Analyzing the Competitiveness of Transit-Integrated Ridesourcing Systems

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This thesis contains sections that have been previously incorporated in journal articles and conference proceedings, noted below:

Chapter 3: Trip Typology and 903 Flex Analysis

Two journal articles and one conference proceeding form the basis of the research described in this chapter, including the introduction of spatial characteristics analysis, methodology, results, discussion, and conclusions.

"Spatial Characteristics of Transit-Integrated Ridesourcing Trips and Their Competitiveness with Transit and Walking Alternatives": Published in March 2020 in the Transportation Research Record. This paper was co-authored by myself and my supervisor, Dr. Chris Bachmann. I was the primary author of this paper.

"Temporal Changes in Transit-Integrated Ridesourcing Trip Patterns": Presented in June 2020 at the 55th Annual Meeting of the Canadian Transportation Research Forum. This paper was co-authored by myself, Emma Swarney, and our supervisor Dr. Chris Bachmann. I was responsible for the study conception, the methodology, and draft manuscript preparation. Emma worked as our undergraduate research assistant to implement changes to the transit and walking alternative matching algorithm.

"Longitudinal Analysis of Transit-Integrated Ridesourcing Users and Their Trips": Published in February 2021 in the Transportation Research Record. This paper was co-authored by Emma Swarney, Devin Feng, and our supervisor Dr. Chris Bachmann. Emma and I were co-first authors on this paper, and I worked with Emma daily on all stages of the project, from study conception through changes and implementation of some of the methodology, to building the final manuscript. The paper finishes the work started in our "Temporal Changes" paper, and extends the framework first built in the "Spatial Characteristics" paper.

Chapter 4: RP-SP Survey and Chapter 5: System Evaluation

One conference proceeding shares sections with these chapters, including the survey design and results, and the mode choice model design and results.

"Your Transit Driver has Arrived: Suburban Preferences for Transit-Integrated Ridesourcing": Presented in June 2022 at the 57th Annual Meeting of the Canadian Transportation Research Forum. This paper was co-authored by myself and my supervisor, Dr. Chris Bachmann. I was the primary author of this paper.

Two other chapters make use of information that has been published in these bodies of work:

- **Chapter 1: Introduction**: Similar points of discussion introducing the topics covered in these publications.
- **Chapter 2: Literature Review**: Some references and literature discussion concerning ridesourcing, shared mobility, surveys, and mode choice models.

Abstract

Ridesourcing platforms operated by transportation network companies are becoming increasingly popular. Municipal transit agencies have rapidly launched integrated systems with ridesourcing vehicles to extend the reach of their fixed-route transit networks and as a response to changes in the transportation system. These integrated systems have not been critically evaluated, and agencies are implementing ridesourcing systems without much precedence or guidance concerning the integration of transit and ridesourcing. Past research on demand-responsive transport assumed the majority of trips were booked a day or more in advance using subscriptions. This research considers how ridership may change due to the immediacy and convenience of app-based booking for on-demand transit.

The objective of this research is to determine the spatial characteristics of transit-integrated ridesourcing networks that best support and encourage use of the greater transit network. A series of spatial attributes were identified based on literature and existing systems, which formed the basis of the research. A recent transit-integrated ridesourcing pilot in Waterloo, Ontario was evaluated for competitiveness with other alternatives and to observe changes in spatial and temporal characteristics. Through this evaluation, a trip typology was developed that other transit agencies can use to evaluate the spatial competitiveness of their transit-integrated ridesourcing systems. The findings of the evaluation indicate that the trips taken in the pilot were mostly complementary to transit, and that the pilot was both growing in weekly ridership and trending towards trips that do not compete with fixed-route transit.

A revealed-preference/stated-preference survey was conducted in the same geographical area as the former pilot to determine the combinations of spatial attributes that would best entice residents. 230 responses were gathered from the survey. Qualitative questions from the survey revealed that COVID-19 was not perceived as a deterrent for fixed-route transit or transit-integrated ridesourcing, that car ownership and bicycle ownership correlated with the respective likelihood of driving or cycling, and that fare card or pass ownership did not correlate with the likelihood of taking transit. The lack of familiarity among respondents with the pilot that had previously operated in the area indicates that poor advertising of the service may have been a contributor to ridership not meeting agency targets.

A non-linear Bayesian mixed logit model was estimated using the stated-preference portion of the survey, using 2990 best and worst observations (13 scenarios from each of the 230 respondents). The model was applied to a series of representative trips through scenario analysis to determine how mode share would change under various combinations of spatial and operational characteristics. Respondents were found to have similar perceptions of transit-integrated ridesourcing and fixed-route transit. For time attributes (e.g., total, wait, walk), respondents showed the highest sensitivity in the 5-10 minute range. Adjusting the demand patterns of the transit-integrated ridesourcing service to be more permissive of different origin-destination pairs considerably increased the expected mode share for transit-integrated ridesourcing, but may require caution due to the negative impacts in some scenarios for fixed-route transit. The largest shifts in mode share came from directly charging for parking, where the mode share for auto dropped from over 90% to under 50% in most cases.

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After over a decade at Waterloo, I have much to be thankful for and many people to appreciate that helped me along my unconventional journey from an undergraduate student in nanotechnology engineering studying very small things to a doctoral candidate in civil engineering studying very big things. I was fortunate to find my passion for public transit in undergrad and be able to dedicate my working time toward furthering that love. I know not everyone is fortunate enough to have that opportunity.

First, I want to express immense gratitude and thanks to my supervisor, Prof. Chris Bachmann, who took me in as one of his very first master's students, and who I have been fortunate enough to have as a mentor for over eight years. Chris is incredibly resourceful and intelligent, yet also very practical and down-to-earth, which has been an incredible combination to have in a supervisor. I have greatly appreciated our frequent and open conversations, which helped me find a positive relationship with academia, clarify my career motivations, and strengthen my hot takes on land use and transportation. His guidance in and support of my research, teaching, jobs, and life gave me the confidence to continue in graduate studies with certainty.

I also want to thank Prof. Jeff Casello, who co-supervised my master's thesis and was part of my examining committee. Jeff taught my favourite undergraduate course (transit), which I was fortunate enough to be a TA for in almost every year of my graduate studies and teach as the instructor twice, using his excellent course structure as my foundation. My experience with the course was only one of many great opportunities Jeff enabled. He has had valuable feedback and perspectives throughout both my master's and doctoral studies, and I am grateful for his wisdom and guidance.

Thanks to Prof. Liping Fu and Prof. Clarence Woudsma for agreeing to be part of my examining committee and providing thorough feedback in my comprehensive exam and thesis. I would also like to thank Prof. Catherine Morency for agreeing to be my external examiner and providing feedback on my final work. All three of them bring valuable and different perspectives on transportation.

I have been able to interact with many other great students and staff in engineering and planning that have made my time at Waterloo more colourful. In particular, Devin Feng, Jessica Keung, and Tina Lin have been incredible friends and fellow graduate students throughout this process. I am so thankful for our wide-ranging chats, ad-hoc therapy sessions, Starbucks breaks, and off-campus hangouts – my time as a doctoral student would have been much lonelier without them. Devin, Ming Xu, Rudi Rendel, and Tori Kim were also my teaching assistants when I taught transit. I honestly could not have pulled the course off each time without their help, all of them are incredibly capable and reliable. Emma Swarney was a great URA, then a great co-op student, and helped me finish the final part of the 903 Flex project. It has been rewarding to help Emma nurture her own love for multimodal transportation, and I am grateful for her help during her time in our group. The staff in the Department of Civil and Environmental Engineering have also all been wonderful and have helped me at various points in my graduate studies. Eleanor Wilson and Jessica Rossi in particular provided many long, entertaining, and therapeutic conversations – thanks for being my staff-side hype team.

Many of the graduate students I have mentioned and later worked with were also students I taught at some point in my graduate studies. There are many more students I taught that I am grateful to have met and learned from. I believe teaching is a two-way process, and I learned a lot from their experiences and perspectives. I have special appreciation for the civil engineering class of 2019, who I met on their first day at Waterloo as their SuperHuge in undergrad, who patiently sat through my first (bad) tutorial as a teaching assistant in my master's, who were my classmates in infrastructure planning in my doctoral studies, and who were my first students as a lecturer for transit.

There are academics and agencies that (in some cases, indirectly) helped me complete my research and expand my academic horizons. Will Towns at Grand River Transit was instrumental in providing me the full database of 903 Flex trips, which spurred much of the subsequent research. Prof. David Hensher, Prof. John Rose and Prof. William Greene wrote the excellent book *Applied Choice Analysis*, which I was attached to as I worked to complete my survey research and model. Prof. Rose also provided me with guidance in a crucial stage of my survey development. Prof. Vukan Vuchic wrote the *Urban Transit* duology, which is an incredible reference for public transit that I still refer regularly. Sawtooth Software gracefully provided a free version of their Lighthouse Studio software, without which I would have had a much harder time completing my survey, and the technical staff were incredibly helpful in diagnosing some more arcane software and theory issues I ran into.

I have an excellent friend network outside of Waterloo (although many of whom I met here) that continue to make my life better. Zac Young, Nan Huang, and Cody Hutt have been incredible friends for a long time – I am thankful for our frequent and lengthy conversations about urbanism, gaming, work, and our life joys and stresses. Rob Reid, Kristina Lee, and Filzah Nasir were wonderful apartment-mates that broadened my perspectives and brought me joy in our time living together. Anand Lopez and Rana Isak helped drag me out of my apartment to go to events or do exercise, which ensured I avoided becoming a stereotypical grad student shut-in. Chris Warren introduced me to Overleaf and LaTeX, which I have been sure to evangelize to all the other graduate students (and my supervisor Chris, to limited success).

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Dedication

For my partner Michael, who spent countless hours helping me through my thought processes and buoying my spirits on my more stressful days. I am excited to start the post-graduate school part of our lives together.

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List of Abbreviations

ADA aggregate dissemination area

APTA the American Public Transportation Association

ASC alternative-specific constant

DARP dial-a-ride problem

DART dial-a-ride transit

DRT demand-responsive transport

FSA forward sortation area

FTA Federal Transit Agency

GRT Grand River Transit

HBO home-based other

HBS home-based school

HBW home-based work

i.i.d. independent and identically distributed

IIA independence from irrelevant alternatives

IVTT in-vehicle travel time

LRT light rail transit

MNL multinomial logit

RLH root-likelihood

RP revealed-preference

RP-SP revealed-preference/stated-preference

SP stated-preference

TAZ traffic analysis zone

TCRP Transit Cooperative Research Program

TIR transit-integrated ridesourcing

TNC transportation network company

TRB the Transportation Research Board

TTS Transportation Tomorrow Survey

VKT vehicle kilometres travelled

Chapter 1

Introduction

1.1 Shared Mobility

Shared mobility is a broad and expanding category of mobility services, encompassing delivery sharing, vehicle sharing, and passenger ride sharing (Shaheen & Chan, 2016). Terminology for different forms of shared mobility services are beginning to mature, and often differ between academic literature and public discourse. Reviewing this terminology may seem trivial, but it is essential in understanding the nuance between different modes.

Figure 1.1 depicts the growing definitions of different forms of shared mobility. Shaheen and Chan (2016) consider shared mobility to be a set of as-needed mobility options that users share with each other, and use the terminology to reference private-sector services, specifically excluding publicly-owned and operated demand-responsive transport (DRT). Feigon and Murphy (2016; 2018) adopt a broader definition across their reports, defining it as any form of shared-use service, including publicly-owned and operated demand-responsive transport (DRT) and conventional fixed-route public transit.

Passenger modes that fall in the broad definition of shared mobility can be differentiated by several attributes, as shown in Table 1.1. Modes whose vehicles and systems are operated by an individual, or private transport (e.g. user-owned personal auto, walking, user-owned bicycles), and conventional fixed-route public transit are included for comparison. Ownership differentiates whether the mode is offered through a private agency, a public agency, the user, or a driver. Ridesourcing and ridesplitting services specifically use driver-owned vehicles with a privately-owned dispatching system. OD flexibility indicates the degree of origin and destination personalization. Personal modes allow passengers to pick up users at or near their origin and destination, while limited modes only allow for

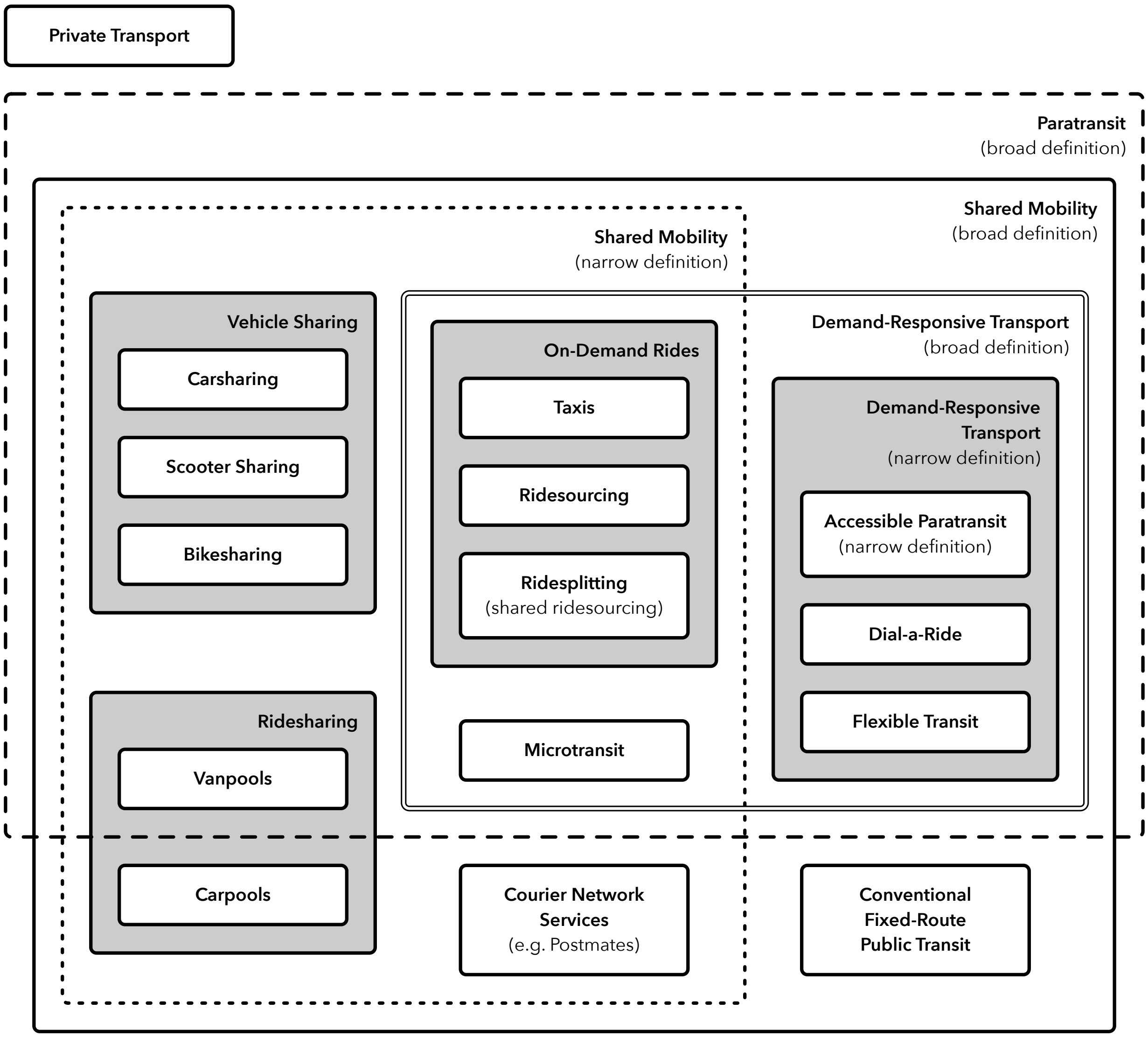


Figure 1.1: Definitions for forms of shared transportation modes, adapted from (Feigon & Murphy, 2016, 2018; Kittelson & Associates et al., 2013; Shaheen & Chan, 2016; Teal et al., 2020; Vuchic, 2007)

travel between a flexible set of locations or drop-off zones in a network. The directness of the route is indicated by how personal the route is and whether the ride is shared or not. Partially personal routing indicates that the route of the trip is influenced by the passenger and other passengers or system design characteristics (e.g., routes that slightly deviate). Shared rides require the passenger to accept that rides could be shared with strangers, which introduces some deviations between a passenger's origin and destination as other passengers are picked up or dropped off. Modes can also be offered to the public, or have limitations on who is able to use it. Modes that are offered privately are typically as part of a service with a list of registrants or are provided at the discretion of the owner.

Table 1.1: Characteristics of shared mobility passenger modes

Mode	Vehicle / System Owner	OD Flexibility	Routing	Shared Ride	Availability
Private Transport	*User*	*Personal*	*Personal*	*No*	*Private (owner discretion)*
Accessible Paratransit	Public agency	Personal	Partially personal	Yes	Public (mobility limitations)
Dial-a-Ride	Public agency	Personal or limited	Partially personal	Yes	Public (booked in advance)
Flexible Transit	Public agency	Limited	Partially personal, fixed area	Yes	Public
Microtransit	Private agency	Limited	Partially personal	Mixed	Private (service)
Ridesharing	Driver	Personal	Personal	Yes	Private (owner discretion)
Ridesourcing	Driver and private agency	Personal	Personal	No	Private (service)
Ridesplitting	Driver and private agency	Personal	Partially personal	Yes	Private (service)
Taxis	Driver or private agency	Personal	Personal	No	Public
Vehicle Sharing	Public or private agency	Personal	Personal	No	Private (service)
Conventional Fixed-Route Public Transit	*Public agency*	*None*	*Fixed*	*Yes*	*Public*

Similar to the use of 'shared mobility', paratransit and DRT have evolved to have two intended meanings. The broad definition of paratransit is a suite of services that fall between private transport and conventional public transport (Vuchic, 2007). A narrow definition uses paratransit as a colloquial synonym for accessible paratransit, which is a publicly-operated personalized service available to people with mobility limitations (City of Regina, n.d.). The narrow definition is used predominantly in municipal transit agencies, in part because most transit agencies are legally mandated to offer it under human rights legislation (National Aging and Disability Transportation Center, n.d.), or voluntarily offer it to as a way of meeting accessibility needs (Ontario Human Rights Commission, n.d.). Even among individuals that follow the broader definition, the use tends to be limited to publicly provisioned services or taxis in practice, ignoring newer forms of shared mobility.

The broad definition of DRT includes taxis, ridesourcing, microtransit, and other modes that are traditionally operated to some extent through private partnership, because when those modes are integrated with a transit-agency they have similar passenger-facing characteristics to dial-a-ride transit (DART) (Teal et al., 2020). The narrow definition of DRT tends to be more prevalent (previously referred to in this thesis as 'publicly-owned and operated DRT'), and only refers to on-demand service provided as part of a public transit network (Kittelson & Associates et al., 2013). This includes DART, accessible paratransit, and flexible transit (e.g. route-deviated, request stops), which are all offered through a public agency with shared rides and personalized or partially personalized routing and origins/destinations. The narrowest use of DRT refers only to dial-a-ride transit (DART) service, which is somewhat synonymous with DRT in the same way that paratransit is synonymous with accessible paratransit. Dial-a-ride transit is increasingly becoming a somewhat antiquated term, since many DART services may be booked through an app or website like other on-demand services, but is still one of the most common ways to refer to this mode of transport due to convenience.

Furthermore, the term ridesharing is often applied to many forms of shared passenger rides, from informal carpooling between friends to app-based driver-passenger matching services. The latter services are differentiated in literature as 'ridesourcing' (Curtis et al., 2019; Shaheen & Chan, 2016), and the companies that tend to offer ridesourcing services through digital platforms are referred to as transportation network companies (TNCs).

Because of the overlapping and somewhat complex definitions of these terms, particularly for paratransit, this thesis uses 'shared mobility' to refer to the broad spectrum of modes and mobility options between private transport and conventional public transit, which all require some sharing of the vehicle or ride, but have some element of flexibility in service. The use of the term 'paratransit' is avoided, in favour of more descriptive modes (e.g. accessible paratransit), and 'DRT' is used where necessary in the broader sense to refer to shared modes that are integrated in some way with the transit system. Finally, 'ridesourcing' is used to discuss individual ridesourcing (non-shared rides) and ridesplitting (shared rides) through a TNC-style booking system, unless a distinction is required. Other terms introduced in the figure and table are not directly relevant to this research, but are included for completeness and are defined in the glossary.

1.2 Growth of Ridesourcing

Municipal transit agencies are experimenting with integrating different forms of shared mobility in an effort to increase their transit reach into suburban areas, which are harder to service, in ways that complement existing public transit networks (Feigon & Murphy, 2016). Traditional efforts to expand service have been through DRT, typically either through flexible transit or DART for general service, and through accessible paratransit for people with mobility limitations. The success of these traditional DRT services has been limited, as the bulk of travel has been done through personal auto or conventional public transit for the past few decades in Canada. Part of this may be because limited technology available for dispatching vehicles in older DRT services meant that rides often needed to be booked well in advance (often up to 24 hours), while regular transit service and personal auto tended to be predictable and instantaneous.

With the advent of more immediate and connected technology, primarily due to smartphones, transit agencies have considered a wider range of modes to integrate with transit. Ridesourcing is one of the newer shared mobility options that transit agencies have piloted in their networks, in part due to the reliability of their routing algorithms, the quality of their mobile apps, and their immediate service, which have made ridesourcing more popular than DART. Some cities in North America have entered into partnerships with TNCs, who operate app-based platforms connecting passengers and drivers through a standardized fare structure and set of policies. There is belief that ridesourcing, along with other shared mobility services, can help potential passengers more easily connect to the existing transit system (Shaheen & Chan, 2016). Ridesourcing service that is integrated into the public transit agency is referred to in this research as transit-integrated ridesourcing (TIR).

TIR falls in the same family of modes as DRT. While traditional forms of DRT rely on pre-scheduled trips typically booked at least a day in advance (Rodman, 2022), transit-integrated ridesourcing uses app-based booking to schedule on-demand ridesourcing-style service operated through partnership with a transit agency. Ridesourcing that operates privately originally differed from taxis in a similar way: TNCs that operate ridesourcing services invested heavily in quick and easy-to-use apps that users preferred over taxi dispatch services. The simpler and more immediate methods for receiving service may positively influence the desirability of ridesourcing as part of the transit system. Ridesourcing can be provisioned either as a private travel mode or pooled with other passengers, which is sometimes differentiated by the term ridesplitting (Section 1.1). Throughout this thesis, TIR is considered a ridesplitting service integrated with public transit. In practice, this results in characteristics similar to DART (Table 1.1), but without requiring advance booking.

Although some cities have integrated ridesourcing into their networks, or in some cases, have built entire networks around ridesourcing (Town of Innisfil, 2019), there are few independent analyses of the trip patterns in ridesourcing systems, particularly TIR systems. As a result, the success or failure of these services is often reported by the public agency or the private operator, who often do not share the corresponding individual trip data with external parties. Part of the success or failure includes understanding how TIR impacts the greater transportation system. The influence TIR has on public transit ridership, auto deterrence, private ridesourcing, taxis, and active transportation is still not fully understood.

1.3 Problem Statement

Ridesourcing platforms operated by TNCs have experienced rapid growth over the past decade, prompting transit agencies in North America to consider integrated service with TNCs of some form, either due to competition concerns or a belief that ridesourcing may provide new ways of expanding the reach of public transit, specifically in suburban or lower-density regions. Several transit agencies have launched pilots to integrate ridesourcing with existing fixed-route transit service (e.g., the Region of Waterloo), and in some cases, have completely relied on ridesourcing. While integration on some degree may expand use of public transit, most agencies are implementing ridesourcing pilots without much precedence or guidance on how TIR systems can be implemented to encourage ridership. The design of TIR networks should ensure changes in mode share that improve the share of active transportation and public transit, yet the characteristics that lead to these outcomes are poorly understood. If transit agencies integrate ridesourcing into their networks without considering behavioural factors and mode competitiveness, transit agencies could be responsible for contributing to lower fixed-route transit and active transportation use, inequitable communities, and ineffective projects.

