transit where service is sparse. Disconcertingly, I identify a category of trips where public transit is highly competitive. Ridehailing had a slower travel time and most certainly higher cost than an equivalent transit ride. And surprisingly, a category of only ridesplitting trips is identified. To continue my investigation of this ridehailing data, I then estimated models to understand the factors informing its demand.

I estimated several models that regressed the average daily ridership of the 77 Chicago community areas onto several variables representing social vulnerability, population characteristics, recreational activity density, and transit accessibility. Given the spatial nature of the ridehailing dataset, I utilized a Spatial Durbin model which accounts for a community's direct effect on ridehailing demand and its indirect effect on neighboring communities. Additionally, I modeled the demand for private ridehailing and ridesplitting separately, owing to the surprising result in the K-Prototype analysis that ridesplitting represented its own category of trips. Much of what has been found in the literature was confirmed in this study. Communities that had higher population density, a younger population, smaller households likely without children, and more recreational activities (bar and restaurant density as a proxy) are correlated with more private ridehailing and ridesplitting demand. This study also added to the discourse on the status of ridehailing platforms as competitors or as complementary modes to public transit. The model results indicate that better transit accessibility measured by the average walking time to a heavy rail transit station is correlated with more private ridehailing and ridesplitting trips. And lastly, a difference between the two modes is identified. To represent the social vulnerability of a community, I develop an index to account for the intersectionality of race, poverty, and access to transportation and regress demand on it. The Spatial Durbin modeling results reveal that more social vulnerability is correlated with ridesplitting trips but less private ridehailing demand. Unfortunately, the ridehailing data cannot be paired with personal data about the riders and only community-level factors can be used. Therefore, I turn to survey-based data to understand individual-level mode choice to understand the tradeoffs between cost, travel time, privacy, and other variables affecting the decision to use shared mobility.

I collected individual-level mode choice behavior by designing a choice experiment for car and transit commuters. The focus of the study is to understand microtransit being used as a commute mode. Attributes of interest centered around novel (to ridehailing) mode attributes that blur the line between demand responsive and traditional public transit. The choice experiment is a pivoted, D-efficient design that also incorporates realism. Not only is the current commute and its attributes used as the reference alternative, but the microtransit alternatives' cost and travel time reflect realistic values. For example, the choice experiment presented to car commuters was designed in a way to ensure that microtransit costs were always lower than driving, while at the same time never microtransit would never outperform driving in terms of speed. For transit commuters, microtransit was always just as fast or faster than their current commute but costs were always greater. In the survey, I also account for latent attitudes including the respondents' comfort in COVID risky situations as the survey was distributed at the beginning of the COVID-19 pandemic. After estimating an Integrated Choice and Latent Variable model for each commuter group, I found that car commuters' utility towards microtransit was insensitive to travel costs but was sensitive to travel time, the number of people sharing the vehicle, and COVID risk perception. Conversely, transit commuters were sensitive to cost while being insensitive to out-of-vehicle travel time and COVID risks. While the COVID Comfort latent variable is not a statistically significant variable in the transit commuter choice model, public transit did see a drastic decline in ridership due to lockdowns which closed several businesses, companies shifting to teleworking, and several transit agencies reducing services. With the prolonged pandemic bringing the possibility of permanent shifts in mobility, I again turn to survey-based data to understand the pandemic's effect on public transit, MoD, and micromobility from the perspective of a transit user.

Data collected from a comprehensive transit survey conducted by Chicago's Regional Transit Authority revealed many of the effects of COVID-19 on public transit. Nearly 80% of transit users significantly reduced their ridership. After modeling the decision to reduce transit ridership, teleworking and employment status are highly impactful. Those who teleworked a majority of the week were nearly 8 times as likely to lapse in ridership than those who do not, and riders who are unemployed are nearly twice as likely to lapse in ridership. 20% of respondents indicated they are unlikely to use transit at pre-pandemic levels once all health concerns have been alleviated. Concerningly, Asian, Black, and Hispanic transit users are more likely to not return. For public transit to be part of an equitable pandemic recovery, research is needed to understand how transit can attract those who did not intend on returning. One solution is to integrate the public transit fare system with other shared mobility services. The survey found that 38% of respondents are willing to increase their transit usage if fare integration is implemented. Modeling these responses, Asian and Hispanic riders are more willing to increase their ridership with this feature. Altogether, these results highlight the negative impact of COVID and the opportunities for transit agencies and private mobility companies to collaborate.