1.4 Research Objectives

The goal of this research is to determine which spatial characteristics of TIR best support and encourage use of the greater transit network in regions with suburban densities and travel patterns. A suburban area of the Region of Waterloo with former TIR service is used as the focus of this research, to best understand how similar areas would respond to different spatial characteristics of TIR. To achieve this goal, a series of objectives are defined:

1. Document and propose TIR system types based on existing integrations, literature-based proposals, and unstudied combinations of individual attributes
2. Collect spatial, temporal, and passenger characteristics of existing TIR trips
3. Assess the current trip characteristics of existing TIR trips and develop a typology of trip types based on their competitiveness with public transit and active transportation
4. Design and conduct a revealed-preference/stated-preference (RP-SP) survey comparing various forms of public transit, TIR, private ridesourcing, and active transportation
5. Estimate a discrete mode choice model from the survey data
6. Quantify the range of mode share impacts of TIR under different system configurations
7. Determine the TIR system characteristics that maximize active transportation, transit ridership, and TIR mode shares
8. Propose guidelines supporting policies and regulations aimed at increasing the probability of positive external impacts for TIR systems

Each objective was achieved through different methods. A literature review was conducted for the first objective. Travel data from a former TIR pilot was used for the second and third objectives. An RP-SP survey in the former pilot area was used for the fourth and fifth objectives. A sensitivity analysis was used for the sixth and seventh objectives. To complete the research, the eighth objective was met by synthesizing the findings of the other objectives to understand how best to encourage system integration and ridership.

1.5 Scope

This research focuses on TIR models for suburban areas in Ontario. Specifically, the Region of Waterloo is used as a study area. Grand River Transit (GRT), which is the regional transit agency, operated a series of three flexible transit pilots in 2019, one of which was a TIR service operated through RideCo in a low-density suburban neighbourhood (Grand River Transit, 2019c). The core of GRT's conventional transit network is a north-south light rail transit (LRT) line, which connected to the TIR pilot, and a series of recently redesigned east-west express bus routes. While an exhaustive understanding of TIR impacts would incorporate detailed studies on every suburban region in the province, the intent of this research is use the study in Waterloo to develop terminology and practices for consideration in other regions, and as a starting point for understanding how residents in Ontario may perceive attributes of TIR in comparison with other modes.

The inspiration for this research comes partly from autonomous vehicles, which are a frequently discussed form of future shared mobility in passenger transportation. Autonomous vehicles are not the focus of this research, but the application of these results to autonomous vehicles may be valid with minimal changes to the parameters. Autonomous vehicles without a driver are discussed in literature as operating similarly to existing ridesourcing systems: the passenger hails the vehicle from a TNC, the vehicle picks them up and takes them to their destination, then the vehicle drops them off and moves on to the next passenger (Jin et al., 2018; Nazari et al., 2018; Hyland & Mahmassani, 2018). The only practical difference to the passenger in TIR is that there is no driver present if the service is automated, but passengers are still likely to 'source' rides from TNCs, which is a minor shift from the current model of sourcing rides from drivers *working* for TNCs. If the characteristics of active transporation and transit-positive TIR can be determined, then there is some direction toward how an automated version of this service would best be integrated to positively support other modes.

1.6 Thesis Structure

This thesis consists of five chapters. Chapter 1 introduces the research. A brief introduction to the growth of ridesourcing and its relationship to public transit is provided. The problem identified is a lack of understanding on which characteristics of ridesourcing integrated with public transit best support fixed-route transit networks, leading to the objectives of this research and the scope of the project.

Chapter 2 reviews the relevant literature in the topics of shared mobility, the historical basis for integrating shared modes with transit, the state of ridesourcing and how it has shifted perceptions of transit integration, recent Canadian TIR systems, the current understanding of preferences and attributes for TIR, and the synthesis of TIR characteristics in the form of system types. The gaps in the literature show that while there are recent advances in understanding TIR, and there are many precedents for how to integrate shared modes into conventional transit networks, attempts to integrate ridesourcing with transit networks have key differences from traditional DRT that require new behavioural analyses and a detailed and rigorous evaluation of the impact on other modes under various scenarios.

Chapter 3 analyzes the 903 Flex TIR pilot that operated in the Region of Waterloo from 2018-2019. 4536 completed trips were reviewed, covering the entirety of the pilot's operation. Trips were compared to the closest public transit, cycling, and walking alternatives for competitiveness. A trip typology is proposed which identifies TIR trips based on their competitiveness with public transit alternatives. Trip types, users, and alternatives are assessed spatially and temporally to understand the impacts of the pilot.

Chapter 4 discusses the design, dissemination, and findings of a RP-SP survey that studied attributes of TIR. The survey was conducted in the same area as the 903 Flex pilot, to understand which organizations of TIR would best serve residents in the area. Respondents were asked to compare TIR, auto, fixed-route transit, cycling, and private ridehailing using varying attribute levels, and were asked additional questions before and after the stated-preference (SP) section. General survey completion and uptake statistics, demographics, COVID-19 influences, and the revealed-preference (RP) section are assessed.

Chapter 5 continues from the survey results, presenting the methodology and results of a mode choice model calibrated from the SP section of the survey. A system evaluation is conducted using elasticities determined from the findings of the model, and a sensitivity analysis of scenarios that consider multiple design objectives and existing system types. The sensitivity analysis connects the attribute elasticities from the survey findings to the expected impacts of different TIR system types, to determine which types best meet a variety of different goals.

Chapter 6 concludes the research and proposes guidelines for implementing TIR in suburban areas like the 903 Flex area. Thesis contributions are identified and future work items are suggested.

Chapter 2

Literature Review

2.1 Evolution of Demand-Responsive Transport

Fixed-route conventional public transit typically focuses on urban mass travel along high-density corridors. While providing high-frequency, high-coverage transit in dense urban areas is cost-effective for a transit agency, providing adequate coverage in suburban areas can be challenging due to the lower ridership and increased operating cost per passenger (Aex, 1975). Demand-responsive modes that offer door-to-door or personalized service, like taxis, have been active in some form since the sixteenth century, when hackneys and fiacres first operated in European cities (Vuchic, 2007). In the context of new on-demand pilots and services, a review of prior DRT systems is essential to understand the prior technologies, successes, and failures in on-demand transit.

The integration of demand-responsive modes with conventional public transit was not seriously explored until the 1970s. Flexible transit that blends elements of fixed-route transit and DRT (e.g., route deviation) also became more common in the 1970s, further developing in the following decades (Koffman, 2004). Increased environmental awareness, social concerns about the quality of life in urban areas, and high oil prices caused by an energy crisis sparked a desire to shift users away from auto-dependency (Higgins, 1976; US Transportation Systems Center & US Technology Sharing Program Office, 1974). At the time, fixed-route transit and taxis were the dominant non-auto vehicle-based modes. Public transit was economically restricted to higher densities, and taxis offered a high quality of service but at a high user cost, leaving a gap in the low-density, low-cost shared mobility space. The rapid spread of suburbs throughout the preceding decades further contributed to the increased importance of finding ways to service low-density areas. Many agencies turned to transit-integrated DRT to reach transit-poor areas, which combined the occupancy efficiency of public transit with the flexibility of taxis. DRT services were intended to feed into the fixed-route transit service, replace low-performing fixed-route services in off-peak hours, and shift users from auto.

Dial-a-ride transit (DART), where a user calls a centralized dispatch service to book a ride, was one of the most common integrated DRT innovations in the 1970s (US Transportation Systems Center & US Technology Sharing Program Office, 1974). The development of DART in this period varied between the United Kingdom, the United States, and Canada. British systems were first offered as small off-peak specialized services, then as regular intensive urban services with formalized control offices and high passenger loads. Both types of systems were unsuccessful and most did not last more than a few years. A third type found more success, as a rural system providing connectivity to urban areas. Generally, DART was found to have longer staying power if they were a niche marginal service, the transit agency found ways to provide the service at a lower cost, or the systems filled a niche that could not be served by fixed-route transit (Oxley, 1980). In the United States, because of the lower density and transit usage, there was more effort to develop long-lasting DART systems, although these systems tended to have lower productivity and higher subsidies than British ones (Oxley, 1980). The Canadian DART experience fell somewhere between the British and American experiences, with better productivity than American systems (Oxley, 1980) and higher success due to harsher winters and lower car ownership than in the United States (Higgins, 1976). The most successful system was the Regina Telebus, which operated for over a decade. The system operated using prescheduled service like other DART systems, and was first used to replace fixed routes with the highest operating subsidies (Tasker, 1973). Riders were charged an extra fare (10 cents on top of the fixed-route 25 cent fare), and the end goal was to replace all high-subsidy fixed-route service with the Telebus.

Ultimately, even with the Telebus's success, the system was cancelled in the 1980s (Scott, 2010), as were most other DART systems. A notable failure was the Santa Clara County DART, which provided an early set of warnings for other operators considering DRT systems (Carlson, 1976). The Santa Clara system was started in 1974, after the Santa Clara County Transit District (SCCTD) took over all bus operations and set a goal of covering 97% of the population. After under six months, the DART was discontinued for four main reasons. First, passenger communication was poor, with potential passengers needing to call multiple times over multiple hours to successfully book a ride. Second, the entire county was included on the service on the first day, so smaller issues like booking and routing problems became much larger because of the scale of operation. Third, a 5-10 minute wait time standard was set (requiring 334 buses during peak service) but only 40-50 buses were available, so wait times were much longer in practice. Passengers therefore only ended up using the service if it was booked well in advance and they had a long enough time window to get a return trip. Fourth, shortly after service started, the Santa Clara County Superior Court ruled that the SCCTD was illegally operating the DART service in competition with the existing taxis, requiring the agencies to buy out the competing companies immediately or discontinue service. The DART service was discontinued before negotiations with taxi companies ended. The primary takeaways for transit agencies were to begin small, manage passenger expectations around service quality, ensure processes were tested and clear, and consider the impact on other modes including taxis.

In a retrospective of British DART systems, Nutley (1990) identified high labour costs, low ridership potential, low potential for fare increases, poor diversion from auto versus other modes, and poor coordination with fixed-route transit as the main failures of their DARTs systems. In many cases, DART systems were replaced by flexible minibuses with route deviation and hailed stops that connected the origin-destination pairs with the highest demand from the on-demand service. The replacement flexible minibuses then tended to have higher ridership with lower operating costs, and in turn many of these minibuses slowly were replaced with conventional transit. Enoch et al. (2004) evaluated the cause of failure for a series of Australian and British DRT systems, finding the main issues to be poor partnerships with private partners and taxis, ineffective marketing, too much flexibility in trips, lack of commitment, and poorly budgeted long-term financing. In some cases, DRT worked better in lower-density, suburban land uses, but some systems still had challenges in areas with highly transit-hostile designs (i.e., challenging layouts to serve in a timely fashion).

The state of practice on providing suburban transit service between the popularity of DART and the advent of ridesourcing may be best reflected through reports from the Transit Cooperative Research Program (TCRP), an American-based research program operated jointly by the Transportation Research Board (TRB), the Federal Transit Agency (FTA), and the American Public Transportation Association (APTA). Their first guidelines on suburban mobility in 1999 reviewed existing cases of suburban transit provision and proposed recommendations and warnings based on these experiences (Urbitran Associates et al., 1999). Among the recommendations were controlling cost, choosing vehicle types of appropriate size, and ensuring that shared mobility options like DART provided good linkages with fixed routes. There was also acknowledgement that DRT services with a lack of zonal structure or linkage to fixed-route transit resulted in prohibitive costs. An update to these guidelines (Urbitran Associates et al., 2006) found that flexible transit options like deviated fixed-route services were proving less popular with passengers, and more flexible options like DART, airport shuttles, and specialized accessible transit were more favourable. Incorporating accessible paratransit into generalized DRT services was also seen as one method of keeping down costs by removing the need to maintain two DRT services. A separate review of flexible transit options (Potts et al., 2010) found that while implementation methods varied for different users, there was a prevailing conclusion among agencies that flexible transit of any form was useful for transitioning away from full demand-responsive service in areas with common destinations, and that flexible services were a good way to integrate suburban residents into the fixed-route network.

2.2 Transit-Integrated Ridesourcing

With the advent and growth of ridesourcing, transit agencies have placed renewed efforts into exploring on-demand transit service including TIR (Section 1.2). In its most literal form, TIR is a publicly-integrated, shared, on-demand service using an app-based platform to immediately book rides from drivers in driver-owned vehicles (typically cars). The primary difference from DART is the ability to immediately book service in a more user-friendly fashion. Many systems are comparable to TIR, and are categorized as such in this research. Comparable systems are specifically integrated into a public transit agency, open to the general population, able to be booked immediately using a mobile app, and default to shared rides.

2.2.1 Demand Patterns

One of the clearer distinctions between TIR systems is the set of permitted demand patterns in the system. Figure 2.1 reviews the most common permitted demand patterns for TIR systems and spatially demonstrates sample trips that could be made using each pattern. The simplest pattern is many-to-one (Figure 2.1, A), where riders can make trips starting or ending at a central location, to or from any location in the service zone, which is typically a major transit hub offering intercity service (Klumpenhouwer, 2020). If the transit agency has more locations (generally less than 10) that they have identified as important hubs, they may use a many-to-few pattern (Figure 2.1, B), where riders can make trips starting or ending at the designated hubs, to or from any location in the zone (US Transportation Systems Center & US Technology Sharing Program Office, 1974). In both the many-to-one and many-to-few configurations, trips must start or end at the hub(s). Other riders

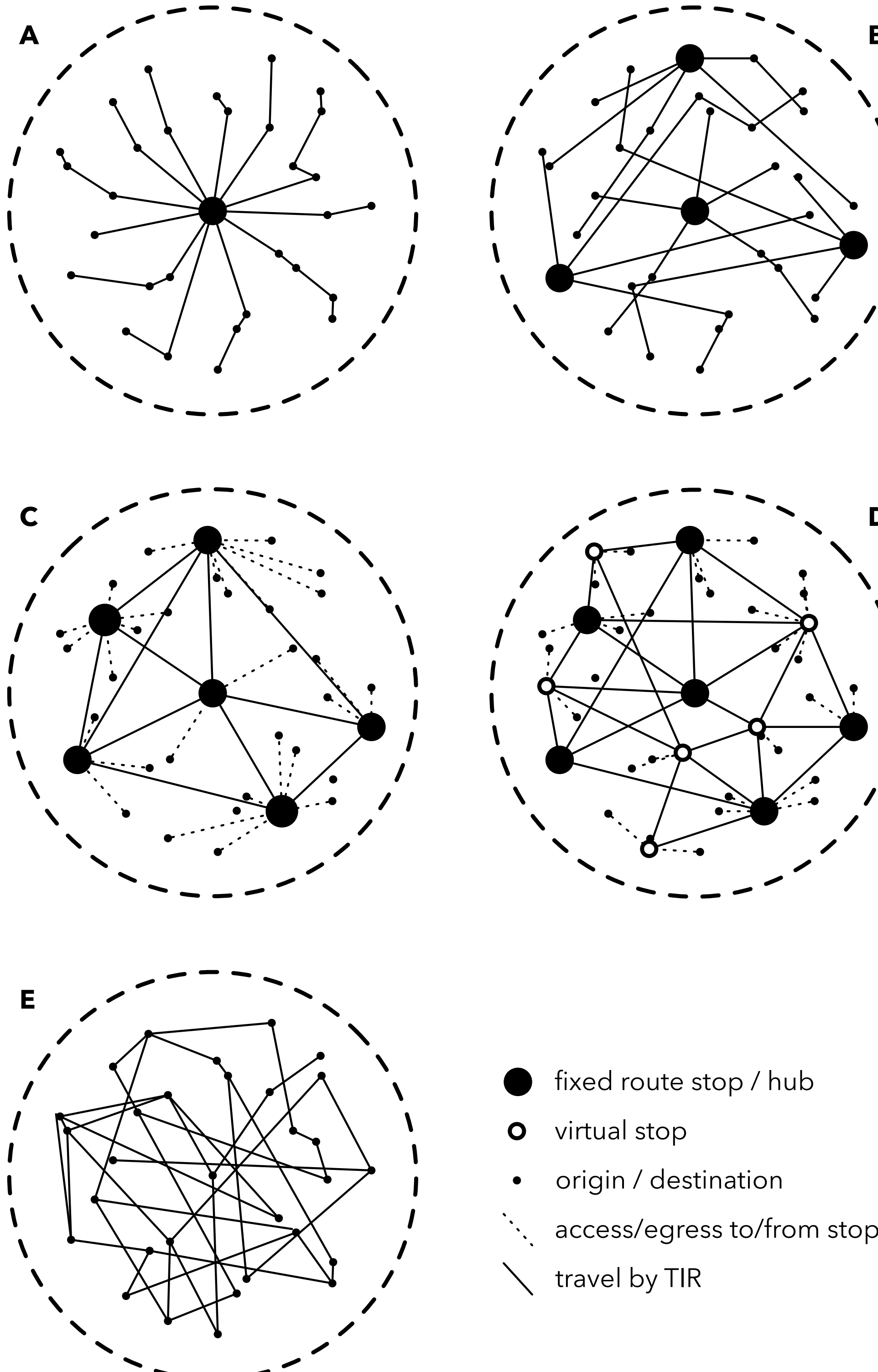


Figure 2.1: Differences in transit-integrated ridesourcing travel across permitted demand patterns. A: many-to-one, B: many-to-few, C: many-to-many (fixed-route stops), D: many-to-many (virtual stops), E: many-to-many (door-to-door)

may be picked up on the way to the hub, and multiple riders may be dropped off in one trip when leaving the hub, if riders are all in a generally similar travel path between the first/final location in the route and the hub. These systems are generally used for first/last-mile commuter service connecting to higher-order, fixed-route urban or intercity transit; smaller towns with highly monocentric travel patterns (e.g., an older, dense 'Main Street' surrounded by rural housing); or large, rural regions with multiple smaller towns or population centres.

Systems may also choose a many-to-many pattern, where TIR trips can be made between any two eligible locations in the network (Klumpenhouwer, 2020). The most restrictive pattern allows travel only between stops that support existing fixed-route transit, like bus stops (Figure 2.1, C). This may be convenient for agencies that want to use TIR as a replacement for fixed-route service in off-peak hours (e.g. late night service), and want to keep the stop locations the same in both fixed-route and on-demand service to minimize rider confusion. Transit agencies may choose add virtual stops (Figure 2.1, D), which are locations that are only serviced by the on-demand service but not by the fixed-route service. Virtual stops can be placed in locations that are relatively far from fixed-route stops to minimize access and egress time to the on-demand network for riders. Finally, a system may choose to not have any official stops, and allow complete door-to-door service (Figure 2.1, E). Each pattern has its own advantages: both the fixed stop and virtual stop many-to-many patterns allow for simpler and more direct routing compared to the door-to-door service, because there are a finite and deliberate number of origin-destination pairs, while the door-to-door many-to-many pattern eliminates access and egress time.

2.2.2 Recent Canadian Systems

TIR has rapidly expanded within Canadian transit agencies (Table 2.1), particularly in the last three years. Some systems are operated through an upper-tier regional (R) or county (C) government, but most are operated by lower-tier or single-tier local governments (primarily cities). Most of the recent TIR systems were launched with the intent of replacing fixed-route service in low-ridership routes. The growing market of TNCs with quick, improved, and established routing algorithms has lowered the barrier for transit agencies to consider adding TIR to their networks.

Pantonium, RideCo, Spare, and Via tend to be the most popular TNCs for TIR in Canada, and have provided the platform for most new systems. In a prior TIR system, Airdrie Transit used Cowboy Taxi, which was an upstart TNC based out of Airdrie. The

Table 2.1: Recent Canadian transit-integrated ridesourcing systems

Start	End	Location	Vehicle	Platform	Many-to	Fare	Weekday	Weekend / Holiday
2015	2016	Milton, ON	Car	RideCo	One (door)	Lower	Peak	None
2017	2019	Airdrie, AB	Unknown	Cowboy Taxi	Few (virtual)	Same	Unknown	Unknown
2017	–	Innisfil, ON	Car	Uber	Mixed (door)[a]	N/A	24-hour	24-hour
2018	–	Belleville, ON	Bus	Pantonium	Many (fixed)	Same	Night	Sat (eve-night), Sun (morn, eve-night)
2018	–	Longueuil, QC	Car	Via	Many (virtual)	Same	Peak	None
2018	2019	Waterloo (R), ON	Car	RideCo	Many (virtual)	Same	All-day	None
2018	–	York (R), ON	Car	Routematch	Mixed[b]	Same	Mixed[b]	Mixed[h]
2019	2019	Bowen Island, BC	Minibus	DoubleMap	Mixed[c]	Same	Eve	Morn-aft
2019	–	Calgary, AB	Van	RideCo	Many (virtual)	Same	All-day	Sat (all-day), Sun/Hol (mid, aft)
2019	–	Cochrane, AB	Minibus	RideCo	Many (virtual)	N/A	All-day	Sat (mid)
2019	–	Okotoks, AB	Minibus	RideCo	Many (door)	N/A	All-day	All-day
2020	–	Barrie, ON	Bus	RideCo	Many (virtual)	Same	Morn-aft	Sat (morn-aft)
2020	–	Chatham-Kent, ON	Minibus	Spare	Many (virtual)	Same	Eve-night or all-day	Sunday (morn-aft)
2020	–	Durham (R), ON	Van	Spare	Many (mixed)[d]	Same	All-day	Sat, Sun (all-day)
2020	–	Medicine Hat, AB	Bus	Spare	Many (virtual)	Same	Eve	Sun (All-day)
2020	–	Niagara (R), ON	Van	Via	Many (door)	Same	All-day	Sat (all-day)
2020	–	Regina, SK	Bus	Pantonium	Many (fixed)	Same	Eve-night	None
2020	–	St. Albert, AB	Bus	Pantonium	Many (fixed)	Same	Eve-night	Sat (eve-night), Sun (morn-aft)
2021	–	Cobourg, ON	Bus	RideCo	Many (virtual)	N/A	All-day	Sat (all-day), Sun (mid)
2021	–	Edmonton, AB	Minibus	Via	Many (virtual)	Same[e]	All-day	Sat (all-day), Sun (morn-aft)
2021	–	Fort Erie, ON	Van	Pantonium	Many (virtual)	N/A	All-day	Sat (all-day)
2021	–	Guelph, ON	Minibus	RideCo	Many (virtual)	Same	Morn-aft	Holiday (morn-aft)
2021	–	Hamilton, ON	Bus	Spare	Many (virtual)	Same	All-day	All-day
2021	–	Leduc, AB	Minibus	RideCo	Many (virtual)	Lower[f]	Morn-aft	None
2021	–	Milton, ON	Minibus	Spare	Many (virtual)	Same	All-day	Sat (all-day)
2021	–	North Bay, ON	Bus	Via	Many (virtual)	Same	Eve-night	Sat (eve), Sun (all-day)
2021	–	Saskatoon, SK	Bus	Spare[g]	Many (fixed)	Same	Morn-aft	None
2021	–	Sault Ste. Marie, ON	Bus	Via	Many (fixed)	Same	None	Sat, Sun (eve-night)
2021	–	Spruce Grove, AB	Minibus	RideCo	Many (virtual)	Lower[f]	All-day	None
2021	–	St. Thomas, ON	Minibus	Via	Many (virtual)	Same	All-day	Sat (all-day), Sun (morn-aft)
2021	–	Winnipeg, ON	Bus	Via	Many (virtual)	Same	Eve-night	Sat (peak or morn-aft), Sun (morn-aft or all-day)
2022	–	Airdrie, AB	Minibus	RideCo	Many (door)	Same	Morn-aft	Sat (all-day), Sun (morn-aft)
2022	–	Quebec, QC	Van	Via	Many (virtual)	Same	All-day	All-day
2022	–	Strathcona (C), AB	Bus[h]	Spare	Many (fixed)	Same	Eve-night	Sat, Sun (all-day)
2022	–	Waterloo (R), ON	Minibus	Spare	Many (virtual)	Same	Peak	None
2022	–	Welland, ON	Bus	RideCo	Mixed[i]	Higher	All-day	Sat (all-day), Sun (mid, aft)

[a] Innisfil Transit uses many-to-many (door-to-door) at a flat discount from a standard Uber rate, but uses many-to-few (door-to-door) for flat fare trips

[b] York Region Transit uses many-to-one (door-to-door), many-to-few (door-to-door), many-to-many (door-to-door), and many-to-many (fixed-route stops) at widely varying times and days of operation depending on the zone

[c] Translink used many-to-many (door-to-door) on weekends and many-to-one (door-to-door) on weekdays

[d] Durham Region Transit uses virtual stops in the urban zone and door-to-door in the rural zone

[e] No payment on board but expected to pay on prior/following fixed-route service trip

[f] Leduc Transit and Spruce Grove Transit run intercity routes that are charged at higher rates

[g] Saskatoon Transit was switching to Spare from Pantonium at the time of writing

[h] Strathcona Transit plans to move to minibuses if pilot is successful

[i] Welland Transit uses many-to-many door-to-door service in a rural zone and many-to-one door-to-door service from the rural zone to the central transit station

system's failure was primarily attributed to issues with Cowboy Taxi's provincial licencing, resulting in Airdrie having to shift to a more expensive routing system (MacIssac, 2019). Translink used a service from DoubleMap for their pilot on Bowen Island, and York Region Transit uses Routematch, which was owned by Uber until recently. Uber and Lyft, the more dominant TNCs, have primarily explored transit integrations in the United States. In Canada, Uber has a partnership with Innisfil to provide their service and a generally larger presence in the Canadian ridesourcing market, and Lyft has some limited service in Vancouver and the Greater Toronto Area (Lyft, 2022). Both companies have purchased transportation software companies, and in some areas have added public transit routing to their apps.

Most Canadian TIR systems operate using a many-to-many pattern, typically with virtual stops. Virtual stops tend to be placed with the rider-facing goal of having low access/egress times, while minimizing the number of potential trip pairs and deviations that need to be made by the on-demand service. Systems that use fixed-route stops tend to also use full-sized buses. Agencies with these systems may choose this pattern-vehicle combination because it requires minimal infrastructure investment, since it uses the existing stops and buses from the fixed-route service, so it is easier for agencies to pilot before committing fully. A small number of agencies use door-to-door service instead of virtual stops.

Some current systems do not operate using a many-to-many pattern. Durham Region has multiple many-to-many zones: urban areas have small zones surrounding neighbourhoods or city centres with virtual stops, and the entire rural area in the region operates using door-to-door service. Fixed-route service connects between different urban zones and some rural zones. Innisfil uses many-to-few for seven major destinations or hubs ($4.00-$6.00 per trip), and offers a $4.00 subsidy on Uber rates for many-to-many travel within the town. To minimize cases where riders book two subsequent many-to-few trips to save costs (from an origin to a hub, then immediately from the hub to a destination), Innisfil places a limit on the number of trips riders can make each month (Pentikainen & Cane, 2019). York Region uniquely offers a variety of targeted services in small zones throughout the region under their Mobility On-Request banner that have varying permitted demand patterns, which include many-to-one, many-to-few, and many-to-many with fixed-route stops and door-to-door service. Welland uses fixed-route transit in the central urban area, and TIR in the outer regions. Service operates many-to-many in the outer area, but is many-to-one to access the central transit station.

For systems that have fixed-route transit in addition to TIR, there are typically no differences in fare between the two services. Two TIR systems have cheaper fares than fixed-route transit (Leduc and Spruce Grove), although the fixed-route routes are intercity buses, and one system (Welland) has more expensive fares than fixed-route transit. Service hours vary greatly among the systems. Innisfil's system is the only one that operates with 24-hour service. Many of the other systems operate either using all-day service (from morning to evening or late night) or only evening and late night service. Evening and late night service tends to be on systems that are replacing fixed-route service in less popular hours.

2.3 Preferences and Attributes of Importance

2.3.1 Attributes in Algorithms

One of the primary areas of research in DRT systems is the dial-a-ride problem (DARP). The DARP aims to design demand-responsive routes that balance minimizing passenger inconvenience and operating costs (Cordeau & Laporte, 2007). Algorithms used in prior DARPs use varying attributes to represent passenger inconvenience. While applications of the DARP are outside of the scope of this research, the attributes used in the objective functions and constraints of DARP algorithms can indicate what prior research considers valuable in a passenger's utility function for on-demand transit.

Two of the earliest DARP algorithms were CARS and ADAR (Haines & Wolff, 1982), developed at MIT in the late 1970s and early 1980s. CARS used a linear objective function that added new trip requests to the DRT vehicle that would have the lowest travel time increase for on-board passengers and passengers waiting for a pick-up. The function was constrained by the value of three attributes: wait time, in-vehicle travel time (IVTT), and total time (i.e., the time between booking a vehicle and drop-off, which is the combination of wait time and IVTT). ADAR was later developed to overcome shortcomings in the CARS algorithm, and used a quadratic objective function with five attributes: wait time, IVTT, total time, pick-up deviation, and drop-off deviation (the differences between expected and actual pick-up and drop-off time, respectively), which was considered a more realistic solution to DRT dispatching.

Since then, many new algorithms have been developed. Cordeau and Laporte (2007), Ho et al. (2018), and Molenbruch et al. (2017) collectively review the state of DARP research and algorithms since the 1980s, and further explain DARPs. Cordeau and Laporte (2007) identify total distance, wait time, IVTT, and drop-off deviation as common DARP passenger criteria, either in the objective function or in the constraints of DARPs, and identify the ability in many algorithms to allow for time windows, which are boundaries on the expected pick-up and drop-off times (in a way, representing maximum allowable deviations and wait times). Larger time windows make it easier for the operator to schedule passengers but can be perceived as decreased service quality, since the passenger must plan for a wider possible range of pick-up or drop-off times (Bruun, 2014). Ho et al. (2018) and Molenbruch et al. (2017) further support the commonality of IVTT, wait time, and time windows. Most research focuses on pure on-demand service (i.e., single-ride DRT trips without the use of fixed-route transit), but some DARPs include service integrated with fixed-route transit that account for transfers (Häll et al., 2009; Posada et al., 2017).

2.3.2 Related Models and Surveys

Previous mode choice models that considered DRT did not fully account for new ways to integrate on-demand service like ridesourcing into a public transit system, but provide some hints about potential responses. Earlier stated-preference surveys and models found that the ability to book DRT closer to the desired departure time indicated a positive preference for the mode. The ability to book 2 hours before leaving instead of 24 hours was considered significant or would be expected to improve the share of DRT (Ben-Akiva et al., 1996; Benjamin et al., 1998), and the marginal benefit of booking 15 minutes before leaving was assumed to be due low to doubts about the system's ability to dispatch service quickly enough (Ben-Akiva et al., 1996). The ability of a system to provide 15 minute booking would not be a major concern in current ridesourcing services. Considerable increases in ridership were also estimated when the return trip was also available within 15 minutes of receiving a return call. However, the booking of traditional DRT systems is different in nature from how ridesourcing systems function, and residents may have different perceptions of TIR than what could be extrapolated from earlier literature.

Some recent literature has explored how residents perceive ridesourcing or TIR. Yan et al. (2019) authored one of the only studies to consider mode choice modelling specifically for TIR, but their study was limited in focus to a fairly homogeneous population of university students and staff without consideration of fares or monetary costs. Yan et al. (2021) later conducted a survey with predominantly lower-income residents comparing the existing fixed-route-only transit systems with a combined fixed-route and TIR system, finding stronger support for TIR from respondents who were male, lived in transit-poor areas, did not own a car, and were younger than 40. This was not a stated-preference survey, but did consider TIR. Sweet (2021) used driverless and human-driven transit, ridesourcing-style vehicles, and a combined alternative similar to TIR in a stated-preference survey, finding the cost penalty for sharing the vehicle was not statistically significant for the TIR alternative (suggesting an indifference in paying more to not share for this mode), and a higher preference for the mode among respondents who were not male. Alonso-González et al. (2020) conducted a survey in the Netherlands comparing direct on-demand, last-mile on-demand, and fixed-route only service to understand how respondents valued time and reliability, but did not include other modes that may compete with the service like auto or cycling. Saxena et al. (2020) compared respondents' existing travel choice (either auto or transit) with a new TIR mode using pivoted stated-preference experiments, finding interest in the mode for work trips but less interest for non-work trips.

A wider body of literature has explored the ways that ridesourcing is perceived, but not necessarily as an integrated part of the transit system. Perceptions in some cases vary for some attributes. Individuals have been found to be more open to shared rides, including ridesplitting, if they were young adults (Azimi & Jin, 2022; Kang et al., 2021; Lavieri & Bhat, 2019; Young & Farber, 2019), seniors (Alonso-González et al., 2021), male (Kang et al., 2021), female (Alonso-González et al., 2021), had lower-incomes (Azimi & Jin, 2022), or had a higher willingness to pay for lower travel times (Alemi et al., 2019). For ridesourcing as a whole, individuals have been found to be more open when they are young adults (Asgari & Jin, 2020; Lavieri & Bhat, 2019; Shoman & Moreno, 2021), had lower-incomes (Asgari & Jin, 2020), had higher-income (Lavieri & Bhat, 2019; Shoman & Moreno, 2021), or had no children (Azimi & Jin, 2022). Liu et al. (2019) found that ridesplitting was perceived worse than ridesourcing, and both were perceived worse than public transit. Ridesourcing has also been found to be used more often for non-work trips (Acheampong et al., 2020; Feigon & Murphy, 2018; Young & Farber, 2019). In summary, our current understanding of these emerging modes is still in its infancy and user perceptions may be heterogeneous and evolving over time, as evidenced by the contradictory research findings in the literature to date.

Table 2.2 reviews recent relevant models. The included models were estimated using the results of preferential surveys that included a variant of TIR. Models were either purely SP, providing all respondents the same series of trip scenarios, or were SP with an RP reference from which the model pivoted. In most cases, models were either simple multinomial logit (MNL) or mixed logit with classical estimation and linear attributes. Models typically considered home-based work (HBW) trips, but some models also considered other trip purposes like leisure or shopping. Even though some models have multiple alternatives, the corresponding survey did not always show all alternatives to each respondent. Some surveys used scenarios, where different alternatives were shown in each scenario, or compared an

Table 2.2: Recent dial-a-ride and transit-integrated ridesourcing preferential models

Authors	Model[a]	Size	Type	Alternatives							Trip Purpose	
				A	C	RH	RS	T	TIR	W	Work	Other
Abe (2021)	MNL, mixed	1708	RP-SP[b]	X[c]	X[c]	–	–	X[c]	X	X[c]	X	Leisure
Alonso-González et al. (2020)	MNL, mixed	1006	SP	–	–	–	X	X	X	–	X	Leisure
Chavis and Gayah (2017)	MNL, NL	177	SP	–	–	X[d]	X[d]	X	X[d]	–	X	–
Ryley et al. (2014)	Mixed	409	SP	X[c]	–	–	–	X[c]	X	–	Unspecified	
Saxena et al. (2020)	Latent class	176	RP-SP[b]	X[c]	–	–	–	X[c]	X	–	X	School, social, medical, shopping, other
Sweet (2021)	Mixed	1684	SP	X	X	–	X	X	X	–	X	Shopping, restaurants
Yan et al. (2019)	Mixed	1163	RP-SP[b]	X	X	–	–	X	X	X	X	–
Zgheib et al. (2020)	Mixed	392	SP	X	–	–	–	X[c]	X[ce]	–	X	–

[a] All models used classical estimation with linear attributes
[b] RP component is a reference trip for SP pivot
[c] Alternative in survey dependent on scenario or on respondent's reference trip or choice
[d] General alternatives used that included these alternatives in the descriptions ('flexible route', 'individual')
[e] TIR options included ridesourcing, ridesplitting, service, and taxis to get to and from the BRT

alternative of study against the respondent's reference trip from an RP section of the survey. Fixed-route transit (T) was an available alternative in every survey. Auto (A, which includes drivers and passengers) was another common alternative. Cycling (C), ridehailing (RH, which includes private ridesourcing and taxis), ridesplitting (RS), and walking (W) were also alternatives used in these surveys and the resulting models.

Table 2.3 reviews the attributes used in the models in Table 2.2. The most common time attributes measured in models were wait time, walk time (i.e., access and egress time), and either IVTT or total time. Total time does not differentiate between types of time, and is presented as a more general estimate of how long the respondent would take to travel from the origin to destination. Other time attributes included the time to transfer, for trips with multiple legs, and the time to park for auto. Costs were typically measured as fares. Operating cost per unit distance or time, parking, and fuel costs were used for auto modes in some of the models' corresponding surveys. Other attributes included the autonomy of the vehicle, the number and relationship of additional passengers, the number or time impact of additional stops, reliability of the travel time or the pickup time, the number of transfers, and whether passenger-facing map apps used GPS augmentation.

2.4 System Types

DRT is a broad transportation mode covering a variety of implementation techniques. The methods for implementing DRT, specifically TIR, can be categorized into system types. System types describe the *macro-scale*, spatial attributes of a TIR system. The primary attributes that differentiate these systems are access/egress distance, zonal patterns, permitted demand patterns, and directness. Access/egress distance determines how far a passenger must travel from their true origin or destination to reach the nearest TIR service pick-up or drop-off location. Permitted demand patterns describe the permitted trip types (Section 2.2.1) and bound the number of possible origin-destination pairs in the system. Zonal patterns identify if the trips and/or the TIR vehicles are limited to zones in the greater service area. Directness indicates if the ride is shared or unshared. Shared rides would be less direct than unshared rides, since other passengers would be picked up or dropped off between the passenger's origin and destination.

Table 2.4 relates the system type attributes with the expected passenger impacts. By connecting system type attributes to passenger impacts, respondents to passenger-facing surveys can answer questions about impacts they are most sensitive to, and these preferences can be translated to understand how different system types would appeal to different

Table 2.3: Attributes in recent demand-responsive transport and transit-integrated ridesourcing preferential models

Authors	Attributes (Time)					Attributes (Other)	
	Total	Wait	Walk	IVTT	Other	Costs	Other
Abe (2021)		X	X	X	Transfer[a]	Fare	Passenger relation
Alonso-González et al. (2020)	X	X			Transfer	Fare	Reliability (alternative estimates)
Chavis and Gayah (2017)		X	X	X		Fare	GPS location in maps
Ryley et al. (2014)			X	X		Fare, operating, parking	Pickup reliability
Saxena et al. (2020)		X	X			Fare	Additional passengers, transfers
Sweet (2021)	X					Parking, fare	Automation, additional passengers
Yan et al. (2019)	X	X	X	X[b]	Park	—	Transfers, additional pickups
Zgheib et al. (2020)		X	X	X		Fuel, parking, fare	

[a] Transfer time directly measured as ‘frequency’ of following trip leg
[b] Attribute measured in model but not directly asked in survey

populations. Service that uses virtual stops instead of providing door-to-door service would be expected to have higher access/egress times, since travel does not connect to the passenger's true origin or destination, and lower wait times, since vehicles could travel along quicker routes between a finite number of origin-destination pairs. Fixed-route stops would be expected to have even longer access/egress times and shorter wait times since they are not always placed within a short walking distance to everyone in a service area, and therefore further limit the distance a vehicle may need to travel to reach a new passenger. Systems with zone-limited trips would be expected to require more transfers and have higher transfer times, because trips across an entire service area would require transfers between zones. Zone-limited vehicles could have lower wait times, due to the lower maximum distance needed to travel from dropping off one passenger to picking up another one, but could be negatively impacted by the number of vehicles allocated to each zone. Across permitted demand patterns, less restrictive systems (like many-to-many) minimize the potential number of transfers, since passengers can more directly reach their destinations. Shared systems are less direct, since other passengers interrupt trips with pick-ups and drop-offs in between other passengers' trips, so from a passenger perspective, more stops would be expected with longer general IVTT.

Table 2.5 relates additional attributes with the expected passenger impacts. Transfer intergration and fares do not change the spatial configuration of a TIR system, but do change how the passenger perceives the system. Transfers between a TIR vehicle and fixed-route transit can be integrated, to minimize the time a passenger spends waiting at a transfer location. This would shift a passenger's trip later, adding wait time at the expense of lower transfer times. Different fare systems can also be considered, which change the cost for the passenger. Using the fare structures from fixed-route transit (Vuchic, 2004), systems could be configured to use free transfers, flat surcharges, zonal surcharges, or sectional surcharges on top of the fixed-route transit system, each of which would have variable impacts on out-of-pocket cost.

Recalling the characteristics of shared mobility passenger modes (Table 1.1), these attributes consider different cases in endpoint flexibility (through access/egress distance, zonal, and permitted demand patterns) and different cases in routing and shared ride cases (through directness). The public system ownership of the mode and the publicly-available use of the service are maintained in all cases. Each endpoint flexibility, routing, and shared ride combination introduces tensions. More endpoint flexibility via more permitted demand patterns, larger zones, and shorter access/egress distance is desirable for the passenger but increases the cost of the system. More personalized routing and the ability to have non-shared rides is also desirable to the passenger, but also requires higher costs because of

Table 2.4: System type attributes and expected passenger impacts

Category	Value	Expected Passenger Impact
Access/egress distance	Door-to-door service (0 m)	Base case
	Virtual stops (>0 m)	↑ access and/or egress time, ↓ wait time
	Fixed stops (>0 m)	↑↑ access and/or egress time, ↓↓ wait time
Zonal patterns	No zones	Base case
	Only trips limited to zones	↑ number of transfers, transfer time
	Trips and vehicles limited to zones	↑ number of transfers, transfer time, variable impact on wait time, depending on trip-per-vehicle ratio
Permitted demand patterns	Many-to-one	Base case
	Many-to-few	↓ number of transfers, transfer time
	Many-to-many	↓↓ number of transfers, transfer time
Directness	Unshared ride	Base case
	Shared ride	↑ additional stops, in-vehicle travel time

Table 2.5: Additional attributes and expected passenger impacts

Category	Value	Expected Passenger Impact
Transfer integration	Ad-hoc (not timed with other vehicles)	Base case
	Timed transfer	↑ wait time, ↓ transfer time
Fares	Free transfer (no additional fare)	Base case
	Flat surcharge	↑ out of pocket cost
	Zonal surcharge	↑ out of pocket cost (lower than flat with shorter trips, higher than flat with longer trips)
	Sectional surcharge (fare by distance)	↑ out of pocket cost (much lower than flat with shorter trips, much higher than flat with longer trips)

service duplication.

2.5 Literature Gaps

While shared mobility research is increasing, there are key gaps that are not fully addressed in the existing literature:

- The unique characteristics and appeal of ridesourcing requires guidelines on DRT, specifically TIR with app-based immediate booking, to evolve to accommodate for these factors
- Transit agencies are incorporating ridesourcing projects, but with little guidance on the best ways to integrate these services to create mode shifts that encourage desirable modes (fixed-route transit and active transportation)
- Much behaviour-focused research examines ridesourcing as a completely separate alternative to transit. There is also little research on how TIR specifically competes with or complements transit, while the ridesourcing base of comparable literature is quite large.
- The body of literature examining mode choice models for TIR is quite small (Tables 2.2 and 2.3), with many opportunities available to determine how people perceive different forms of integration. Existing research does not always consider TIR as a complete alternative to current alternatives, does not include a complete selection of alternatives, focuses on a more transit-captive demographic, or does not account for attributes that vary between system types.

This research aims to make progress toward filling these gaps, by connecting how operational characteristics impact behaviour, expanding the body of literature for TIR mode choice models, and developing a typology for trips based on fixed-route transit proximity. Chapter 3 reviews an existing pilot and explores competitiveness using a newly developed trip typology. Chapter 4 conducts a survey with a complete set of alternatives and a set of attributes relevant to system type impacts. Chapter 5 builds a mode choice model from the survey results and applies the results back to finding preferences for the system types identified in the literature. Chapter 6 outlines guidelines for how agencies may consider implementing TIR in the future.

Chapter 3

Trip Typology and 903 Flex Analysis

The first output of this research is a trip typology, which categorizes transit-integrated ridesourcing trips based on their competitiveness with active transportation modes and public transit. The typology was then applied to an analysis of the trips from a transit-integrated ridesourcing pilot in Waterloo. Changes in user and trip characteristics were measured using the trip typology and other relevant factors available in the data set.

The trip typology is a new method for assessing the spatial competitiveness of transit-integrated ridesourcing systems, which may be used for assessment of other systems to determine how transit-integrated ridesourcing spatially competes with alternative modes. The analysis of the transit-integrated ridesourcing pilot, which incorporates the typology, is the first comprehensive spatial analysis of a transit-integrated ridesourcing system.

3.1 Background and Data

In 2018, the Region of Waterloo launched three one-year pilot projects to test shared mobility options through its transit agency, GRT. Figure 3.1 depicts the service areas for each of the pilots and the route for the ION, the Region's LRT line. One project was launched in each of the three cities in areas with high requests for transit but no plans to introduce regular fixed service before 2021 (Grand River Transit, 2019d). In Kitchener, the largest city, a weekday bus (901 Flex) connects three fixed stops around a mall with three on-demand stops that must be booked in advance (Grand River Transit, 2019a). In Cambridge, the more suburban of the three cities, a subsidized taxi (902 Flex) offered in conjunction with a local taxi company was offered 7 days a week as both a scheduled shuttle-like service and a service connecting users between any two flexible stops in the service area (Grand River Transit, 2019b). In Waterloo, the smallest of the cities, but with two large universities (Waterloo and Laurier) and hence a large student presence, a partnership with RideCo was formed to offer weekday ridesourcing (903 Flex) during specified hours in an under-serviced transit area west of the universities. Initially offered surrounding peak hours, the service expanded to operate from 7:30 am to 10:00 pm, and trips could be made between any two of the supporting stops for the same price as a bus fare, with free transfers to the fixed-route bus service (Grand River Transit, 2019c). Due to low weekly ridership, the Cambridge subsidized taxi ended in August 2019, and the Waterloo ridesourcing pilot ended in December 2019 (Grand River Transit, 2019e). The Kitchener service continued to operate until 2022 (Grand River Transit [@grt_row], 2022), and two more flexible-stop buses were introduced in other parts of the region. GRT also designed a demand-responsive transit service in Breslau in a partnership with Metrolinx (Grand River Transit, 2020a), which launched in 2022. This analysis focuses on the 903 Flex, which was the ridesourcing service in Waterloo.

During the 903 Flex's operation, GRT made a series of changes to the pilot in response to feedback from users. Table 3.1 outlines the changes made to the pilot and the transit network over the pilot's operation. Three broad operating periods are defined, which are used for the remainder of this research. The first period covers pilot trips taken between the launch of the pilot service and the launch of the ION. The ION's first full weekday of service also coincided with changes to almost every bus route in the regional transit network. The first period is broken down into three sub-periods, capturing trips taken between milestones where the pilot underwent further changes. Due to the relatively low trip count in each sub-period, these sub-periods were combined into one larger period for temporal analysis. The second period covers the launch of the ION to the end of August 2019, during which users adjusted to the new fixed-route transit network that interfaced with the pilot. The third period starts at the final service change, where capacity was added intermittently during the peak-hour, and some stops were adjusted. The third period is split into two sub-periods (3a and 3b) that are both used for temporal analysis, due to the high volume of trips taken in the final four months of the service.