In Chapter 7, I summarize my research, synthesize the results of each study to gain a broader perspective on shared mobility, discuss the limitations, and possibilities for future research. I conclude that ridehailing is generally used for irregular trips and is unlikely to unseat traditional modes as a commute option. Hardly used as a transit access mode, ridehailing can act as an alternative to poorly accessible transit. The determinants for demand at the community level generally follow what has been found in the literature. Higher population density, higher density of recreational activities, and communities that are more suitable for multi-modality are correlated with higher ridehailing demand. At the individual level, car commuters are highly sensitive to travel time while transit commuters are sensitive to the cost of microtransit alternatives. Because of the pandemic, public transit ridership drastically decreased and travelers became more likely to shift towards private modes. There is an opportunity for transit, MoD, and shared mobility to work together, though, and aid in an equitable pandemic recovery.

7.2 How is Ridehailing Utilized?

Ridehailing utilization is analyzed several different ways. It is the first question I asked at the beginning of this journey, and from there spawned the subsequent questions on demand determinants. Though it is the first question and the motivation behind the K-Prototype analysis, the answer to it can be bolstered by synthesizing the results of all studies.

The analysis revealed distinct categories of trips which accounted for the ridehailing trip data, weather, transit performance, and taxi connectivity. The categories, or ‘prototypes,’ showed that ridehailing is used to fill the gaps in transit service. One of the main categories of trips was defined by poor transit performance when compared to the other categories. More evidence can be found in the results from the Spatial Durbin modeling of ridehailing demand, where more demand is correlated with communities with higher vulnerability indicators (e.g. large share of minority population, many families living below the poverty line, single parenthood, etc.). These communities with higher vulnerability also have relatively poor access to transit when compared to affluent neighborhoods that are served with high heavy rail and bus frequencies due to their proximity to the business core of Chicago. Therefore, it is likely that they are using ridesplitting, which offers lower fares than private ridehailing and often times with the same travel time performance, to fill in an accessibility gap that transit could not.

Additionally, ridehailing can be highly competitive with transit which supports the findings from Babar and Burtch (2017) and Erhardt et al. (2021). A different prototype identified in the analysis was defined by public transit having lower travel times than the ridehailing trip. And most certainly, these trips were cheaper. The research literature warns against dominated alternatives in choice experiments because respondents will not examine tradeoffs beyond attributes when the choice is straightforward, yet the empirical data shows that ridehailing was still chosen over highly competitive transit services. This highlights the need to understand the role that pooling plays in mode choice, where public transit has the highest degree of sharing. Indeed, the microtransit alternatives for car commuters in chapter 6 always had a lower price and, in some choice scenarios, the same travel time, yet there were instances of respondents never choosing microtransit once. It is likely that microtransit will need a much steeper fare discount to be competitive with the private automobile for commuting. For public transit commuters, more respondents were willing to switch to microtransit though not a substantial amount. Unlike their car commuter counterparts, there was no strong indication that microtransit would replace their status quo commute mode. The analysis found that many of the transit users are captive riders, constrained by small budgets, so in regards to commuting it is unlikely that microtransit will take away from public transit ridership. Ridehailing then is highly competitive for non-commute trip purposes.

The Regional Transit Authority conducted a survey to find the effects of COVID-19 several months more into the pandemic than the Israeli microtransit survey, allowing for an analysis of travel behavior after the initial onset of the pandemic. Prior to the pandemic, there was a somewhat complementary relationship between ridehailing and public transit. Overall, only 2.2% of all transit riders use ridehailing as an access mode. When looking at individual transit services, 0.8% of CTA riders, 2.5% of Metra riders, and 1.0% of Pace riders use it to access transit. CTA riders had the lowest rate of using ridehailing to access transit because they likely have other alternatives such as active modes, meeting my expectations because this transit service has the highest stop density. The highest rate being for Metra riders is unsurprising, as this service serves a sparse network in the suburban areas of Chicagoland as a commuter service for higher-income earners. Pace riders are typically captive riders, so they likely do not have access to a household vehicle and ridehailing is the next best alternative. However, the rate of ridehailing as an access mode is lower than Metra riders likely due to budgetary constraints. During the pandemic, ridehailing shows larger percentages of substitution rather than complementing transit.