GRT provided the trip database, which contained all 4536 ridesourcing trips (rides) made by 178 unique users during the 903 Flex's operation. The attributes used for analysis included pick-up and drop-off locations (to generate trip alternatives), pick-up time (for time-of-day analysis and trip alternative generation), travel time (for comparison against other modes), unique user IDs (for temporal user analysis), shared ride status, and payment methods (for inferences into multimodal transit use). The database also included driver identifiers, driver rating, and notes from the customer or RideCo, which were not used in

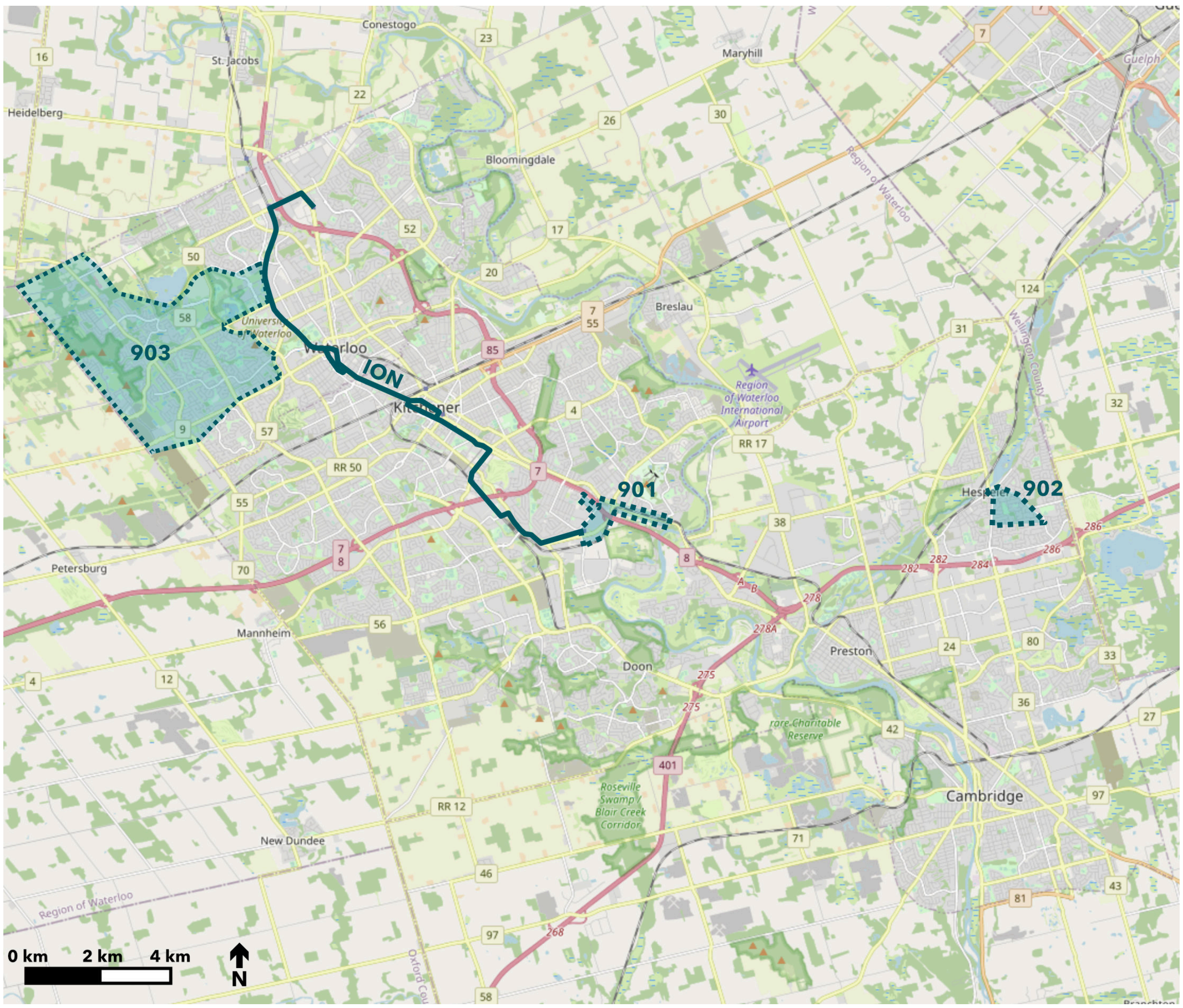


Figure 3.1: ION light rail transit route and 2018 pilots areas in the Region of Waterloo

Table 3.1: 903 Flex operating periods, including major milestones and trip counts

Period	Start Date	Milestone	Trip Count
1a	26 November 2018	First week of service	63
1b	11 March 2019	Conversion from peak hour service to continuous all-day service, 2 bus stops added	341
1c	6 May 2019	Service hours adjusted later, 5 virtual stops added, 5 bus stops added	657
2	24 June 2019	First full weekday of light rail transit service, transit network reorganized	1334
3a	3 September 2019	Variable peak-hour service temporarily	1117
3b	4 November 2019	reintroduced, 2 virtual stops added, 1 bus stop added, 1 bus stop moved	1024
End	20 December 2019	Final day of service	

the analysis.

Figure 3.2 shows desire lines between the origin–destination (O-D) pairs representing all rides in the pilot, separated by operating period (1, 2, 3a, and 3b). GRT placed virtual stops (white circles) to achieve a maximum 5 min access and egress walk to the transit network in northwest Waterloo, which increased coverage in areas where existing fixed-route services (grey lines) were poor. Some bus stops (black circles) were made a part of the 903 Flex pilot. The blue desire lines for each period connect virtual stops and bus stops in the network, with thickness weighted by trip frequency throughout the operating period. The top five most popular stops in each period are identified in larger circles with their share of trip origins/destinations.

Of the 4536 rides in the dataset, 2828 rides did not have pick-up and drop-off times that matched the reported ride time (i.e., the in-vehicle time). To find the available transit alternatives and conduct ride time comparisons, a cleaning procedure was developed and used to match the departure and arrival times to the reported ride times. A detailed breakdown of the process is outlined in Appendix A. Generally, the reported ride time was assumed to be correct and the times were adjusted to match the ride time to better compare rides with potential alternatives. Preserving the actual departure time was prioritized where possible since it was used in more analyses.

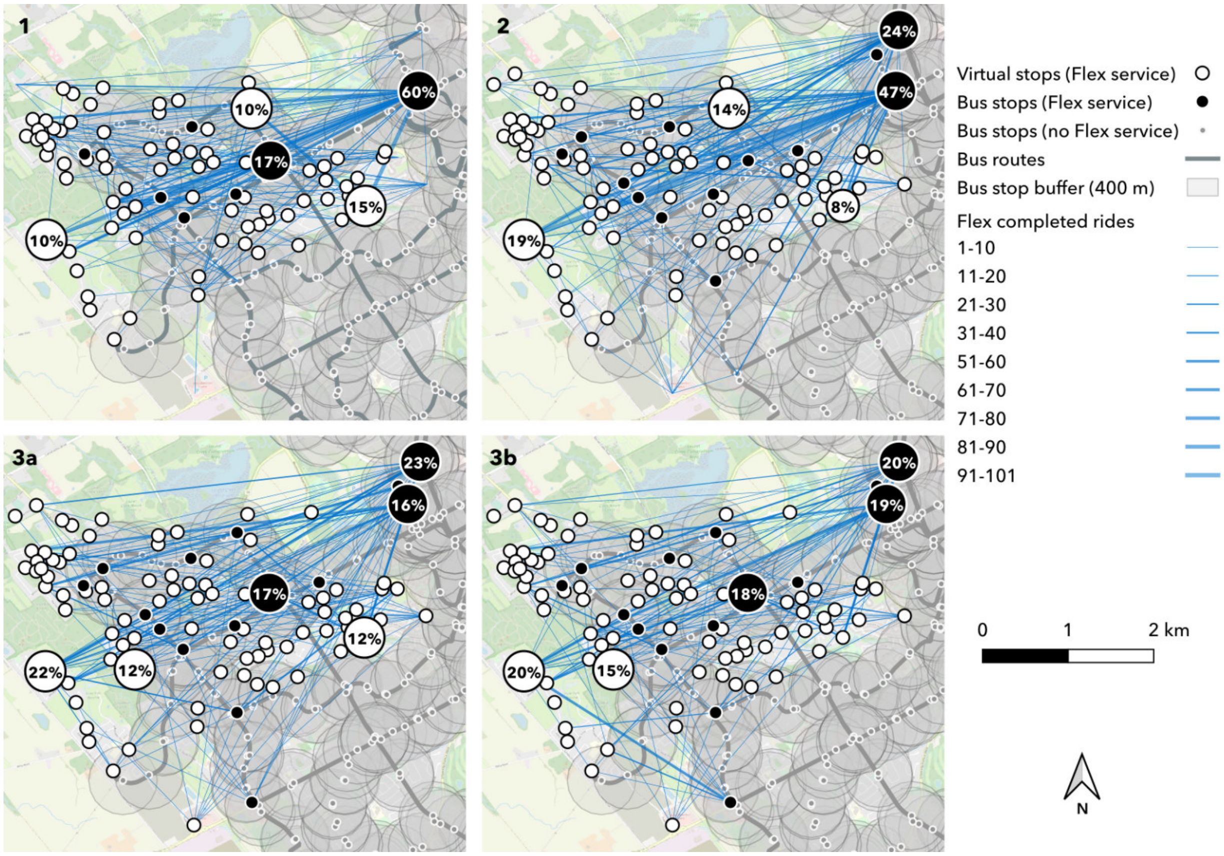


Figure 3.2: Ridesourcing pilot trips for different operating periods in northwest Waterloo. Base layer using OpenStreetMap imagery, GIS layers partly sourced from the Region of Waterloo (Grand River Transit, 2019c; OpenStreetMap contributors, 2019; Region of Waterloo, 2019)

3.2 Methods

This analysis consists of three major steps. First, multimodal alternatives to the pilot rides were generated, which were used to determine the competitiveness of a user's other travel options at the time of their ride. Second, a spatial characterization framework was developed and applied for all trips in the pilot, which was used to determine whether the pilot encouraged integration or competition with fixed-route transit. Third, temporal user-level trip-making behaviour and changes in spatial characteristics, trip frequency, and other available ride characteristics were measured, to comprehensively examine what factors may have influenced user trip-making frequency and trip types throughout the pilot.

3.2.1 Generating Walking, Cycling, and Transit Alternatives

Multimodal alternatives were generated for each ride to temporally assess the most competitive options that each user could have taken *instead* of using the ridesourcing pilot. The alternative trips provide insight into the options available to the user at the time they booked their ride. A standardized process and trip pattern (Figure 3.3) were used to generate each alternative trip, including the arrival time for each mode.

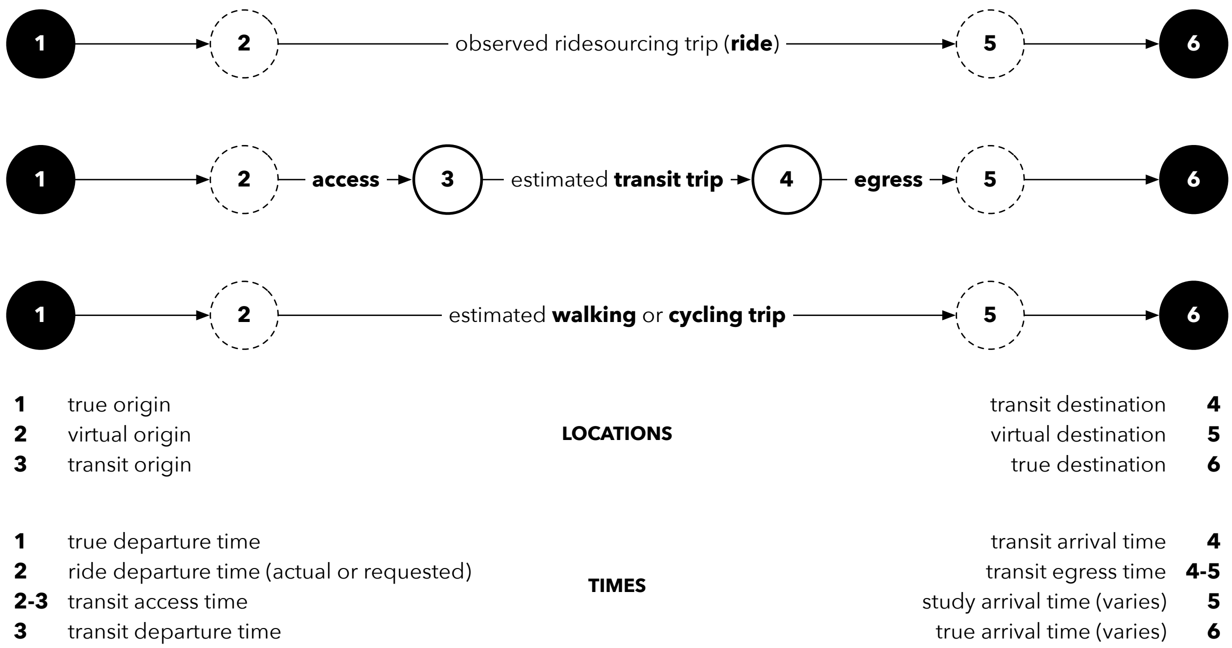


Figure 3.3: Trip terminology and pattern for ridesourcing, transit, walking, and cycling

Two assumptions were made when generating alternative trips. First, it was assumed that the origin and destination for both walking and transit trips would be the same as the ride's origin and destination (i.e., the virtual origin and destination). Setting the origins and destinations equal for each mode effectively assumes that the user first travels to the virtual origin, then decides to make a trip using ridesourcing, transit, cycling, or walking. After the trip is completed, the user then walks or takes transit from the virtual destination to their true destination for each alternative. The travel between the true and virtual origins and destinations (points 1 to 2 and points 5 to 6 in Figure 3.3) were not modelled in this analysis, as the true origins and destinations for each user were not observed.

The second assumption is that the departure time for each alternative trip is equal to the requested ride departure time or the actual ride departure time, whichever is earlier. The requested time indicates when the user was intending to take the trip, since the ridesourcing service offers the ability to book trips in advance. However, a user picked up earlier than the requested time means the user was ready to make the trip and therefore would have been able to use one of the alternative modes (transit, cycling, or walking) at that time to complete their trip.

The implications of these assumptions are important for interpreting the results of the research: by using the ride's virtual origin and destination for alternative modes, the effectiveness of the ridesourcing option is presented with favourable conditions since every other mode needs to deviate to the virtual stops; by choosing the requested or actual ride departure time, it is assumed that the user *needs* to make the trip at the same time they took the ride.

Trip times for transit, walking, and cycling alternatives were generated with OpenTripPlanner 1.4.0 using GTFS files from OpenMobilityData for transit stop, route, and schedule data (Grand River Transit, 2020b), OpenStreetMap for road and trail network layers, and Python 3.6 for API requests. Five GTFS feeds were used, corresponding to GRT's seasonal schedules. OpenTripPlanner required the coordinates of the start and ending points of the journey, the date of the journey, and the time the user had requested to be picked up.

Preliminary versions of this work used two more laborious methods to generate alternatives. The first method involved hand-entering the active transportation origin-destination pairs into Google Maps and using a spreadsheet to search through transcribed transit schedules. This manual technique worked well with the small set of trips originally provided by GRT (585 out of 4536 total trips), but was unmanageable for the whole dataset. The second method replaced the hand-coded spreadsheet with a Python script that searched through GTFS files. This was quicker and less prone to human error, but was ultimately less effective than using OpenTripPlanner, which is designed to find the most effective trip option in the same way as a typical user. For the remainder of the research, OpenTripPlanner replaced both of the previous methods for estimating all trip alternatives.

Transit Trips: Transit alternatives were generated using the default settings in OpenTripPlanner to produce transit trip components, including access time, travel time (including transfers), and egress time. Walking times for transit access and egress use a walking speed of 1.33 m/s, which converts to 400 m over 5 min, and empirically aligns with average walking speeds in this area from other trip planners like Google Maps. If more than one itinerary was returned, the preferred transit alternative was selected by minimizing the combined access and egress walking time (which in turn reduced walking distance), reflecting the trip that would be most spatially competitive with the pilot ride. A maximum number of transit transfers was not set because spatial characteristics were of greater importance in this study. Driving itineraries were generated from the virtual origin to the virtual destination, and the virtual origin to transit origin (Section 3.2.2, for determining trip types with no reasonable transit alternative.

Walking and Cycling Trips: Walking alternatives used a walking speed of 1.33 m/s. Cycling alternatives used the 'balanced' option in OpenTripPlanner, which equally weighs bike-friendliness, speed, and elevation when generating a cycling itinerary. This option was selected because the preferences of users were unknown, making the most balanced option the least presumptive.

Trip components from the generated transit alternatives were used to characterize the transit context operationally and spatially. The number of transfers taken, wait times, and travel times were extracted from OpenTripPlanner for transit service analysis. For active transportation alternatives, travel time was the only trip component extracted and analyzed. Access and egress walking times are key descriptors of the transit context and can be spatially characterized like ridesourcing trips.

Headways for the transit trips were calculated by emulating the process used in the OpenTripPlanner web interface. Three trips were used: the preferred transit alternative, and a previous and next trip using the same route number(s). Previous trips were found by setting the arrival time 1.5 min earlier than the preferred transit alternative, and following trips were found by setting the departure time 1.5 min later than the preferred transit alternative. Due to limitations in the route filtering parameters, previous and next trips may arrive at the same location but in the other direction of a transit route (e.g. the original trip was southbound and the next trip uses the northbound direction). Some trips in the GTFS feed also arrived only a few minutes after a previous trip on routes with typically longer headways, but it was unclear whether this was an error or a trip with a genuinely shorter headway. Because of these limitations, estimated headways therefore may be shorter than the true headway of the trip, but in aggregate should provide a reasonable sense of how frequently buses would have arrived for users in the pilot had they instead used transit.

It is important to emphasize that the alternatives generated were not always desirable. In some cases, walking, cycling, or transit trips could be over an hour long, which most passengers would not accept as an alternative for these trip lengths. However, including *all* alternatives in the choice set is essential in understanding the full suite of cases where transit-integrated ridesourcing was the selected alternative. Including only cases where walking or cycling were competitive (e.g., where walking or cycling trips were close to the same length of time as transit-integrated ridesourcing) would mask the undesirability of these alternatives for more arduous trips. While walking and cycling are encouraged at shorter trip lengths, and transit is encouraged at longer trip lengths, there were cases where the existing network did not support these alternatives. By showing all possible alternatives, these alternative-poor scenarios can be identified and ideally improved in future transportation infrastructure improvements.

3.2.2 Spatial Characterization Typology

Once multimodal alternatives were generated for each ride, sets of statistics and characteristics for each trip could be generated. Each ride was assigned a competitive alternative mode depending on which alternative arrived at the virtual destination first. The time savings or loss from using ridesourcing were calculated based on the difference between the arrival time from the competitive alternative mode and the actual arrival time of the ride. For all trips, the transit alternative's headway was recorded to determine whether there was correlation between headway and ridesourcing usage. Time ratios comparing walking, cycling, and transit to ridesourcing were generated using a modified version of the calculation used in TCRP studies (Feigon & Murphy, 2016). In the report, time ratios are calculated using average wait times and actual travel times. In this research, walking, cycling, and transit alternative time ratios were calculated using the actual waiting times and actual travel times for each trip.

Four distance measures were tracked in relation to the competitive transit trip: access distance, egress distance, minimum access/egress distance, and maximum access/egress distance. Access and egress distance refer to the travel distance from the virtual origin to the competitive transit trip's origin stop, and from the competitive transit trip's destination stop to the virtual destination, respectively. The minimum and maximum access/egress distance are the minimum and maximum of the two distances, respectively, which are valuable for analyzing large numbers of trips at once. A low minimum distance indicates that at least one of the virtual stops is close to their nearest transit stop, whereas a high minimum distance indicates that both virtual stops are far from their nearest transit stop. In contrast, a low maximum distance indicates that both virtual stops are close to the nearest transit stop, whereas a high maximum distance indicates that at least one of the virtual stops is far from their nearest transit stop.

Trips were then categorized into types, based on transit access/egress characteristics using these four distance measures. Figure 3.4 presents the proposed typology, which includes

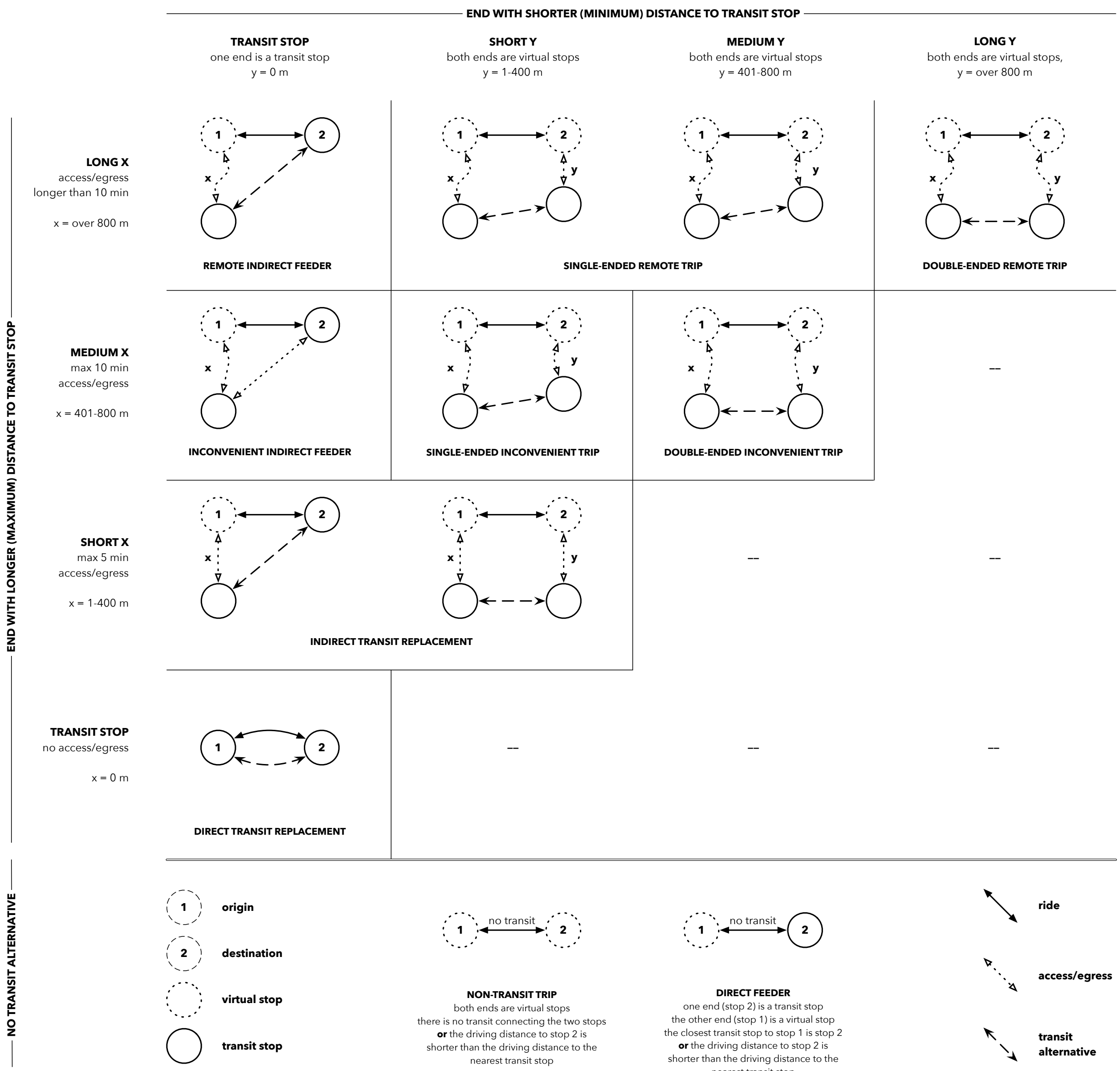


Figure 3.4: Ridesourcing trip types based on transit access/egress distances

the major trip types that are identified as *non-transit trips*, *feeders*, *transit replacements*, *inconvenient trips*, and *remote trips*, based on the combination of access/egress distances to/from a virtual stop to a transit stop. Each trip type is based on the categorization of access and egress distances. Access and egress distances fall within four categorizations: at a transit stop (a negligible walk), convenient (400 m away or less by walking), inconvenient (401 m to 800 m away by walking), and remote (more than an 800 m walk away). Distance bins are based on generally accepted distances users are willing to walk to reach transit: every 400 m represents an estimated 5 min of walking time. Trip types are a useful tool for describing how the ridesourcing trip competes with or complements transit. For example, *transit replacements* imply a duplication of services, *remote trips* imply poor transit access, and *direct feeders* imply that service connects immediately to the nearest transit stop. In addition, trip types are useful when analyzing user choices over time, effectively connecting user preferences with ridesourcing services.

Trips with a medium or long maximum transit access/egress distance (top two rows in Figure 3.4) include rides that have at least one ridesourcing stop that is far from transit (greater than 5 min). *Indirect feeders* are rides that connect a virtual stop to a transit stop that is not one of the closest transit stops. Indirect feeders may still integrate the user into the transit system but could also potentially compete with existing transit options. *Inconvenient trips* are rides where one virtual stop is 5 min to 10 min (401 m to 800 m) away from the nearest transit stop, and the other is some distance away from the nearest transit stop, up to 800 m, representing trips that more dedicated transit users with longer acceptable access/egress distances may be willing to make, but that some users may find too difficult. *Remote trips* are rides where one virtual stop is more than 10 min (800 m) away, and the other is some distance away from the nearest transit stop. Remote trips are inconvenient for effectively all users on at least one of the ends, because the access or egress time (or both) is very long. Inconvenient and remote trips are further categorized as single-ended and double-ended, indicating whether both sides fall into the same category of inaccessibility (e.g., a single-ended remote trip may be 1000 m from the nearest transit stop on one end, but 500 m away on the other, so only one end is 'remote'). Users taking these transit poor trips are expected to shift from driving. For single-ended inconvenient trips, some users who are more walking-friendly may shift from transit. Users taking remote indirect feeders are expected to shift from driving and boost transit service, since they connect to the transit network. Users taking inconvenient indirect feeders are expected to shift from transit if they are walking-friendly, and to take more transit if they are walking-averse.

Trips with a short maximum transit access/egress distance (third and fourth rows in

Figure 3.4) are categorized as *transit replacements*. *Direct transit replacements* are rides connecting two transit stops, and therefore directly compete with transit. *Indirect transit replacements* are rides that connect a transit stop to a virtual stop that is within a 5-minute (400 metre) walking distance from another transit stop, which is not as strongly connected as two transit stops, but still competes with transit. Transit replacements are most likely to shift users from transit.

Trips with no transit alternative (bottom row in Figure 3.4 are special cases that don't neatly fit within the developed typology. *Direct feeders* are rides that connect a virtual stop to the nearest transit stop, which have no transit alternatives and compete only with active transportation and driving. *Non-transit trips* are rides that connect a virtual stop to another virtual stop, with the same characteristics of having no transit alternatives and competing only with active transportation and driving. In addition to access and egress times, these trips were given an additional qualifier based on driving distance. The driving distance qualifier addresses the incorrect categorization of trips as transit replacements or indirect feeders when the nearest transit stop by walking was different than the nearest transit stop by driving (because of vehicle-free routes such as pedestrian trails). A qualifier for direct feeders and non-transit trips comparing driving distance to the nearest transit stop with driving distance to the destination reduces these mischaracterizations, and cases in which users are taking a trip between two spots in the same neighbourhood. This follows the original intent of the typology, which is to determine whether users are making transit-supportive trips. If a user is unable to walk to the nearest transit stop, then a 'good' trip for the user to take would be the one that is nearest by driving (i.e., by ridesourcing) because transit is not accessible. Generally, the categorization scheme for non-transit trips and direct feeders is restrictive and represents a conservative estimate of trips that have no transit option. Users taking either of these trip types are expected to shift from walking and cycling on shorter trips, and from driving on longer trips. Direct feeders are also expected to boost transit service since they connect users directly to transit stops.

3.2.3 User Classification

Users were classified by trip-making frequency to identify trip-making behaviours and patterns throughout the ridesourcing pilot. The three user groups include frequent, average, and infrequent users, which represent three levels of pilot adoption and corresponding trip sample sizes. Criteria for user groups were chosen using engineering judgment to ensure that characterizations of user groups reflected sustained trip making behaviours and considered sample sizes within each group. Frequent users (53 users, 3697 trips) include those who took an average of at least one ridesourcing trip per week over a period of at least two months, ensuring they had some regularity in their ridership over a length of time roughly equivalent to the shortest periods (3a and 3b). Infrequent users (56 users, 75 trips) include anybody who has two trips or less throughout the entire pilot, which was about a third of the riders. Average users (69 users, 764 trips) include everybody in between; that is, users who took three or more trips throughout the pilot but did not meet frequent user criteria.

This research analyzes trip type and frequency changes over time using these user groups. First, total trips taken by each user group were split based on trip type. Comparing the trip-type splits of user groups can reveal whether certain trip types were typical or appealing for more frequent users. Second, the analysis examines whether trip types changed over time; that is, whether unique users changed trip-making behaviours. This analysis only tracks trips made by the frequent user group because the average and infrequent groups do not have enough trips per unique individual to support an analysis across periods. Since frequent users capture a larger sample of trips per unique user, this group better represents behaviours over time than more infrequent user groups. Third, another longitudinal analysis of frequent users seeks to understand whether individual trip frequency increased as the pilot progressed. The number of trips made by frequent users were compared across pilot periods (including 1a, 1b, and 1c) to understand how many users increased, decreased, or stabilized their use over time. The time of day that 903 Flex trips were taken was analyzed to make inferences about temporal user behaviour. Trip times were binned into 6 categories corresponding to rush hours and peak periods for Waterloo, ON based on the time the vehicle picked up the user from the origin: morning rush hour (7:30 a.m. to 8:29 a.m.), morning peak period (6:30 a.m. to 7:29 a.m. and 8:30 a.m. to 9:29 a.m.), midday off-peak (9:30 a.m. to 2:29 p.m.), afternoon peak period (2:30 p.m. to 4:29 p.m.), afternoon rush hour (4:30 p.m. to 5:29 p.m.), and evening off-peak (5:30 p.m. to 10:00 p.m.).

3.3 Results

3.3.1 Spatial and Temporal Trip Characteristics

Table 3.2 lists a summary of ridership and time statistics for the 903 Flex, as well as the most competitive transit, walking, and cycling alternatives. Trips are divided into periods (Table 3.1). Daily ridership spiked in period 2, then remained relatively constant afterwards. Shared rides and multiple users per booking identify two different ride statistics: a shared ride indicates that multiple bookings used the same ride, while multiple users per booking indicates a shared ride through one booking. The share of shared rides and the average daily ridership were small in period 1, but larger in the later periods. Users tended to book multiple users per booking at the same rate (10-14%), no matter the period in which they were using the service. Ride times and alternative trip times did not change greatly over the pilot: the mean ride time and cycling alternative trip time were fairly consistent (about 7 min), the mean walking alternative trip time was slightly longer in period 2, and the mean transit alternative trip time with or without estimated wait time was shorter at the start of the pilot. Median trip times were also calculated, but showed similar results, falling within a maximum 8% change from the mean value.

Table 3.2: Ridership and temporal statistics for 903 Flex and alternatives by period

	1	2	3a	3b	Total
903 Flex Pilot					
Period length (operational days)	143	49	43	35	270
Unique users	68	103	88	68	178
Daily ridership, mean (bookings/day)	7.37	33.4	26.0	30.1	25.5
Shared rides (%)	20.2	35.8	25.5	30.9	28.5
2+ users per booking (%)	14.0	9.67	12.4	11.9	11.9
Ride time, mean (min)	7.21	7.07	7.05	6.95	7.08
Competitive alternatives					
Transit trip time, no wait time, mean (min)	22.5	26.5	28.2	27.8	26.2
Transit trip time, with wait time, mean (min)	34.6	38.4	36.7	36.9	36.7
Cycling time, mean (min)	12.9	13.9	12.8	12.7	13.1
Walking time, mean (min)	46.4	49.6	46.0	45.3	47.0

The times users were picked up across 903 Flex periods was relatively uniform across all periods (Figure 3.5). Off-peak trips were very dominant across all periods, consistently representing two-thirds of trips taken in each period. Midday off-peak trips were the most popular (33-44%), followed by evening off-peak trips (25-31%). For periods 1b-3b, these were also the longest segments in the day (5 hours for midday, 3.25 to 4 hours for evening). Trips during peak hours accounted for 10-16% of trips in each period.

Table 3.3 lists the shares of trip types over time for each period. Indirect feeders consisted of over half of 903 Flex rides in periods 1 and 2 and remained the primary trip type in the latter periods. Transit replacements, which are the most transit-competitive types, peaked in period 2, and were relatively stable in the other periods, with a very slight decline

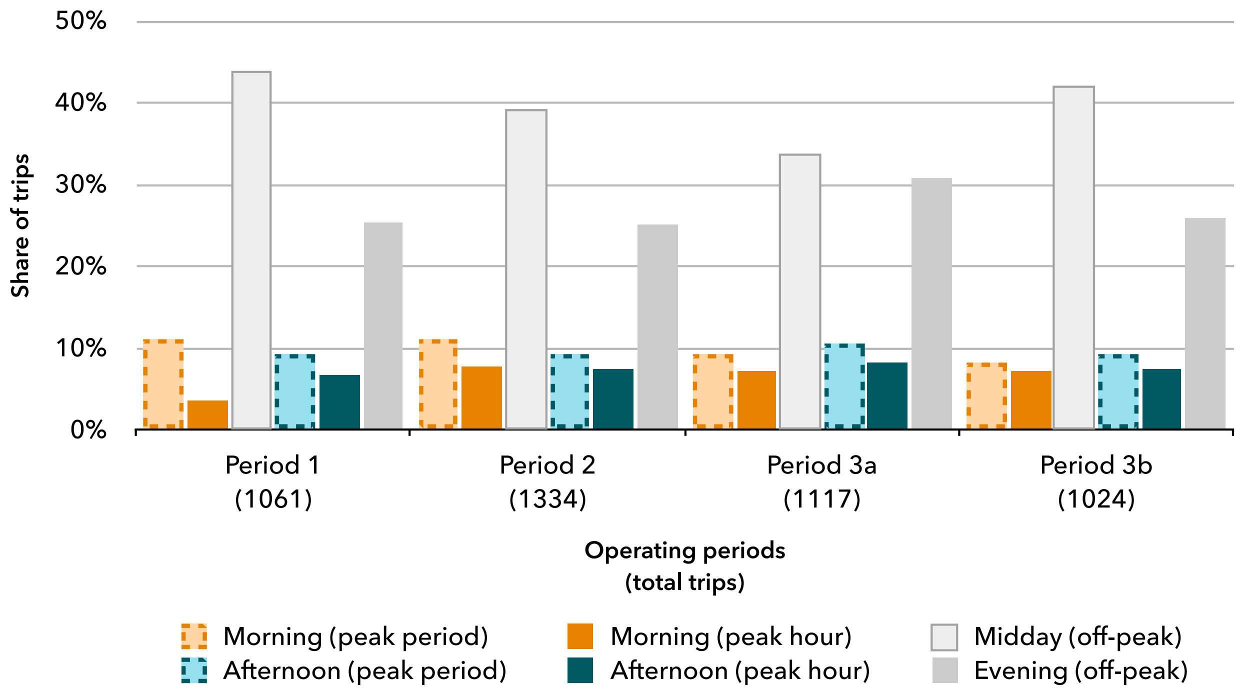


Figure 3.5: Pick-up times by time of day by period

toward period 3b. The peak in period 2 could have been due to free trips that were made available during the period with the introduction of the LRT service (see Table 3.1). Additionally, during that time period, free coupons were handed out to users, which may have also contributed to transit replacements being taken more frequently. Direct feeders, non-transit trips, inconvenient trips, and remote trips, which are the least transit-competitive types, increased from 19% of all trips in period 1 to 45-51% of all trips in periods 3a and 3b. Notably, 85% of non-transit trips were taken by the second-most frequent user in the pilot between the same O-D pair (Rock Elm / Pasture Rose and Columbia Forest Long Term Care). One of the more popular stops (Hagey / Columbia) shifted location after period 2, causing some former indirect feeders to turn into inconvenient or remote trips, but this shift was not solely responsible for the increase; the combined total of transit poor trip types (indirect feeders, inconvenient trips, and remote trips) grew from 65% in period 2 to 76% in period 3a.

The access, egress, minimum access/egress, and maximum access/egress distances for each transit alternative, which form the basis for trip types, were separately assessed (Figure 3.6). Results were placed into bins of distances between the virtual stop and the nearest transit stop. A time of 0 m (i.e., the virtual stop was located at a transit stop) was a common value, warranting separation from the rest of the bins. Over 80% of rides began or ended at a transit stop (i.e., minimum access/egress of 0 m). Eight percent of

Table 3.3: Competitive transit alternative trip types for each operating period

	1		2		3a		3b		Total	
Ride type	No.	%	No.	%	No.	%	No.	%	No.	%
Transit replacement, direct	35	3.3	188	14.1	26	2.3	37	3.6	286	6.3
Transit replacement, indirect	116	10.9	163	12.2	120	10.7	87	8.5	486	10.7
Indirect feeder, inconvenient	371	35.0	317	23.8	123	11.0	95	9.3	906	20.0
Indirect feeder, remote	334	31.5	348	26.1	279	25.0	342	33.4	1303	28.7
Inconvenient, single-ended	44	4.1	26	1.9	41	3.7	85	8.3	196	4.3
Inconvenient, double-ended	14	1.3	33	2.5	64	5.7	55	5.4	166	3.7
Remote, single-ended	118	11.1	113	8.5	273	24.4	202	19.7	706	15.6
Remote, double-ended	8	0.8	30	2.2	71	6.4	37	3.6	146	3.2
Direct feeder	9	0.8	4	0.3	12	1.1	16	1.6	41	0.9
Non-transit trip	12	1.1	112	8.4	108	9.7	68	6.6	300	6.6
Total	1061		1334		1117		1024		4536	

rides began and ended at a transit stop (i.e., maximum access/egress of 0 m).

3.3.2 Users and Trip-Making Frequencies

The weekly ridership for the 903 Flex for the pilot duration (November 2018 to December 2019) steadily grew over time (Figure 3.7). Ridership was separated into new and unique users per week. The first user took their first trip in the last week of December 2018, and starting in mid-January 2019, there was at least one user per week. The number of weekly unique users increased rather steadily, starting in March 2019, and peaking in November 2019. This increase was paired with a regular cadence of new users, which stabilized to between two to four new users weekly. The largest spikes in new users occurred in April 2019 (midway through period 1b, 13 users) and three times in period 2 (11-12 users each time).

Figure 3.8 shows the number of rides taken per unique user, during the whole operation of the pilot, expressed in percentiles. Many users took very few rides during the pilot's operation: 20% of users had taken only one trip, and 50% had taken less than eight. 12 users (7%, above the 93rd percentile) took over 100 trips over the year. These dominant users accounted for 44% of all the rides in the pilot. Most of the dominant users took at least one trip in each period and tended to have a small consistent set of preferred origin-destination pairs. The user with the highest ridership took 359 rides and was the only user to take more than one ride per operational day on average. The frequent, average, and infrequent categories are not considered here because they do not perfectly align with the

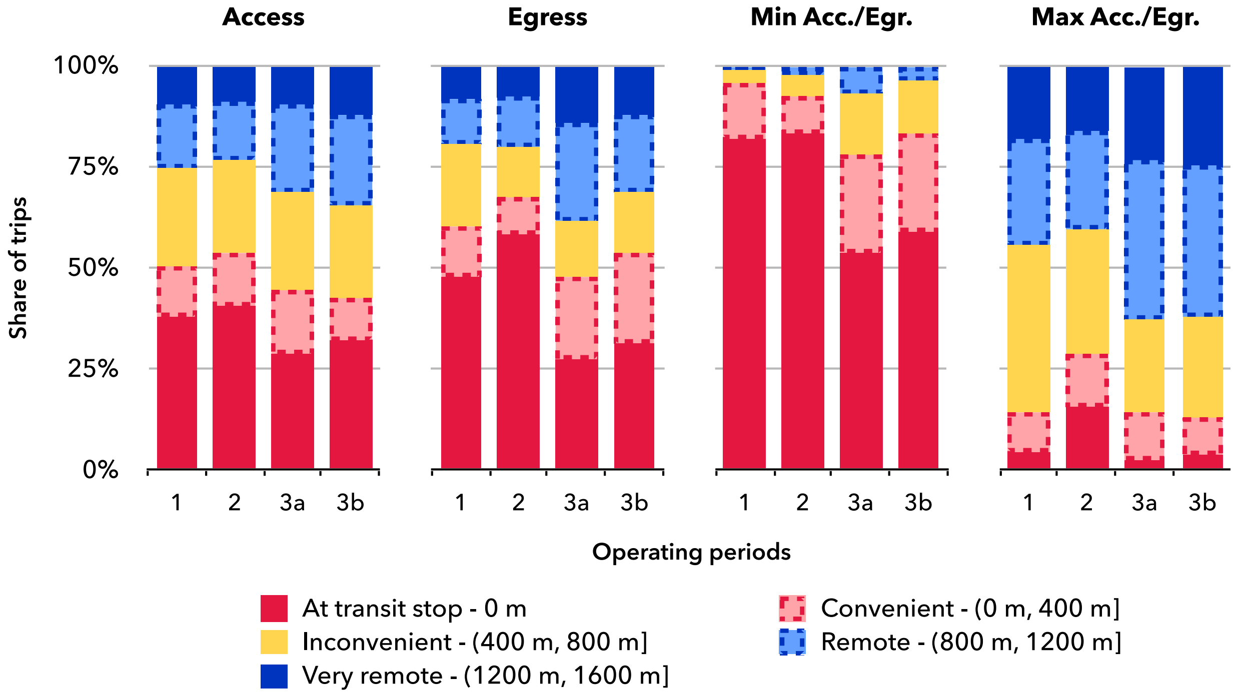


Figure 3.6: Access, egress, minimum, and maximum distances between virtual stops and nearby transit stops by period

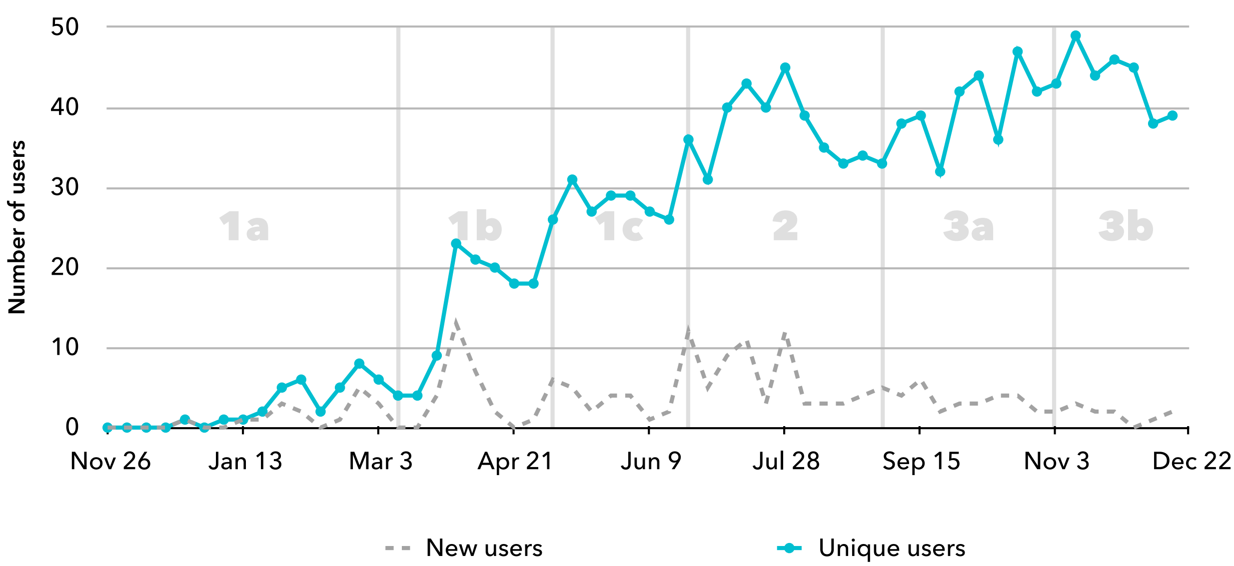


Figure 3.7: 903 Flex weekly ridership statistics

number of rides taken by a user, but generally the more frequent users were in the higher percentiles and infrequent users were in the lower percentiles.

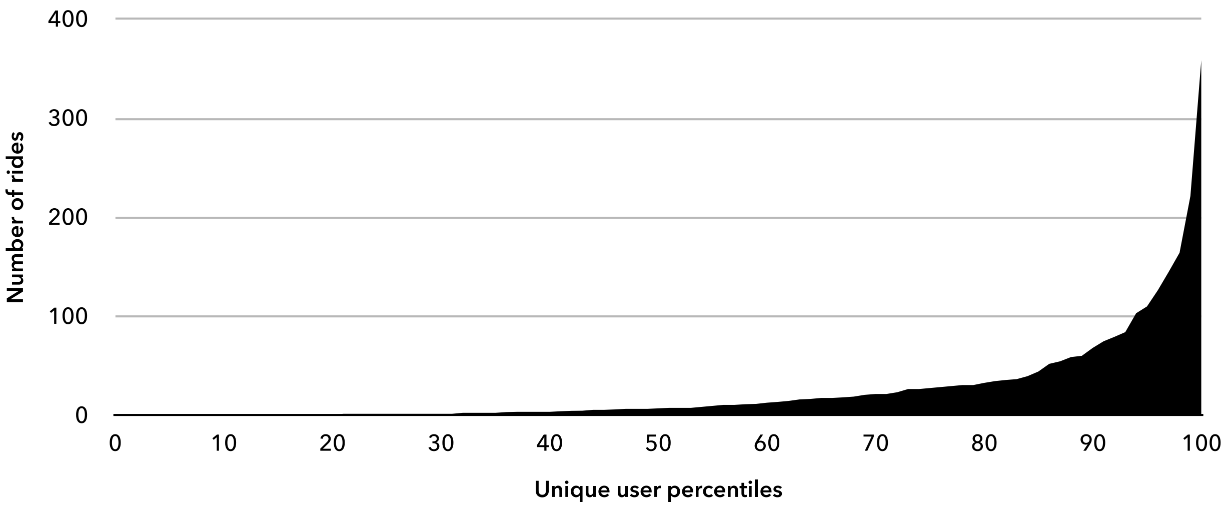


Figure 3.8: Number of rides taken by users in percentiles

Trip types evolved across users with different trip-making frequencies over time (Figure 3.9). The shares for all users for each period are given in Table 3.3. Users were binned into frequent (53 users), average (69 users), and infrequent (56 users), based on their trip-making frequency and their total number of trips. Total rides for each column are listed in brackets along the bottom axis (e.g., 16 total rides by infrequent users in period 1) to provide scale for comparison. Remote trips consist of single-ended and double-ended remote trips, and inconvenient trips consist of single-ended and double-ended inconvenient trips. Frequent users took a smaller share of transit replacements compared to the other two user bins (7-20% vs. 11-52% of trips per period), infrequent users took a smaller share of indirect feeders (0-22% vs. 39-72% of trips per period), and average users took a smaller share of inconvenient and remote trips (6-26% vs. 16-62% of trips per period). Excluding period 1, frequent users took a larger share of direct feeders and non-transit trips (9-12% vs. 0-6% of trips per period). Generally, frequent users took a higher share of more transit-supportive trip types (i.e., trips that are not transit replacements) than users in the less frequent user bins, and had a significantly different share of transit-supportive trip types from average users ($X^2(1, N = 4461) = 240.04, p =< .001$) and from infrequent users ($X^2(1, N = 3772) = 67.07, p =< .001$).