22% of transit riders substituted transit for ridehailing. Looking at the different transit agencies, 28% of lapsed CTA riders, 26% of lapsed Pace riders, and 10% of Metra riders substituted their transit usage for ridehailing. The lower percentage of riders switching to ridehailing from Metra are likely not switching to ridehailing because that mode serves primarily higher-income commuters from the suburbs to downtown Chicago, which is heavily affected by telecommuting. For Pace riders, the relatively higher rate of substitution for ridehailing is likely to fill in the gaps of service while taking into account the health risks posed by COVID. And the switch to ridehailing from CTA riders is the highest likely from many of these riders already being multi-modal, having lower car ownership rates so ridehailing is has less competition, and concerns about transit safety.

In summary, ridehailing utilization is tied to its highly competitive nature. The K-prototype analysis saw several trip types that are also seen in the literature, using ridehailing for airport trips, in rough weather, and as a substitute for transit. From the Spatial Durbin results, communities with higher vulnerability indicators are using ridesplitting when transit access is poor. Without more details about trip purposes and riders in the Chicago ridehailing dataset, survey data can shed more light on ridehailing utilization. Microtransit is unlikely to be used as a commute mode, where the Israeli study found car and transit commuters alike are likely unwilling to switch to microtransit for a plethora of reasons ranging from the cost-travel time-privacy tradeoffs to COVID risk perceptions. Extremely small evidence of a complementary relationship is seen in the RTA survey data with 2.2% of transit riders using ridehailing as an access mode. Using the same data, the high competitiveness of ridehailing with transit is evident during the pandemic. 22% of transit riders substituted their lapsed ridership with ridehailing.

7.3 What are the Determinants of MoD Demand?

Determinants of ridehailing demand are observed from each of the datasets used in this dissertation. The large Chicago ridehailing dataset allowed me to understand demand factors at the community-level, while survey-based data gave insights into individual level decision-making.

The Chicago ridehailing data revealed and confirmed many of the factors found in the ridehailing literature. Higher population density, higher density of recreational and leisure activities, and higher transit accessibility are positively correlated with ridehailing demand (Rayle et al., 2016; Yu & Peng, 2019). When ridehailing rides are differentiated by private rides and ridesplitting, more nuance can be seen from a community sociodemographic perspective. Communities with higher indicators of social vulnerability are correlated with more ridesplitting trips but fewer private trips. Survey data reveals more about decision-making at the individual-level.

The microtransit study is able to understand decision-making from the perspective of car and transit commuters. Additionally, this study examines novel (ridehailing) features not listed in **Table 13**. For microtransit, the determinants of demand for it being a commute mode are interesting with a highly realistic choice experiment uncovering the steep tradeoffs needed for commuters to switch to it. The choice experiment for car commuters considered scenarios where the cost for microtransit was always less than the cost for commuting by car, taking into account parking fees and operational car costs, yet many commuters never considered microtransit even when the travel times are equal. An interesting result from the choice model for these commuters is that the cost attribute did not significantly impact the utility, stressing the importance of other microtransit attributes such as walking and waiting time. When these values are too high, the likelihood of choosing microtransit decreases. Car commuters also exhibited significant effects for shared mobility familiarity. Those who used ridehailing abroad or have used other sharing services are more likely to use microtransit.

Transit commuters saw microtransit travel times that were as quick or quicker in their choice experiment. While most microtransit attributes are statistically significant and in the direction expected, the model results also show that walking and waiting time do not significantly impact the utility of microtransit. Similar to car commuters with familiarity with shared services, transit commuters already experience out-of-vehicle travel time so may not consider these attributes when examining the microtransit utility.