Changes in trip magnitude over each period were assessed for frequent users, because they took enough trips over a sufficiently long period (eight weeks or more with at least an average of one trip per week) to reveal changes in trip patterns. In Figure 3.10, user

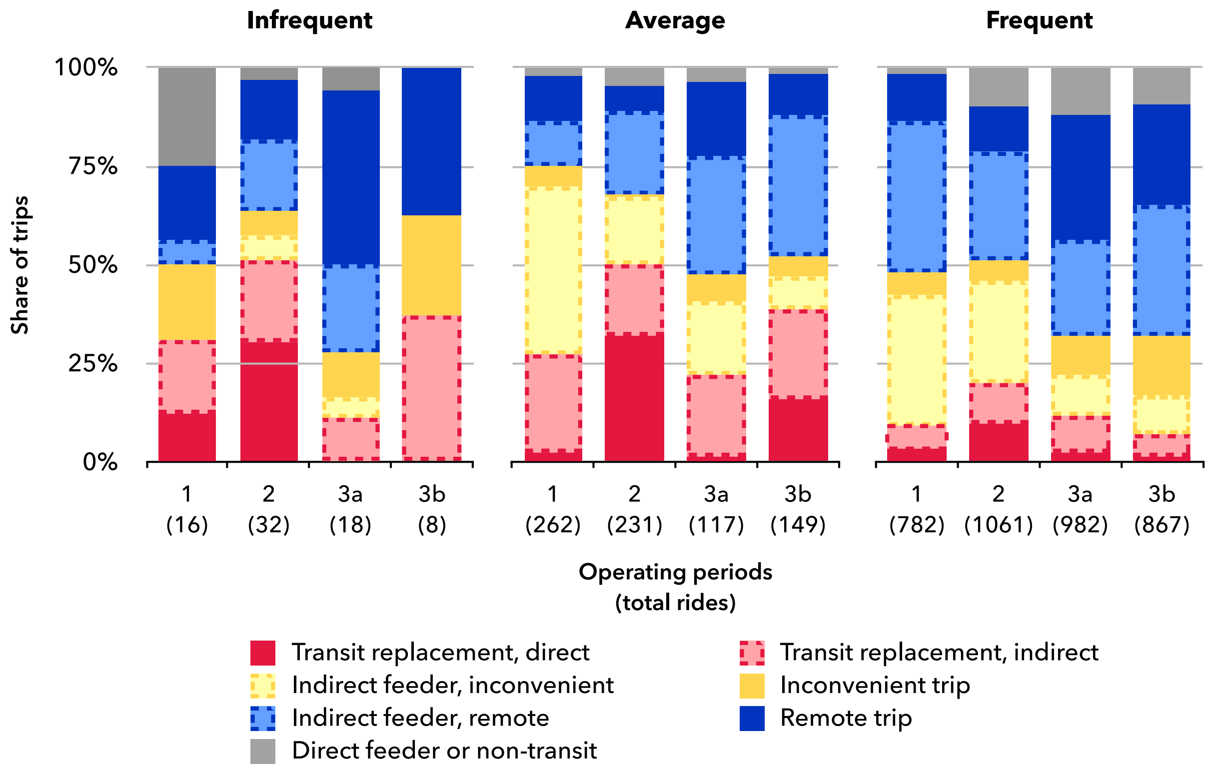


Figure 3.9: Trip types by trip-making frequency by period

behaviour is categorized in each period based on the percent change in trips from the previous period. 'Start' indicates that a user took trips in the current period but made no trips in the previous period. 'Stop' includes users who took no trips in the current period but made a trip in the previous period (i.e., a drop of 100% since the previous period). 'Stable' indicates a user had a percent change between -50% and 50%, and 'Decrease/Increase' represents values below or above those thresholds, respectively. Period 2 represented the largest number of individuals reducing their trip frequency, but few users stopped using the service completely. In periods 3a and 3b, most frequent users continued to increase or stabilize their number of trips.

Changes in trip types for frequent users was also studied but did not reveal substantial changes in trip type over time. 55% of frequent users maintained the same dominant trip type, and 89% of frequent users maintained the same trip type class (medium-high distance from transit, low distance to transit, or no transit).

Figure 3.11 shows the trend in trip types per user, over each operating period. Like in Figure 3.10, period 1 is broken down into the three constituent subperiods. Compared to previous statistics that showed the percent of trips taken overall, this figure weights

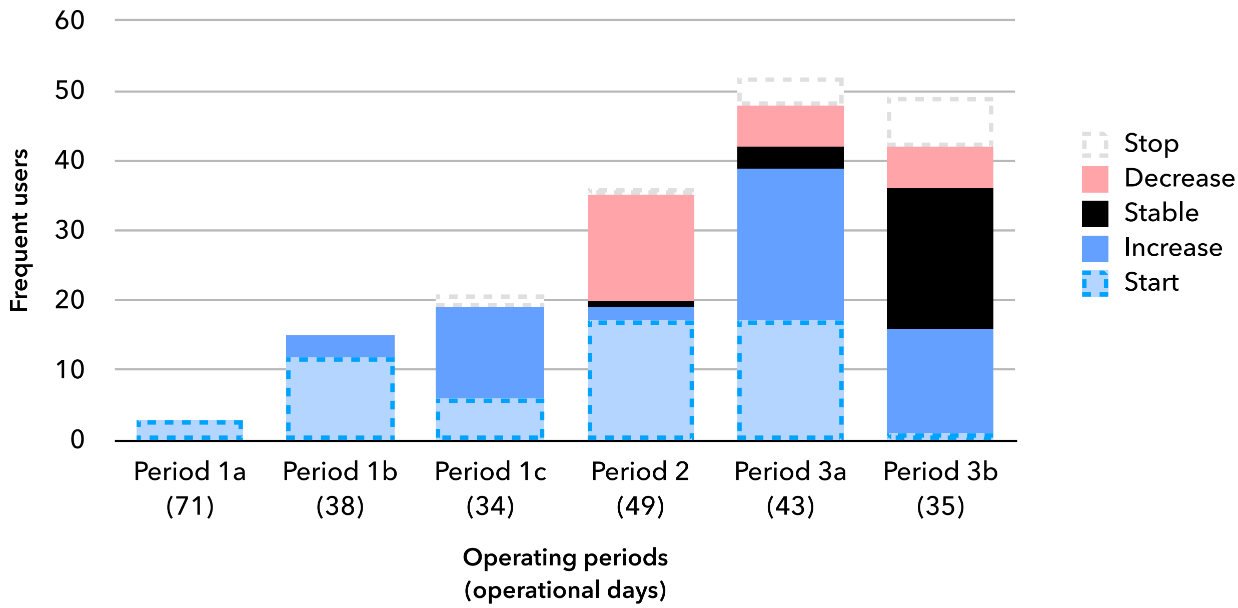


Figure 3.10: Changes in trip magnitude for frequent users by period

trips taken by the number of unique users in that period, broken down by trip type. For example, the average user took 3.44 inconvenient indirect feeders in period 1b. The trip-type shares on a per-user basis correlate with the percent changes (Table 3.3), while also demonstrating the general increase in user attachment. Other than period 1a, each period has a similar number of operational days, yet the number of trips per user continued to increase. The increase in trips per user continued despite Period 2 having the highest number of unique users and daily bookings, and the number of unique users decreasing in both Periods 3a and 3b. Much of the per-user growth was due to increases in trips with high distances to transit on at least one end.

Payment methods used varied greatly, both by users with different trip-making frequencies and across each period (Figure 3.12). Stored-value transit cards were launched in March 2019 (period 1) and became more common across all three user bins. In period 2, two promotions (one for the LRT launch, one targeted at the 903 Flex) resulted in free trips being the dominant 'payment' method. Other forms of payment, which include cash, credit card and missing payment methods, were a larger share for infrequent users and almost negligible for frequent users. Transfers were present across all periods for all user bins: infrequent users paid with transfers at a significantly higher share of their trips in periods 1 and 3 (period 1-2: $X^2(1, N = 49) = 14.71, p =< .001$; period 2-3: $X^2(1, N = 42) = 6.96, p = .008$), average users used them at a fairly consistent rate with no significance between periods other than for period 2 (period 1-2: $X^2(1, N = 498) = 13.49, p =< .001$; period 2-3a: $X^2(1, N = 352) = 12.30, p =< .001$; period 3a-3b:

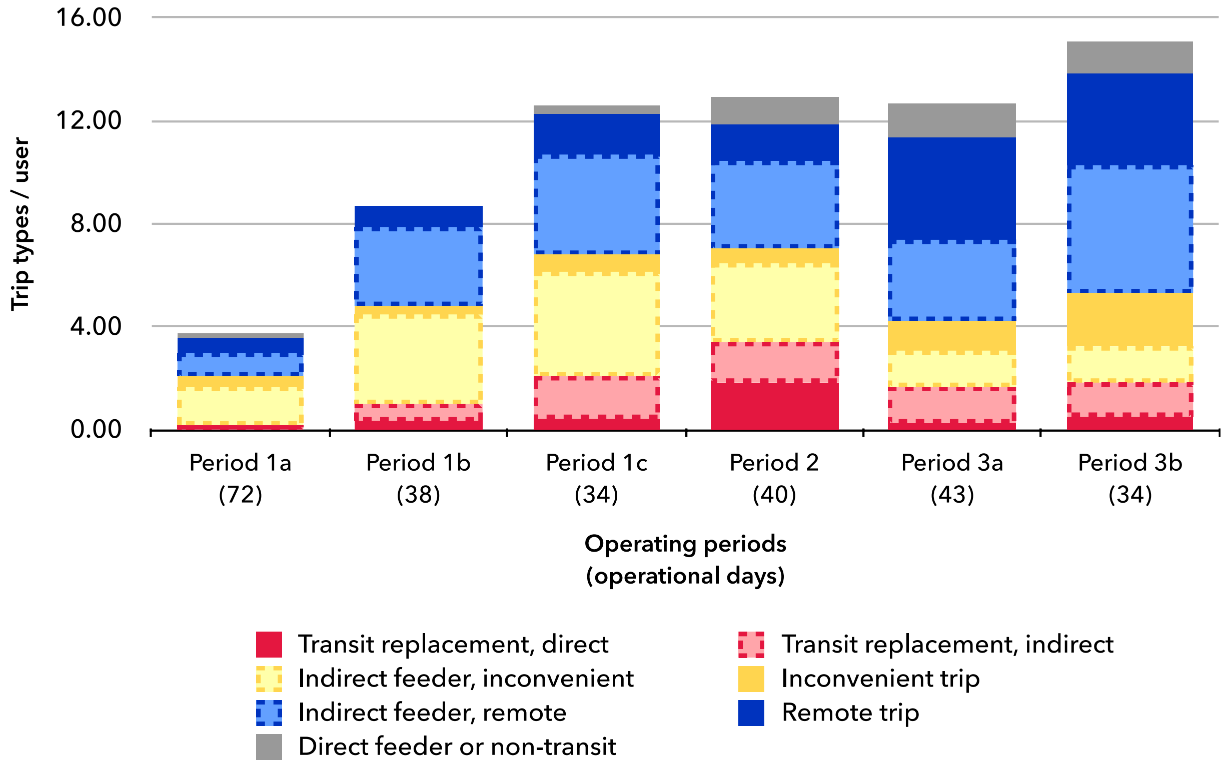


Figure 3.11: Trip types per user for each operating period

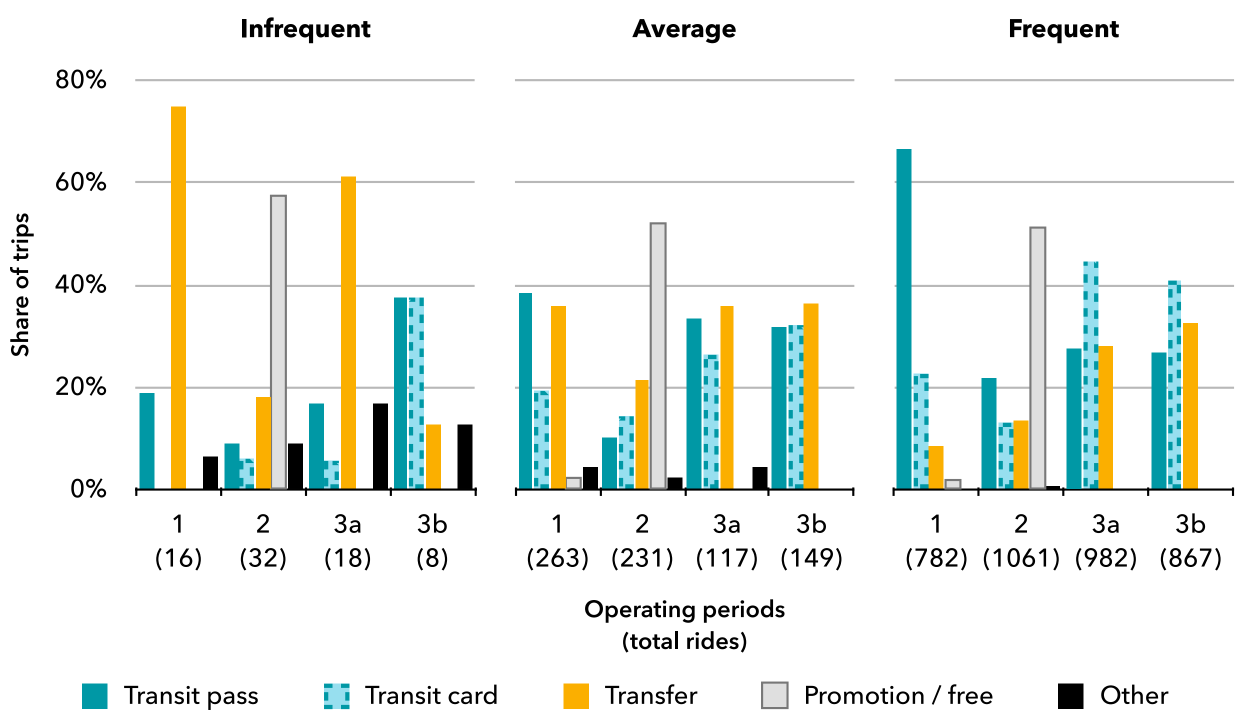


Figure 3.12: Payment methods by trip-making frequency by period

$X^2(1, N = 266) = 2.70, p = .100$; period 3b-1: $X^2(1, N = 412) = 3.90, p = .048$), and frequent users used transfers more in later periods at significantly higher levels (period 1-2: $X^2(1, N = 1848) = 107.50, p =< .001$; period 2-3a: $X^2(1, N = 2048) = 66.31, p =< .001$; period 3a-3b: $X^2(1, N = 1849) = 105.51, p =< .001$). Payments using transfers is an indicator of connectivity with transit: a transfer payment suggests that the ride was part of a greater trip chain that includes fixed-route transit, and that it was likely these trips came after the fixed-route transit trip in the chain, since the users already had the transfer.

3.3.3 Intermodal Competitiveness

Alternative trip times were compared to determine the competitiveness between rides and alternative trip options using transit, walking, and cycling (Table 3.4). Transit and walking alternatives were almost never faster than the ride, although for very short rides, walking was potentially faster if the ride wait time is considered. Cycling was the only alternative that was faster than ridesourcing for a noticeable share of trips, which increased after period 1. Even though walking was the slowest option, there were more cases in periods 3a and 3b where it was faster than taking transit even without transit trip wait time considered. When transit trip wait time is considered, walking was faster for a sizable percent of trips, especially in the first and fourth periods. In periods 1 and 2, cycling was slightly less competitive against transit when removing wait time, which was due to the specific spatial/temporal characteristics of trips going to one transit stop (Hagey/Columbia). This stop was moved for other reasons in periods 3a and 3b, resulting in the same percentage for those periods. When wait time is considered, cycling was faster than transit for almost every trip.

The headways for transit alternatives, rounded to the nearest 5 min for each operating period, were estimated to understand the frequency of available transit trips (Figure 3.13). Trips without a transit alternative and trips where a headway could not be calculated are excluded, but together accounted for 10% of trips or less depending on the period. Headways for trips at most 800 m away or 400 m away from the nearest transit stop are included to depict any variance between maximum 10 min and maximum 5 min access/egress scenarios, where users are more likely to take transit. In the first two periods, headways were mostly divided between 15 min and 30 min headways. In later cases, the distribution shifted more strongly to 15 min headways. Although each of the cases generally had a similar distribution, shorter access/egress distance limits tended to correlate with trips with longer headways, meaning that for trips with reasonable walking distances, buses arrived less frequently.

Table 3.4: Intermodal competitiveness statistics by period

		Trips where Mode 1 is faster (%)				
Mode 1	Mode 2	1	2	3a	3b	Total
All trips		*1061*	*1334*	*1117*	*1024*	*4536*
Cycling	903 Flex	4.9	8.0	8.5	6.9	7.2
Walking	903 Flex	0.0	0.0	0.0	0.0	0.0
Trips with transit alternatives		*1040*	*1218*	*997*	*940*	*4195*
Transit (no wait)	903 Flex	0.5	0.0	0.0	0.0	0.1
Transit (with wait)	903 Flex	0.0	0.0	0.0	0.0	0.0
Cycling	Transit (no wait)	96.5	97.5	100.0	100.0	98.4
Cycling	Transit (with wait)	100.0	99.9	100.0	100.0	100.0
Walking	Transit (no wait)	0.7	0.2	2.8	3.8	1.7
Walking	Transit (with wait)	20.6	16.3	20.3	25.3	20.3

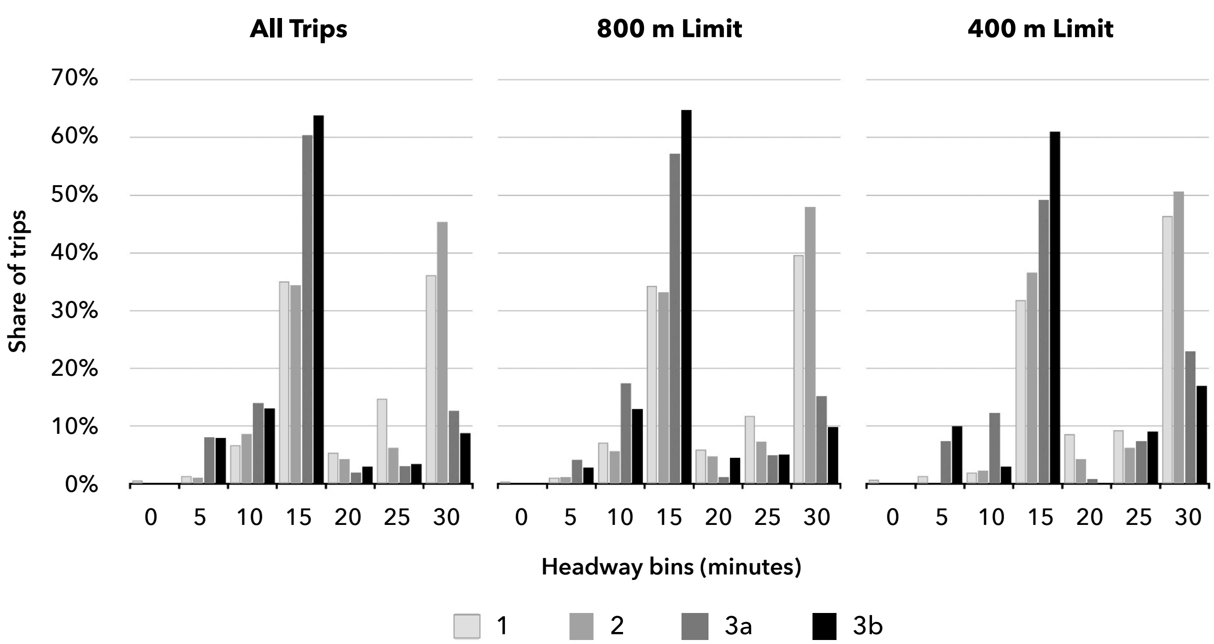


Figure 3.13: Estimated headways for transit alternatives for each operating period

Figure 3.14 shows the cumulative distribution function of time ratios for walking, cycling, and transit alternatives compared with the observed ride times across the entire pilot. Ride times did not include waiting, so these ratios represent the expected best case scenario for ridesourcing. Transit trips were only compared to trips that had a transit alternative (4195 of the 4536 trips). A value greater than 1.0 indicates that rides were shorter, and a value less than 1.0 indicates that walking, cycling, or transit trips were shorter. The majority of walking and transit trips were shown to be at least twice as long as taking a ride. Cycling trips were much more competitive, as half of cycling trips were at worst twice as long as a ride. Most walking trips were over four times as long as a ride. Four transit time ratios are presented, to provide comparisons between theoretical assumptions. The first ratio (blue solid line) compares the ride times against the equivalent transit trips as calculated by OpenTripPlanner, which includes the actual wait times. The second ratio (light grey dashed line) assumes the wait time is equal to half the estimated headway, representing a user's average waiting time. The third ratio (dark grey dashed line) also uses average wait times but adjusts headways to a 15 min maximum, representing a hypothetical high frequency network. The fourth ratio (black dotted line) compares the ride time with a situation in which the user always catches the bus right on time (i.e., the wait time is always 0 min), representing the best-case transit scenario for that trip alternative. Only in the fourth scenario does the wait time assumption make a large difference in the time ratios.

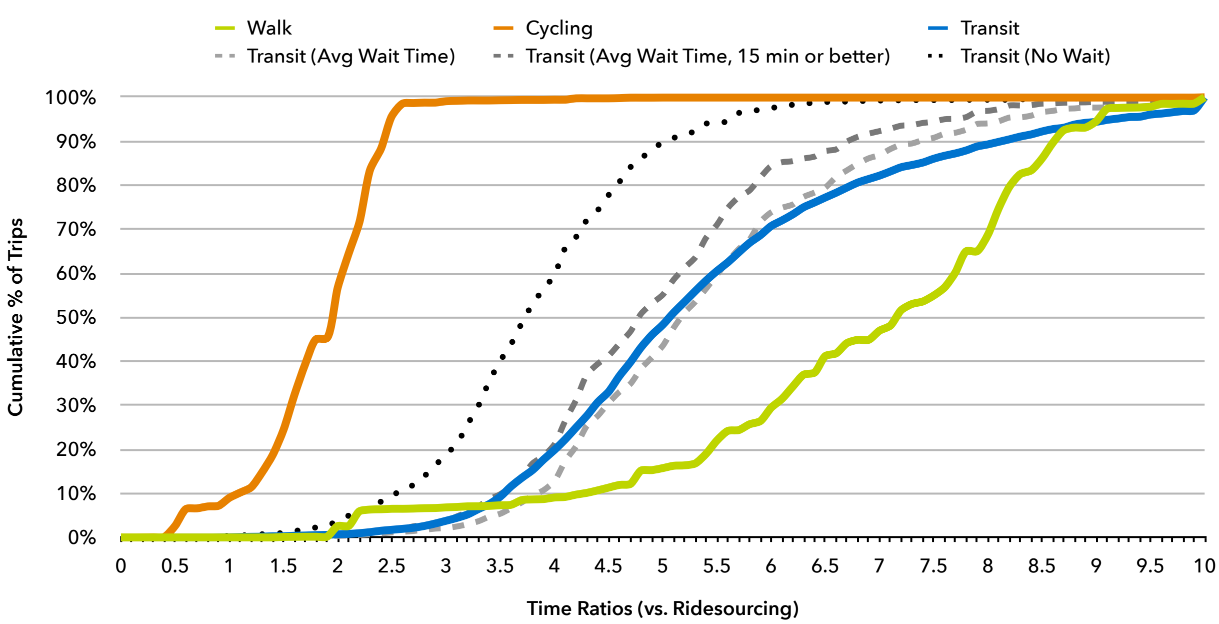


Figure 3.14: Time ratios for walking, cycling, and transit alternatives compared with base rides

Figure 3.15 shows the trip types taken in each period, separated by the number of transfers required for the transit alternative. No alternative transit trip required more than 1 transfer. Direct feeders and non-transit trips were excluded since those trip types have no transit alternatives. The greatest difference between trip categories was that trips requiring a transfer had a significantly higher share of transit replacements (13-63% vs. 6-23% of trips per period), $X^2(1, N = 512.13) = 3.84, p =< .001$. Trip types in the 0-transfer case generally mirror the overall results since trips with 0 transfers made up 82% of the overall transit alternative trips in the pilot.

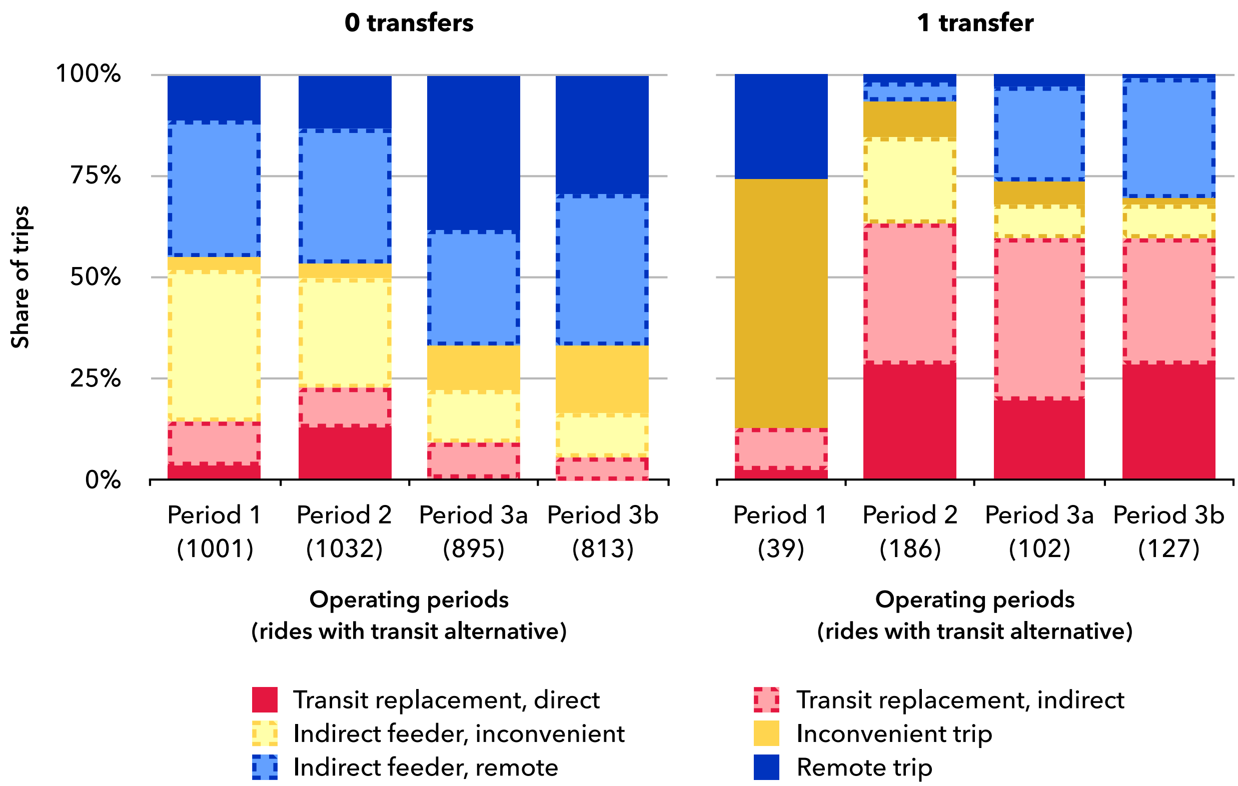


Figure 3.15: Trip types by number of transfers required by period

3.4 Discussion

Daily ridership increased in the later periods of the pilot, suggesting that not only were users making more bookings in aggregate, but existing users were making more frequent trips over time. Consistent with previous findings (Gonzales et al., 2019), user trips appeared to fluctuate less in later periods as users adapted to the pilot's operating parameters. Although individual frequent user trip types did not change greatly, frequent users as a whole shifted toward less transit-competitive trip types, while average and infrequent users had a sporadic but generally larger share of more transit-competitive trip types. The higher share of transit replacements among less frequent groups could be due to sporadic temporal issues more than spatial ones: users may have just missed a transit connection, or their bus may have been out of service, and they were looking for the next best option. These findings suggest that the 903 Flex may have gained success over time if it was continued, but ultimately it was not meeting the desired ridership levels of 7-14 user boardings per hour (Grand River Transit, 2019e).

Rides and their alternatives had fairly stable trip times across all periods of the pilot. The biggest change occurred after the transit network redesign (which coincided with the launch of the LRT system) at the start of period 2, which changed the frequency and trip types, but the lengths of those trips remained fairly constant. The shift from peak-hour service to all-day service in period 1 appeared to introduce a sharp increase in ridership, which makes sense when considering that most trips were taken during off-peak midday and evening service. Users may have been using the 903 Flex during periods when transit was less frequent, which indicates the pilot may have been valuable for non-work trip making. Spatially, trip types trended away from indirect feeders and more toward transit-supportive or complementary modes, suggesting that most 903 Flex trips competed less with transit network over time. There was a sharp increase in transit replacements in period 2, which is likely due to the number of free promotions that were available during the period.

Trips that *would* have been made with one transfer using transit had a much higher share of transit replacements than those requiring no transfers. This finding suggests that transfers may be a large driver in transit replacement trips, since they extend the wait time between routes and introduce uncertainty in travel times. This finding is consistent with other literature (Yan et al., 2019), which indicates that transfers substantially deter transit use.

23% of users paid with transfers, suggesting that these users were connecting from transit. The high incidence of transfers among infrequent and average users suggests these users were using ridesourcing to address a gap in the transit system. Over time, frequent users began to pay with transfers more frequently, further suggesting these trips are specifically part of a fixed-route transit trip chain. 60% of all users paid with transit passes in period 1, shifting to 20-30% per period in the later periods, which may indicate that the initial user base consisted of more frequent transit users, and that from periods 2 and on, the pilot was able to reach users who may not have regularly used fixed-route transit in the past.

Across multimodal alternatives, transit trip times were not competitive with rides.

Cycling times were competitive with 5-10% of rides and were consistently faster than the corresponding walking and transit alternatives. Walking was not a feasible alternative to rides in most cases, and variably competed with transit. Improved cycling infrastructure in this area could potentially improve connectivity to transit.

It is important not to extrapolate the time ratio statistics as representative of all travel in the pilot area. Ride times included in the time ratio only used actual departure to actual arrival (i.e., wait times for the ridsourcing vehicles were not included), biasing the time ratios in favour of ridesourcing. The time ratios for individual pairs will not change and are accurate for a specific origin-destination pair at a given time. However, the contribution to the percent-share in trips, as presented in Figure 3.14, will further bias toward trips that use ridesourcing, particularly because some pairs are counted multiple times, depending on the popularity of that trip in the dataset. This indicates that for the rides made during this study period, ridesourcing was usually a rational mode choice. Almost no trips had time ratios below or equal to 1.0: transit and walking were faster than taking a ride for less than 1% of trips, and cycling was faster for just under 3% of trips. In cases where a mode is cheaper, a time ratio between 1.0 and 2.0 may indicate that the cheaper mode is still viable, since a user may take a slightly longer trip to save cost. Walking and cycling are the cheapest modes, so alternatives with time ratios between 1.0 and 2.0 (1% of all walking trips and 51% of all cycling trips) could be viable options. The low number of walking trips at any value below 2.0 suggests that many of the trips where walking is more competitive in this range are already made through walking (unobserved in these data) or are trips where another mode replaced walking. The out-of-pocket cost of taking a ride is the same as taking the equivalent bus, since the fare is the same, so even though 1-4% of transit trips were up to two times longer than ridesourcing, there is less incentive for a user to intentionally take a longer bus ride. Higher transit use can be encouraged in cases where transit is more competitive by introducing a higher charge for ridesourcing, which would encourage users to use ridesourcing only when it is worth the additional cost. However, increasing the fare should be done with caution, since users who previously drove (instead of taking transit) may just return to driving.

It is unsurprising that many trips are indirect feeders, given the length of the routes and the pilot area's size. The average trip was 4 km long, and some trips were up to 9 km long, stretching from one corner of the pilot area to the other. If the pilot area had expanded, caution would have been needed to avoid encouraging very long rides. One option could have been to limit each virtual stop to a set of other virtual stops and bus stops around them, so that riders are encouraged to feed into the existing bus network. A limitation to this approach could be the infrequent headways on some of the buses that served the pilot area, since many of the alternative transit trips operated at 30-minute headways. Without reliable, higher frequency service, users would likely transition to more expensive, non-integrated ridesourcing options instead.

In some cases, a transit agency may consider replacing low-frequency routes entirely with TIR. Agencies should be cautious about complete replacement of fixed-route services in cases where the ridership on the low-frequency routes is high, since the replacement ridesourcing service may not attract enough ridership or minimize costs to sufficiently justify the replacement. These decisions may require an understanding of the costs associated with operating each option and of mode preferences in the impacted areas.

3.4.1 Limitations

One limitation of the trip alternative generation method was that alternatives assumed users would take the trip with the least amount of walking time overall, which may not reflect true user preferences. For cycling alternatives an equal weighting was given to speed, bike friendliness, and elevation, which may not reflect all users' preferences.

There was an inherent selection bias among users who were attracted to the pilot, limiting the generality of conclusions about travel behaviour more broadly. Demographic data about 903 Flex users was unavailable outside of a voluntary survey. Metrics such as the age of users, gender, income, and disability status would have been useful in understanding the extent to which these factors influenced user behaviour.

This study assumed that all trips started and ended at virtual stops. 'Real' trip alternatives would likely be based off users' true origins and destinations. Because the pilot was restricted to one neighbourhood, there was also an inherent limit to which trips could be made. Although this pilot suggests that transit replacements were in the minority of trip types despite users having no restrictions on their trip making behaviour, this characteristic may not apply to larger pilots where a greater service area is implemented.

3.5 Conclusions of 903 Flex Analysis

Ridesourcing is being considered as an extension of fixed-route transit networks, helping transit agencies broaden their coverage into traditionally poorly serviced areas. This research proposed and applied a typology to assess the competitiveness of TIR with other modes. This typology can be implemented by other agencies that have overlapping fixed-route and TIR networks (Figure 2.1), to assess their spatial competitiveness. Using the

903 Flex pilot data, a spatial and longitudinal analysis of users was conducted, considering a proposed series of trip types using the typology, payment methods, behavioural changes, and competitiveness with other modes.

The data suggest that most trips taken within the pilot duration were complementary to the transportation network and progressed toward more transit-supportive trip types. Although the trends from the 903 Flex pilot were generally positive, over 16% of trips competed with transit, peaking during the promotional period. Agencies should take care in the future to avoid duplication in services, and to avoid detracting users away from existing transit infrastructure.

Ridesourcing projects show potential as supplementary services that can integrate with existing public transportation systems to expand mobility options. Better accounting for multimodal journeys, motivations for increasing user adoption over time, the spatial resolution, and expanding the temporal scope of study would improve the transit agency's understanding of how to best implement ridesourcing projects.

Chapter 4

RP-SP Survey

This chapter describes the design, implementation, and results of an RP-SP survey conducted in northwest Waterloo in 2021. The survey was used to develop an understanding of how residents of this area perceive various TIR systems, which allows for ridership impacts to be estimated for different system types. Because the survey was focused on what a transit agency could do to improve the positive impacts of different system types, the SP experiments prioritized changing attributes of transit or TIR that could be translated into spatial differences of systems.

Section 4.1 details the survey design, following a process adapted from Hensher et al. (2015). Section 4.2 outlines the process for sharing the survey with the target residents. Section 4.3 provides general statistics for how the survey operated, outlines the filtering process for removing outliers, and summarizes the process for administering the appreciation draw. Section 4.4 presents and discusses the findings of the RP parts of the survey, demographic questions, survey statistics, and questions concerning COVID-19 comfort. Full model findings from the SP section are provided in Section 5.2.1 as part of the evaluation component of the thesis.

The survey uniquely contributes to preference literature. Cost, time, and common alternatives have not been included together in previous transit-integrated ridesourcing surveys. The revealed-preference portion uses automatic RP attribute collection, which is uncommon in preferential surveys. The population base for this survey was a general population in an area previously identified as ideal for on-demand transit. The results of the survey and the anonymized dataset will be of use to researchers and other regions implementing their own transit-integrated ridesourcing systems.

4.1 Design

The general process for designing SP experiments was adapted from Hensher et al. (2015). The stages are somewhat cyclical in nature, but are generally presented in the order in which they are first introduced into the design process. The first stage is refining the problem, where the socioeconomic and travel characteristics of the study area are explored, the full list of potential alternatives and attributes are identified, and large-scale exploratory questions are studied to understand what specific questions should be answered through the research and which techniques should be used to answer these questions. The second stage is refining the stimuli, which are the alternatives, attributes, and attribute levels. In this stage, the final list of stimuli is narrowed by considering which stimuli are most necessary for answering the research question and which can be removed to minimize respondents' decision fatigue and survey completion time. The third stage is considering the design elements of the experiment, which include the expected utility functions and the number of choice experiments. The fourth stage is generating the experimental design, where the SP experiments are created and estimated required sample sizes are determined. The fourth stage also includes three additional stages from Hensher et al. (2015) ('generate choice sets', 'allocate attributes to design columns', and 'randomize choice sets'), which are performed automatically by the chosen survey software. Because of the automated nature of how the design is generated, the three omitted stages are included in this stage. The fifth and final stage is constructing the survey instrument, which includes the pre- and post-SP elements. The fifth stage is quite extensive, so it is split into two sections in this chapter (one for before the SP section, which had predominantly RP questions, and one for after, which had demographic and COVID-19 questions).

4.1.1 Problem Refinement

The intended area for conducting the survey was the same part of Waterloo where the 903 Flex previously operated (recall Figure 3.2). This area was previously identified by GRT as an ideal area in Waterloo for TIR service, due to the high number of transit requests but relatively low population density and ridership potential. The survey was intended to capture the same population as the 903 Flex's service area to determine how different configurations of TIR may have performed in this area.

Multiple data sources were used to profile the residents in the study area. Figure 4.1 depicts the combination of traffic analysis zones (TAZs), forward sortation areas (FSAs), and census aggregate dissemination areas (ADAs) that overlap with the study area (Data

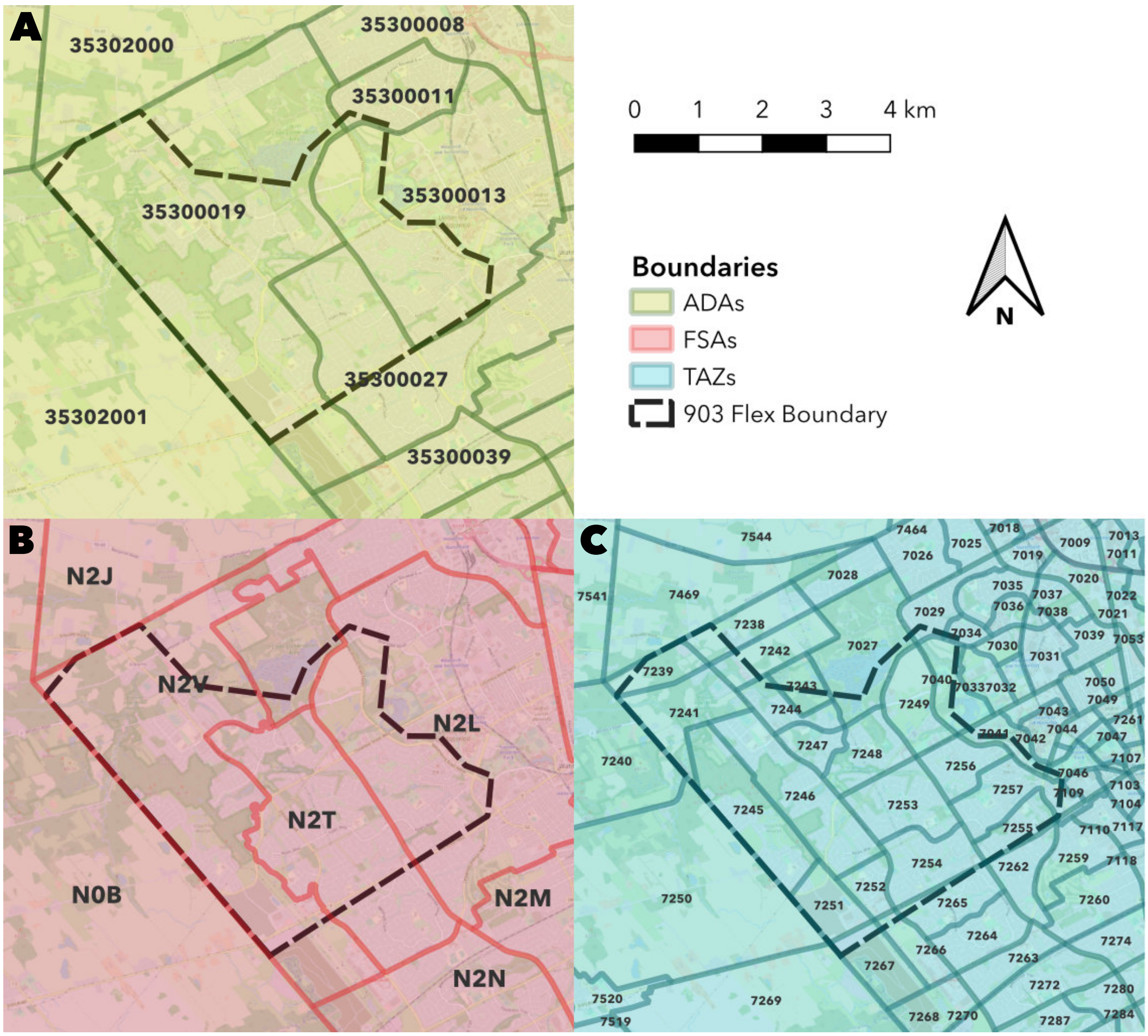


Figure 4.1: Aggregate dissemination areas (A), forward sortation areas (B), and traffic analysis zones (C) overlapping with the study area

Management Group, 2016; Statistics Canada, 2017a, 2017b). TAZs are used by the Transportation Tomorrow Survey (TTS) for aggregating traffic flows into manageable sizes. FSAs, which form the first half of Canadian postal codes, are geographical units used by Canada Post to route mail to the correct region, and are used by Canadian census for some demographic statistics. ADAs are also used by census for demographic statistics, but cover different boundaries than FSAs. FSAs and census ADAs were used to gather census demographics on residents in the study area.

For FSAs, N2V, N2T, and N2L overlap with the study area. All FSAs have portions that are not part of the survey area to varying degrees (N2V with Northfield, N2T with a neighbourhood south of the survey boundary, and N2L with the area around the University of Waterloo, Wilfrid Laurier University, and Uptown Waterloo). N2T was assumed to be the most representative because it had the most overlap with the study area or neighbourhoods with similar characteristics, and N2V was also included because most residents lived within the study area. The non-target population in N2L would greatly outweigh the target population, so N2L was excluded from the background statistics.

For census ADAs, three areas overlap with the study area: 35300019, which was mixed with the neighbourhoods around the Grand River Conservation Area, 35300013, which was mixed with Uptown Waterloo, and 35300027, which was mixed with student neighbourhoods around the universities. Because ADA 35300019 has relatively few residents living outside of the study area and covered a majority of the study area, it was considered representative enough to represent the intended population.

TAZs were easier to include or remove, since they have the smallest sizes and overlap less with areas outside of the study area. TAZs 7238-7239, 7241-7249, and 7251-7257 were determined to best overlap with the study area. In general, TAZs and FSAs were the primary data sources due to the variety of their associated data, and ADAs were used as supplementary data for comparison.

TAZs were used for estimating existing mode shares (Table 4.1). Origin-destination pairs were filtered from the TTS database to start or end in one of the target zones. The origin-only case is also presented for comparison, since both assumptions could be valid: trips that start or end in the area could both reflect people that live in the study area (e.g. a trip ending in one of the zones could be a trip back home from work). In either scenario, the general mode shares were similar, with slightly more walking trips and less driving or transit trips for trips that started in the target zones. Personal vehicle travel, by driving or as a passenger, was the dominant mode in this area (around 85%), and transit, walking, and cycling also had shares over 1%. Rideshare was listed as a general mode in the TTS, but the only rideshare system operating in Waterloo in 2016 was Uber, so all rideshare rides are assumed to be Uber rides.

Table 4.1: Estimated mode share for trips taken by study area residents

Mode	Share, origin or destination (%)	Share, only origin (%)
Auto (driver)	70.0	68.2
Auto (passenger)	15.7	15.9
Cycling	2.0	1.9
Transit	4.9	4.3
- Local	*4.8*	*4.2*
- Local + GO	*0.1*	*0.1*
- GO	*0.0*	*0.0*
School bus	2.2	2.7
Rideshare (Uber)	0.1	0.1
Taxi	0.2	0.2
Walking	4.9	6.6
Motorcycle	0.1	0.1
Other	0.0	0.0

For commutes, ADAs revealed that 84% of HBW trips were made by driving from the study area, 8% as a passenger in a private vehicle, 5% by transit, 2% by walking, and 2% by other modes. The share of walking and transit was slightly lower in this area than in the Region of Waterloo as a whole, and driving and commuting as a passenger were higher. In the two ADAs that overlap with Uptown Waterloo and the University, the share of auto is much lower and the share of transit, walking, and cycling is much higher, so it is possible that the share of those modes may be a little higher, but likely not much higher than the estimates for the whole region.

TAZs were also used to estimate additional transportation-related statistics for individuals (Figure 4.2). Because these statistics are not the primary output of the TTS, the scaling method used in cross-tabulation tends to not provide the same level of accuracy as the primary outputs like mode share, but are the best publicly available estimates for these statistics and are likely within the correct order of magnitude. Driver's licence possession and free parking at work estimates are shown for residents 16 years old or older (since residents need to be 16 years old to work or drive). Transit pass possession estimates are provided for all ages and for residents aged 16 years old or older for comparison. About 88% of the eligible population was estimated to have a driver's licence, which is fairly high and indicates most of the population was able to drive to some degree. Of those who work, most were estimated to have free parking at their workplace, although a considerable minority of people do not. Transit pass possession did not change greatly between the 16 years old or older population versus the general population, and in both cases most people were estimated not to have a transit pass. About a tenth of the population was estimated to have a local transit pass, which is about double the estimated share of transit in the area (Table 4.1). The much higher estimated share of passes may be due to the high share of post-secondary transit passes in the region, most of which are included in full-time students' fees.