Both commuter groups had significant disutility for microtransit attributes such as the number of people sharing the trip and how long before trip departure a trip must be scheduled. Conversely, both commuter groups had no effect on utility of microtransit with the availability of a sheltered boarding location much like what can be found at existing bus stops.

In summary, community-based and individual decision-making affect the demand for ridehailing whether it be private ridehailing, ridesplitting, or microtransit. Population density, recreational activity density, and higher transit accessibility are positively correlated with overall ridehailing demand. These community-based factors point to ridehailing demand being mainly a response to urban restrictions. In highly dense areas where transit accessibility is likely to be high, using a private automobile is costly because drivers consider congestion and parking costs. At the individual-level, ridehailing attributes such as cost and travel play an important role, though trip purpose plays an important role, too (Al-Ayyash et al., 2016; Tarabay & Abou-Zeid, 2019). Seen in the microtransit study are car commuters who may not have found the cost savings worth the travel time and privacy tradeoff, and transit commuters are likely captive and would not consider microtransit as a regular commute option. Therefore, ridehailing is unlikely to be used as a regular commute option. Additionally, demand is likely to depend mainly on attributes relating to the cost and time commitments (in-vehicle travel time, out-of-vehicle travel time, and minimum reservation time) of ridehailing modes rather than “luxuries” such as a sheltered boarding location.

Contextual factors such as trip purpose being commute or non-commute related play an important role in ridehailing demand. The K-Prototype analysis identified evening recreation trips, trips in bad weather, and trips to the airport. These are not regular events. Therefore, it is likely that ridehailing demand is mainly based on the amount of irregular travel rather than regular events such as commuting to work or school. A large contextual factor for ridehailing demand, and more broadly shared mobility demand, is the pandemic which is discussed at length in the following subsection.

7.4 How did the COVID-19 pandemic affect short-term and long-term travel behavior towards public transit, MoD, and other shared modes?

The pandemic began soon after the winter of 2019-2020. Thus began an era where mobility became severely afflicted by hysteria caused by an easily spreadable and fatal sickness. The first analytical chapters utilized Chicago ridehailing data *before* the start of the pandemic, using data from 2018 and 2019. From the onset of the pandemic in March of 2020, shared mobility usage was heavily impacted. In the United States, public transit ridership decreased and private shared mobility companies quickly scrambled to devise and implement strategies that responded to health risks posed by COVID-19, the *perceived* health risks, and severely reduced demand. The latter analytical chapters of this thesis are based on surveys that were distributed in 2020 and 2021 to capture travel behavior towards shared mobility.

During that time, I collected data on mode choice which compared a respondent's status quo commute mode before the pandemic to novel microtransit alternatives. Mode choice in these choice experiments was heavily affected by pandemic perceptions. Indeed, latent variables are important to consider when investigating mode choice and ridehailing (Alemi, Circella, Mokhtarian, et al., 2018; Lavieri & Bhat, 2019a). In both car and transit commuter groups, a latent variable that was interpreted as a respondent's comfort in COVID risky situations, or "COVID Comfort," did indeed affect mode choice. The latent variable had a pronounced effect on microtransit utility as revealed by COVID Comfort having a higher elasticity than cost and time attributes.

In the short-term due to the pandemic, 80% of transit users in Chicagoland reduced their ridership. When modeling ridership status, the most impactful variable was about employment and highlights the motivation to understand the long-term impacts of COVID. Those who teleworked 4 or more days per week are more than 7 times as likely to lapse in ridership than those who do not. Though employment is not controlled by public transit, COVID has caused some companies to consider permanently adopting hybrid teleworking scenarios, if not fully adopting it. Therefore, the shift towards teleworking can severely impact shared mobility, especially public transit, since teleworkers no longer need to commute. Additionally, teleworkers may not need to live in proximity to their place of employment. There is a possibility that populations will shift to areas outside of the urban core where transit obtains most of its ridership. For the long-term, transit agencies must account for these shifts.

In addition to understanding lapsed ridership, respondents were asked their likelihood of returning to their pre-pandemic transit ridership levels once all health concerns were alleviated. 80% of respondents indicated that they will return which still leaves 20% of riders unlikely to return. When modeling these responses, race collectively had the highest impact with Asian, Black, and Hispanic respondents being less likely to return. In general, these population segments are more transit dependent. Therefore, more research is needed to understand why they may not return. Younger transit users are also less likely to return. From a long-term perspective, losing these groups of riders is concerning. It is recommended that transit agencies make a concerted effort to understand why minority and younger riders may not return to transit. Reducing services in response to lower demand in these communities may exacerbate prevailing equity concerns, where reducing services in communities that do not quickly regain transit ridership could permanently drive lapsed riders to less efficient modes. Though as doom and gloom this result is, the RTA analysis also collected data on other opportunities for shared mobility.

Specifically, the RTA survey found that 38% of respondents agreed that they would use transit more if its fare system is integrated with other shared services such as ridehailing and bikeshare, in other words MaaS. Importantly, modeling these responses revealed that Asian and Hispanic users are more likely to use transit more with MaaS. While these minority groups may be less likely to return to transit, they may return if MaaS were implemented. Additionally, this model also finds that those who used ridehailing to access or substitute transit would be willing to increase their transit ridership with fare integration. What the pandemic did in the long-term is open the door for public transit and other shared mobility services to work in tandem. Indeed, the top priorities across most population segments for future transit investments are a seamless travel experience between existing traditional transit services and increased coverage of micromobility.

Overall, the pandemic may have inadvertently induced an opportunity for shared mobility to take a stronger role in urban transportation systems. At the time of writing this dissertation, public transit ridership has yet to rebound to pre-pandemic levels, there is a possibility that riders may not return, and other concerns such as security may linger long after health concerns have subsided. The post-pandemic landscape is ripe with opportunities for public transit agencies and private mobility companies to collaborate and offer an attractive, comprehensive, and efficient travel experience. Hensher (2020) also points out this opportunity for MaaS to play a vital role in pandemic recovery, even promoting beyond the collaboration of shared mobility services to non-transportation services.

To inform the implementation of MaaS, transit agencies and private mobility companies alike ought to take heed of previous pilot programs (Karlsson et al., 2020; Sochor et al., 2016). This is further discussed in the following subsection.

7.5 What are the Societal and Distributional Impacts of Innovative Mobility Services?

Accessibility and mobility are undoubtedly tied to prosperity. With several modes that can quickly bring travelers to their destination, they can optimize resource utilization and use the remaining resources for other purposes. For example, an urban dweller has access to bikeshare, e-scooters, and public transit to serve his needs and does not need to own a vehicle. Rather than spending resources on vehicle ownership, he can use that money for other purposes. On the other hand, rural folk rely on personal vehicles to access destinations that are miles away from each other. In this subsection, I focus on the equity implications of shared mobility. Specifically, I synthesize the results of previous chapters to understand how shared mobility can be leveraged for more equitable accessibility and mobility outcomes.

Shaheen et al. (2017) summarize five barriers to accessing transportation, causing resource burdens on underprivileged households that have few choices. These barriers are spatial, temporal, economic, physiological, and social. Spatial barriers exists when transit stops or other destinations are too far to reasonably access; temporal barriers exist when travelers cannot complete time-sensitive trips; economic barriers exist when a traveler cannot bear the cost of traveling; physiological barriers exist when a traveler has physical or cognitive complications when trying to access transportation; and social barriers exist when a traveler experiences societal exclusion based on race, language, cultural, and political characteristics. This dissertation finds several ways that shared mobility can lower these barriers.

By utilizing the Chicago ridehailing trip dataset and analyzing the demand, I found that greater ridesplitting demand is correlated with a community's vulnerability index. Because communities with higher vulnerability indicators are more likely to have poor access to transportation and more specifically public transit, ridesplitting may be a cost-effective alternative to auto ownership, traditional taxis, private ridehailing, and sparse public transit. Among the barriers to equitable transportation accessibility and mobility, ridesplitting lowers the spatial, temporal, economic, and social barriers. The on-demand characteristic of ridehailing, and by extension ridesplitting, means that users can request a door-to-door trip at any time of day. Indeed, convenience of ridehailing is cited as one of its main attractions (Rayle et al., 2016). Ridesplitting trips are also less expensive than private services to account for the privacy and travel time tradeoffs. Though, because many of the ridesplitting trips occur in less dense areas, the likelihood of a trip being shared and adding extra travel time is lower. Therefore, ridesplitting users in vulnerable communities may very well be using ridesplitting with the same level of service they could have received with more expensive alternatives. On the social side, ridehailing was found to overcome discrimination by traditional taxis that would choose not to serve minority neighborhoods (Brown, 2019). Altogether, the Spatial Durbin analysis of ridehailing demand finds that ridesplitting can lower the barriers to transportation accessibility. However, these findings taken at face-value could leave policy-makers to interpret wrongly that ridehailing's potential has been fully realized.

The proponents of ridehailing hailed it as an opportunity to solve the first-mile-last-mile transit problem, but the RTA study found that only 2.2% of transit users ridehailing to access transit with the highest rate coming from higher-income users. For CTA and Pace which serve a broader customer-base, only 0.8% and 1.0% used ridehailing as an access mode, respectively. Additionally, ridehailing is unlikely to replace transit for commuting in urban areas, especially for captive users. The microtransit choice experiment found low adoption of ridehailing alternatives for commuting. If not as an access mode or to replace transit entirely, how then does ridehailing evolve to achieve equitable transportation accessibility? The results from the RTA analysis may shed some light on the answer.

The third model estimated in the RTA analysis was on the likelihood of increasing transit ridership if the fare payments were seamless across shared mobility services. As discussed previously in this chapter, race was an important factor when examining how MaaS system can promote transit. Asian and Hispanic riders are more likely to use transit with MaaS implementation. Indeed, previous research found that these two population segments were quick to adopt ridehailing and their propensity to be early adopters may apply to MaaS (Lavieri &

Bhat, 2019a). The RTA data also reveals that minority riders' highest general transit investment priority are shared mobility options such as bikeshare and scooter-share. These modes can serve two purposes. Bikeshare and scooter-share can be used to access transit or replace an otherwise unattractive transit trip. Moreover, pairing ridehailing with these modes fills the rest of the mobility and accessibility gap. Additionally, lower-income respondents are also more likely to increase transit ridership with MaaS. In the same way that the fare system for the three transit agencies in Chicagoland can recognize different types of riders (e.g. senior, student, low-income, etc.), it is possible that specific fare considerations can be applied for certain rider segments across all MaaS services. With both traditional and new shared mobility working in tandem, a platform that can seamlessly handle transactions between services contributes to improved transportation accessibility for underprivileged transit users.

Even with much a plethora of benefits, getting multiple service providers to collaborate and engage in fare integration can be challenging. Karlsson et al. (2020) highlights challenges at several levels of implementation. Some of the main challenges include building a shared vision on the role of MaaS and cooperation among stakeholders and operators. Dialogue can start between government agencies and service providers centered around high-level goals. Some examples from pilot programs include MaaS supplementing existing fixed transit routes or identifying where flexible, on-demand services can replace low revenue routes. With the service providers and stakeholders, the challenges are centered on uncertainties over their roles and the fear of being dominated by competitors (Monahan & Lamb, 2022). At the user level, a main challenge is difficulty in changing travel behavior. Karlsson et al. (2020) finds that users assessed the benefits of MaaS based on their specific situation as opposed to the broad availability of connected services, which may still include services that hold no benefit to them at all. Additionally, MaaS benefits may not be fully understood by users until they have been trialed extensively (Sochor et al., 2016).

These challenges, again, highlight the need for greater community engagement at many levels to understand how best MaaS can be implemented to develop an equitable, economically feasible, and environmentally conscious transit system. Lung-Amam et al. (2019) find that cooperation among several interest groups addresses the unique issues faced at the local and regional level. Indeed, given the cross-jurisdictional nature of many transit systems, where buses and rail lines cross several city borders, MaaS implementation may be best handled as a regional question, in the context of the United States, at the Metropolitan Planning Organization level.

7.6 Research Limitations

Several implications are taken from the results of my research, however, there also exists limitations. Firstly, the K-Prototype analysis highly depends on the data provided. Because the purpose of the unsupervised learning technique is to cluster similar trips together, it is limited to the input features to calculate trip observation similarities. I remedy this by utilizing data whose affects are seen in the research literature. Namely, features that reveal poor weather avoidance, transit accessibility, and the competition between taxis and ridehailing. There may very well be other clusters of trips that can be identified as the number of features included in the analysis increases. Another limitation to that study is the aggregation of the data to the Census tract level for the ridehailing origin and destinations. The main purpose of employing K-Prototype is to handle categorical data which was a necessity to handle the origin-destination data. Rather, other studies relied on more computationally efficient K-Means because the GPS coordinates are included in that data (Ma et al., 2019; Xiong et al., 2021).

Another limitation to the research again involves the Chicago ridehailing dataset. Just as the origin-destination pairs of ridehailing trips were spatially censored, the trip dataset cannot be linked back to the riders themselves nor to the other publicly available datasets provided by the City of Chicago. In fact, a Freedom of Information Act request sent to the city did not yield any new information to connect the Chicago ridehailing trips, vehicle, and driver datasets. With this data, the clustering and spatial analysis could have benefitted greatly by analyzing the general trajectory of drivers and a more specific understanding of the efficiency of the trips based on the vehicles used.

Regarding the survey-based studies, several biases can affect the results. Namely, the two biases that may greatly affect the results are response bias and optimism bias. For example, response bias can cause inaccurate choice modeling in the microtransit study. Because they believe it is the more responsible choice or the choice that researchers would like for them to make, respondents could be choosing microtransit in the experiment even when they have no intention to use. Therefore, forecasting demand could provide misinterpreted results (Fujii & Gärling, 2003). Additionally, optimism bias may be present in the COVID-19 lapsed ridership analysis. Specifically, the responses modeled in Chapter 6 are about the intent to return to transit and use transit more with fare integration. Several assumptions about the future, such as having all health concerns alleviated, are very strong. Therefore, respondents may be thinking too optimistically about a decision far into to the future (Næss et al., 2015). While the purpose of these studies was not to forecast demand, future research should consider the affects these biases may have and use this information to examine strategies that address them.

7.7 Future Research

This dissertation covered several aspects of shared mobility. **Figure 27** shows areas where future research can shed more light on shared mobility, especially to understand how shared mobility can be used to increase transportation accessibility. I identify topics that can expand the literature on shared mobility. First, ridehailing trip data can be supplemented with other data to understand more about individual-level mode choice such as in Chapters 5 and 6. The Chicago ridehailing trip dataset does not contain information about the riders or the purpose of the trip. In Chapters 3 and 4, I could only infer these characteristics at the community-level. Second, shared mobility and MaaS should be investigated at the scale of the Chicago ridehailing trips data. While the survey data informs individual decision-making, observing overall shared mobility trends can reveal the scenarios when MaaS is an attractive choice. One such data collection method that can be utilized for both research avenues is mobile trace data used in conjunction with questionnaires (Anagnostopoulou et al., 2020; Calabrese et al., 2013).

The K-Prototype and Spatial Durbin analysis of the ridehailing trips was limited by the data being censored spatially, temporally, and any information about the riders or trip purpose. Mobile trace data used with questionnaires about trip purpose can be used to expand the ridehailing research literature. People opting in to a panel study can provide sociodemographic information such as race, income, employment characteristics, what stage they may be in life. While collecting the mobile trace data, questionnaires can be used to collect information about trip purpose and other data pertinent to mode choice.

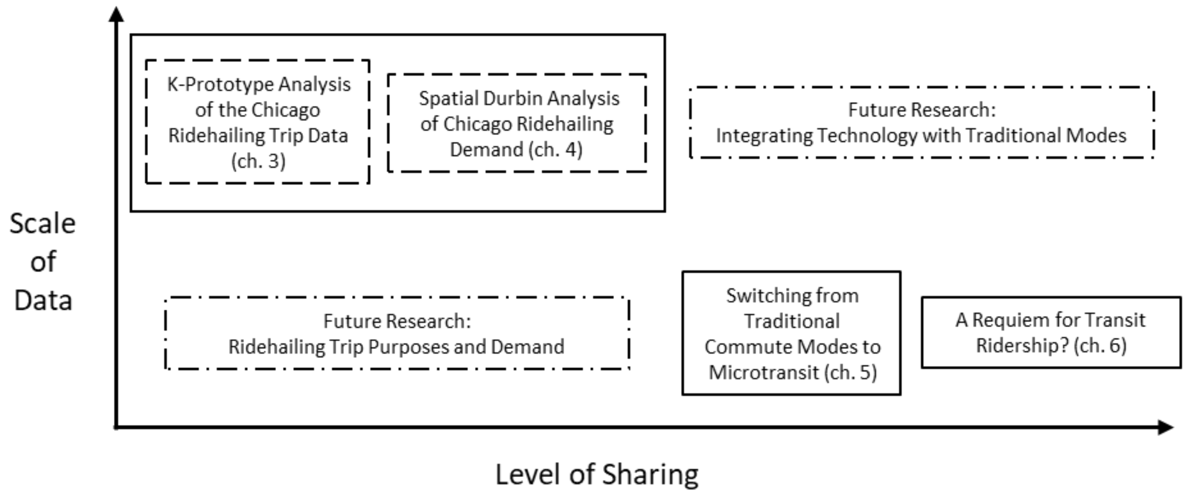

Figure 27 The range of completed research and areas for future research

With this wealth of data, the data can be segmented in several ways and contain rich information on who is making the trip and why. One way the data can be segmented is by trip purpose. Evidence from this thesis points towards ridehailing being used for irregular trips, but whether these trips are to access healthcare, recreational, or shopping activities is unknown. By segmenting trips by their purpose, researchers can disentangle the cost, travel time, and privacy tradeoffs under different contexts. Values of time differs by trip purpose (Lavieri & Bhat, 2019b; Small, 2012), and these values can be used to inform policies such as congestion charging. Another piece of data that can be collected using questionnaires are the travelers' mode choice sets. Multi-modality is a growing body of literature (Kuhnimhof et al., 2012; McLaren, 2016; Scheiner et al., 2016). Heinen and Mattioli (2019) find that multi-modality in England decreased despite overall private auto use also decreasing, revealing a complex relationship between modes and their utilization given that non-autos were not necessarily replacing auto trips. With the availability of new shared mobility services, the following research question can possibly be answered with comprehensive data. What are the effects of ridehailing on multi-modality? By utilizing mobile trace data and pairing it with supplementary data on trip purpose and alternatives that were considered, researchers can better understand when ridehailing has the highest utility and what it is being compared against. Similarly, the general attractiveness of MaaS can be researched.

A major benefit of MaaS is the bundling of several services together, but whether the bundling of services is attractive is not readily known. Transfers in transport systems cause disutility (Garcia-Martinez et al., 2018; Guo & Wilson, 2011; Schakenbos et al., 2016). Additionally, Ton et al. (2020) finds that the mode choice set is often smaller than what researchers assume. Simplicity of travel, using familiar modes with the fewest transfers, could be more attractive than bundling trips together even when it is faster and cheaper. The microtransit and RTA data are survey-based and are subject to several biases. Revealed preferences collected by mobile tracing methods is a solution to avoiding biases in surveys. Collecting big data and understanding shared mobility as a whole may uncover how it can be used to achieve better transportation accessibility. If MaaS is implemented, when does using it make sense?

Encapsulating these future research topics are the long-term effects of the pandemic. While mobility providers have control over their services, they respond to the derived demand for travel which they have little control over. The pandemic forced several companies to institute teleworking, and this has accelerated the normalization of working from home rather than at the office such that it is more a choice rather than a necessity (Parker et al., 2022). During the pandemic, people used teleworking as a means to live in areas without having to worry about physically commuting (Scigliano, 2021). Preliminary research is finding that teleworking is allowing for workers to re-optimize their residential and mode choices (Delventhal et al., 2022). However, Denham (2021) argues that this could inadvertently lead to greater urban sprawl. For shared mobility research to have meaning, it must account for the context in which those services are being utilized and the effects of its availability on current trends in residential choice.

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