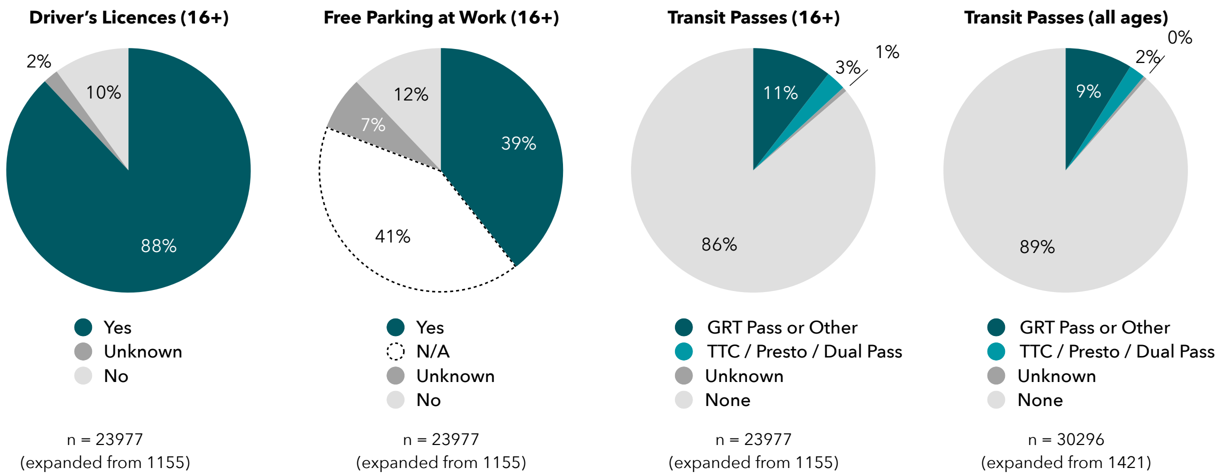


Figure 4.2: Driver's licence possession, free parking at work shares, and transit pass possession estimates from TTS

Figure 4.3 depicts age, gender, and household income as reported by FSA in the 2016 census, supplemented by ADA data. The 2016 census tables did not separate out genders other than male or female (e.g., non-binary), so other genders are not presented in the table. Compared to the region, there is a slightly higher concentration of people aged 15-24 and 45-54 (∼2%), and a slightly lower concentration of seniors (65 and older). The income of this area is also much higher than the region – incomes below \$100 000 are progressively lower than the regional average (under \$45 000 is 26% of the regional population) and incomes above \$124 999 are progressively higher than the average (over \$200 000 is 7% of the regional population), and the median income for the study area is estimated to be \$112 896, while the median income for the region is \$77 530. Generally, this area is slightly younger and considerably higher-income than the average Waterloo area.

Figure 4.3: Age, gender, and income ranges from 2016 census

Additional factors were considered that may impact how people travel in the study area. Work and school were likely high motivators for travel, since those are regular mandatory trips. COVID-19 was likely a depressor on travel, since many businesses and destinations were closed during the pandemic. Recreational and social trips have in some cases been found to be prominent use cases for TIR or other ridesourcing services (Feigon & Murphy, 2016), so a study exploring ridesourcing-based options should consider non-work trips. For active modes (walking and cycling), trip volumes would likely be seasonal. Finally, inclement weather may also be a factor in choosing a sheltered mode versus a non-sheltered mode.

Table 4.2 lists the range of attributes for each existing alternative and TIR from Table 4.1. In the table, 'moto' is short for motorcycle. Past research identified walk time, wait time, ride time, cost, pickup deviation, drop-off deviation, and either IVTT or total time as important factors in DRT objective functions (Section 2.3.1) and past relevant SP surveys and models (Table 2.3). Additionally, different system type configurations (Table 2.4) and other design attributes (Table 2.5) of TIR can cause direct changes in some of these attributes.

4.1.2 Stimuli Refinement

With the full set of eligible alternatives and attributes generated, the next step of the survey design process is to refine the number of alternatives and attributes to minimize decision fatigue and survey length. The full list of alternatives is presented in Table 4.3. In SP surveys, it is recommended to have all alternatives available to decision makers to best reflect their real-world decision-making. However, alternatives are often removed to

Table 4.2: Attributes for existing alternatives and transit-integrated ridesourcing

Attribute	Auto (drive), Moto.	Auto (pass.)	Walk	Transit	School bus	Cycle	Taxi, Uber	TIR
In-vehicle time[a]	X	X		X	X	X	X	X
Wait time[ab]		X		X	X		X	X
Time to park	X							
Pickup dev.		X		X	X		X	X
Drop-off dev.	X	X	X	X	X	X	X	X
Access time[a]				X	X			X
Egress time[a]				X	X			X
Walk time			X					
Fare[b]				X			X	X
Parking fee	X							
Transfer time[ab]				X				X
No. of transfers[a]				X				X
Additional stops[a]								X

[a] Attribute has a direct change based on system type
[b] Attribute has a direct change based on other design attributes

avoid decision fatigue, especially if they are unlikely options or alternatives that can be combined with each other to form a larger alternative.

Some alternatives in the existing set were subject to exclusions: choosing auto as a driver requires that the respondent has a driver's licence, and choosing auto as a passenger indicates the respondent has access to a driver. The high share of driving in the study area also suggested most people would pick driving, if given the option between the two modes. Therefore, the driver and passenger modes were assumed to be mutually exclusive, and were combined into one mode (auto), where the respondent would decide whether being a driver or a passenger was their more likely mode. While passengers would be less sensitive to some of the attributes, like parking cost, it was more feasible to offer the same set of attributes to both drivers and passengers. Motorcycle riders and auto drivers have the same set of attributes, as do taxi passengers and Uber passengers, so each set of modes was combined into auto (driver) and private ridehailing, respectively.

School buses are only available for students in grade school, and children taking school buses are generally already captive to their mode. Additionally, whether children take school buses or not, they generally don't have decision-making power for making trips, so the decision was made to eliminate grade school trips from the survey, school buses as an alternative, and children from the respondent set.

Table 4.3: Alternative selection

#	Alternative	Priority	Exclusions	Priority reasoning
1	TIR	Required	No	Focus mode of the research
2	Transit (GRT bus and ION)	Required	No	Primary comparative mode
3a	Auto (driver)	High	Yes	Majority of trips taken in this area are by driving a car (70%)
3b	Auto (passenger)	High	Yes	Second-most common mode of travel in this area (16%)
4	Cycling	Medium-high	No	Fairly competitive option time-wise, but not a popular mode currently
5	Private ridehailing (taxi/Uber)	Medium	No	Merged taxi and Uber together, similar attributes. May be similar to TIR, useful for comparison but may be less popular.
-	Walking	Medium	No	As popular as taking transit in this area (5%), but not likely for longer trips
-	School bus	Low	Yes	Unlikely to compete with TIR, eliminate school trips from study
-	Motorcycle	Low	No	Unnecessary and takes up a minimal share, merge into auto (driver)

Finally, of the six remaining modes, walking was eliminated in an effort to minimize respondent burden, reduce the required sample size, and because it was considered the least competitive for trips made by TIR. A restriction was added to survey to exclude trips that would be made by walking and focus on longer trips. While both cycling and private ridehailing were less popular than walking in this area, they are more competitive for the longer trips for which TIR would be expected to be more popular.

Attributes to use in the survey were also refined, starting with the full list of attributes from Table 4.2. The selection process is outlined in Table 4.4. A target of three to eight attributes was used as a starting guideline, following industry guidance for gaining useful trade-offs between alternatives without having the respondent default to simplified decision-making schemes (Qualtrics, 2022). Because the primary focus of the survey was to determine sensitivity to different TIR system types, attributes that could be influenced by system types were prioritized (Table 2.4). The number of passengers attribute was removed first because a ridesourcing service offered through transit would be shared by nature, and it made explaining TIR to the respondents easier. Walk time, access time, and egress time were all valuable, and were combined into one metric based on time spent walking. Parking fees and reliability were originally removed, but were reintroduced later to avoid auto domination in responses. Without these two attributes, the only attribute for auto and cycling was IVTT. When conducting survey pilots, test respondents indicated the auto mode was extremely desirable given the shown attributes, and there was no reason to choose other modes. Other researchers in the SP experiment field proposed that adding auto deterrents could help counter auto dominance in the experiments (J. M. Rose, personal communication, 2021, February 24). Finally, while the number of additional stops is influenced by the system type, it was removed because it could be represented in choice experiments by giving longer IVTT time options.

The final part of stimuli refinement is deciding on the levels for each attribute. Table 4.5 lists the final attribute levels used in the survey. Industry guidance recommends at most seven levels for each attribute (Qualtrics, 2022) to minimize the number of experiments needed to get acceptable utility estimates, and literature recommends that at least the endpoints (minimum and maximum values) should be included (Hensher et al., 2015). Utility estimates can only apply between the endpoint values measured in the study, so it is desirable to have the widest realistic range possible so that the estimates are widely applicable. Extra levels are added in between at points either where inflection points are expected or at other points of interest to the modeller. More attribute levels were originally chosen but were removed either due to concerns over auto dominance in the choice set or to minimize the number of design experiments. The eliminated attribute levels are discussed

Table 4.4: Attribute selection

#	Attribute	Priority	Reasoning
1	In-vehicle time	Required	System type correlated
2	Wait time	Required	System type correlated
3	Transfer time	Required	System type correlated
4	Walk time	Required	Walking mode version of IVTT. Combine with access and egress time
5a	Fare	Required	Valuable design attribute component
5b	Parking fee	Medium	Useful for auto comparison to fare. Most parking is free in Waterloo. Combined with fare to make auto less desirable in some scenarios for utility balance
6	Number of transfers	Required	System type correlated
7	Reliability	Medium	Perceived qualitative reliability of the system. Originally removed, but added as quantitative margin of error for total time to balance out auto alternatives
-	Access time	Required	System type correlated, merged with walk
-	Egress time	Required	System type correlated, merged with walk
-	Time to park	Medium	Useful for auto. Generally low search time for parking in Waterloo
-	Pickup deviation	Medium	Accuracy may impact willingness to choose mode. Merged with reliability
-	Drop-off deviation	Medium	Accuracy may impact willingness to choose mode. Merged with reliability
-	Additional stops	High	System type correlated, but could be combined into ride time. Removed and considered as part of IVTT and the sharedness of TIR.
-	Number of passengers	Low	Implied in sharedness, most transit agencies would not offer private rides. Used to distinguish from 'private ridehailing'

in Appendix B.

Table 4.5: Final attribute levels chosen

Attribute	TIR	Transit	Private ridehailing	Cycling	Auto
In-vehicle time (min)	GAPI[a] (1x, 2x, 3x)	GAPI[a] (1x, 2x, 3x)	GAPI[a]	GAPI[c]	GAPI[a]
Wait time (min)	3, 5, 10, 30	3, 5, 10, 30	3, 5, 10, 30	–	–
Transfer time (min)	0, 5, 10, 30	0, 5, 10, 30	–	–	–
Walk time (min)	0, 5, 10, 30	0, 5, 10, 30	–	–	–
Fare / parking ($)	0, 1, 3.5, 8	0, 2, 3.5, 5	GAPI[a] (1x, 2.5x, 5x, 10x)	–	0, 1, 3, 15
Number of transfers	0, 1, 2, 3	0, 1, 2, 3	–	–	–
Reliability	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[c] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 15%, 25%, 50%)

[a] Drive time determined from Google API
[c] Cycle time determined from Google API

For IVTT, instead of using a series of static sample drive and cycle times, respondents entered their origin destination pair into a form, which returned actual drive and cycle times from the Google Directions and Distance Matrix APIs (process outlined in Section 4.1.5). IVTTs in the SP experiments for transit and TIR were then pivoted around the drive times from the Google API to reduce the hypothetical nature of the questions, improve how relevant the scenarios felt for the respondent, and improve the estimated accuracy of the results (J. M. Rose et al., 2019). Because the IVTTs were based around the auto time, IVTT was expressed as a ratio in the transit and TIR utility functions, where the ratio indicates how much longer in multiples the transit or TIR IVTT was versus driving IVTT (e.g., 2x indicates a trip with IVTT twice as long as driving). The range of IVTT ratios for transit and TIR were based on the actual range of transit times in the Region of Waterloo in comparison to driving alternatives, simulating the effects of less direct transit and TIR (reduced from 4x to minimize auto dominance).

A wait time of 3 minutes represented effectively instant service, and 30 minutes generally reflected the worst headway in the existing network in the study area. A transfer time of 0 minutes assumed instant transfers, and 30 minutes assumed the highest expected wait time, following the same logic used for wait times. A walk time of 0 minutes assumed door-to-door service, and 30 minutes represented the practical maximum for combined access or egress in the study area (reduced from 60 minutes to minimize auto dominance).

The transit fare structure was pivoted around the existing transit fare ($3.50), with $0.00 chosen as the minimum to represent a free transit scenario, and $5.00 chosen as the maximum (reduced from $7.00 to reduce auto dominance). The TIR fares were chosen using a pivoting structure off of transit as inspiration ($0.00, Transit-$1.00, same as transit, Transit+$3.00), representing different fare structures seen in TIR pilot projects ($0.00, $2.00, $3.50, $5.00 transit fares resulted in $0.00, $1.00, $3.50, $8.00 TIR fares). Levels could not be directly pivoted off of the transit fare in the choice experiment, since alternatives in experiments are typically not correlated. The resulting TIR fare options ensured that respondents were provided with TIR fares that were free, cheaper than current transit, equal to current transit, and more expensive than current transit cases, no matter how the experiments were arranged individually.

For parking, $0.00 represented the common free parking case, and $15.00 was chosen to represent an extreme hourly parking charge over multiple hours, and in part to find the point at which people who typically chose auto would switch to other modes.

For private ridehailing fares, the best and worst cases used a combination of taxi and UberX rate formulas, reflecting surge pricing cases and other pricing differences between the services. UberX rates needed to be calculated empirically since the formula was not publicly available. Rates were applied per the minutes of auto IVTT in the experiment. Because fares are based on combinations of time and distance for Uber, but only time was captured for the trip entered into the Google API, finding realistic rates required an assumed average speed. The best case assumption assumed a speed of 1.2 min/km (50 km/h), and the worst case assumption assumed a speed of 2 min/km (30 km/h). Applying these ranges to taxi and Uber base fares in the Region of Waterloo, the lowest base rate was found to be just over $1.00 per min (best case Uber), and the highest base rate was found to be $4.20 per min (worst case taxi). Because Uber employs dynamic pricing that has historically had multipliers upward of 9.9x the existing rate (Vedantam et al., 2016), a 10x option was chosen as the maximum surge price. 2.5x and 5x options were chosen to cover more of the lower end of the range of fares.

The range for the number of transfers in each experiment started at 0, representing a direct trip, and ended at 3, representing the generally largest number of transfers empirically found in the region (reduced from 4 to minimize auto dominance).

Reliability was expressed as a deviation of the IVTT. Because the attribute was introduced primarily to minimize auto dominance, the range for auto was higher than the ranges for the other modes. Increments of 5% were used for TIR, transit, private ridehailing, and cycling; and a range from 5% to 50% was used for auto. Cycling was a percentage of the cycle time found in the Google API, and other modes percentage of the drive time in the Google API. It is worth emphasizing that the deviations for TIR and transit were based off of the original drive time (i.e., the IVTT for auto and private ridehailing), not the IVTT presented in the experiment for these modes, resulting in a smaller range for the shared mode reliability metric.

4.1.3 Experimental Design Consideration

After refining the alternative, attribute, and attribute level sets, the expected utilities and the minimum number of required choice tasks can be determined. The first decisions were made around the intended experimental structure. Labelled experiments were chosen, where instead of having generic alternatives defined only by attributes, the alternatives are named and have their own coefficients (alternative-specific constants or mode constants) in a utility function. Labelled experiments are the norm in transportation surveys, and the labels in these surveys are the different mode alternatives. In the survey, the five labels are easily understandable descriptions of the five modes: TIR, transit (GRT bus and ION), taxi/Uber, cycling, and either driving or passenger in a private vehicle. Because of the expected dominance of auto alternatives, the survey used a best-worst case 3 choice-sequence structure, where respondents were asked both the best and worst option among the labelled alternatives. Best-worst tasks were represented in the survey by multiplying the worst task design matrix by -1 (Sawtooth Software, 2022). The structure of the survey was intended to result in a D-efficient mixed logit model. D-efficiency is discussed in Section 4.1.4 and the choice of a mixed logit model is discussed in Section 5.1.1.

The expected utility functions (V) for each of the alternatives, assuming all attributes except mode constants are linear, are:

$$
\begin{aligned}
V_{TIR} =& \beta_4 \frac{IVTT_{TIR}}{IVTT_A} + \beta_5 WTT_{TIR} + \beta_6 TT_{TIR} + \beta_7 WKT_{TIR} \\
& + \beta_8 F_{TIR} + \beta_{12} N_{TIR} + \beta_{13} R_{TIR}
\end{aligned} \tag{4.1}
$$

$$
\begin{aligned}
V_T =& \beta_0 + \beta_4 \frac{IVTT_T}{IVTT_A} + \beta_5 WTT_T + \beta_6 TT_T + \beta_7 WKT_T \\
& + \beta_9 F_T + \beta_{12} N_T + \beta_{13} R_T
\end{aligned} \tag{4.2}
$$

$$
V_{RH} = \beta_1 + \beta_5 WTT_{RH} + \beta_{10} F_{RH} + \beta_{13} R_{RH} \tag{4.3}
$$

$$
V_A = \beta_2 + \beta_{11} F_A + \beta_{14} R_A \tag{4.4}
$$

$$
V_C = \beta_3 + \beta_{15} R_C \tag{4.5}
$$

where β_0-β_3 are the mode constants for each mode, β_4 is the IVTT ratio coefficient for shared modes, β_5 is the wait time (WTT) coefficient, β_6 is the transfer time (TT) coefficient, β_7 is the walk time (WKT) coefficient, β_8-β_{11} are the fare (F) coefficients for each mode, β_{12} is the number of transfers (N_T) coefficient, β_{13}-β_{15} are the reliability deviation (R) coefficients (which differ for cycling and auto), and the subscripts for TIR, transit, private ridehailing, auto, and cycling are TIR, T, RH, A, and C, respectively. Reliability is quantified as the magnitude of the % deviation, so a +/-20% deviation on the auto IVTT would have a value of $R = 20$. Typically, one of the mode constants is set to 0 and the others are estimated relative to that alternative. Hence, the utility function for TIR (Equation 4.1) omits a mode constant. However, due to the way Lighthouse Studio outputs non-linear coefficients like mode constants (Section 5.1.1), all five coefficients have non-zero values in the estimated models. Using linear coefficients and mode constants requires 16 coefficients to be estimated.

Non-linear utility functions are much longer since each attribute level has its own coefficients. As a sample of the larger set of non-linear utility functions, the non-linear auto utility function has the form:

$$
\begin{aligned}
V_A =& \beta_2 + \beta_{11a} F_{\$0.00,A} + \beta_{11b} F_{\$1.00,A} + \beta_{11c} F_{\$3.50,A} \\
& + \beta_{14a} R_{5\%,A} + \beta_{14b} R_{15\%,A} + \beta_{14c} R_{25\%,A}
\end{aligned} \tag{4.6}
$$

where β_{11a}-β_{11c} are the coefficients for each level of auto fare, and β_{14a}-β_{14c} are the coefficients for each level of auto reliability. The highest levels of each attribute are omitted for the same reason why the mode constant was removed in Equation 4.1 (i.e., statistical identification). Utility functions for other modes follow the same conversion and treatments as auto when moving from linear to non-linear utility functions. As a result, using completely non-linear coefficients, 41 coefficients require estimation. Both the linear and non-linear cases assumed main-effects only.

The minimum number of choice experiments is based on the number of parameters to be estimated, or the degrees of freedom (Hensher et al., 2015). The choice of linear or non-linear coefficients greatly impacts the minimum number of experiments because of the greater number of non-linear coefficients. The minimum number of choice experiments required for parameter estimation follows the relationship:

$$S(J-1) \geq H \tag{4.7}$$

where S is the number of choice experiments required, J is the number of alternatives in each choice experiment, and H is the number of parameters to be estimated. Even though best-worst surveys ask respondents for two answers per experiment (one best and one worst), experimental size calculations were performed conservatively assuming each best-worst case was only one choice experiment. Table 4.6 demonstrates the minimum choice experiments required in each scenario using Equation 4.7. Combinations of four level treatments and four interaction treatments were analyzed: level treatments considered 3, 4, and 5 level cases for non-linear attributes and a 2 level case (i.e., linear attributes), and interaction treatments considered non-linear AB interactions, linear AB interactions, and no interactions (main-effects only). AB interactions are also called two-way interactions, and are interaction effects between only two attributes (e.g. wait time and IVTT). The 3-5 level cases did not change the levels for modes and IVTT ratio, which were respectively fixed at 5 and 3 levels. Because of how transfers and transfer time were programmed into the software (Section 4.1.4), interaction effects could not be estimated between these two attributes and are not included in any of the parameter counts in the cases with interactions. Another interaction treatment was considered, where only interactions for attributes used in TIR were explored, but most attributes were in the TIR mode already so these estimates would not be meaningfully different from the scenarios with all AB interactions considered. Because of the large number of attributes included in the model, including only the AB interactions greatly increased the number of model parameters to estimate (i.e., the main effects and the interaction terms) and the minimum required number of experiments. It was decided in the end to only design for scenarios where no interaction effects were estimated, leaving the last four options in the table as design goals. It was decided to leave a buffer between the minimum number required and the final number of experiments asked, to conservatively ensure that reliable estimates could be found. Using 4 levels was considered a reasonable target that would minimize respondent burden while enabling enough experiments to properly model non-linear attributes, since only 10 experiments were required at minimum. Using a 7 to 15 minute guideline for the total length of the survey (Qualtrics, 2020), the number of experiments in this scenario was considered acceptable.

Table 4.6: Minimum choice experiments required for each scenario. Chosen scenario in bold.

Scenario	S (minimum)	J	H
Non-linear attributes, non-linear AB interactions, 5 levels	111	5	442
Non-linear attributes, non-linear AB interactions, 4 levels	68	5	270
Non-linear attributes, non-linear AB interactions, 3 levels	35	5	140
Non-linear attributes, linear AB interactions, 5 levels	20	5	78
Non-linear attributes, linear AB interactions, 4 levels	17	5	67
Non-linear attributes, linear AB interactions, 3 levels	14	5	56
Linear attributes, AB interactions	11	5	44
Non-linear attributes, no interactions, 5 levels	13	5	50
Non-linear attributes, no interactions, 4 levels	**10**	**5**	**39**
Non-linear attributes, no interactions, 3 levels	7	5	28
Linear attributes, no interactions	4	5	16

4.1.4 Generate Experimental Design

With much of the broader experimental design choices decided, the next stage is to determine how to build the experiments. Four options were considered for building the experiments: Ngene, Qualtrics, R, and Lighthouse Studio from Sawtooth Software. Appendix C discusses the software alternatives in greater detail, from which Lighthouse Studio was ultimately selected. Within Lighthouse Studio, four design options were available in the survey design: Complete Enumeration, Shortcut, Balanced Overlap, and Random. Each option reflected a different approach to the generally accepted design principles of minimal level overlap (choosing the same attribute level as infrequently as possible in one task), level balance (showing each attribute level the same number of times throughout the experiments), and orthogonality (choosing levels independently of other attribute levels) (Sawtooth Software, 2022). Random and Balanced Overlap were quickly removed from the set of options. Random designs are only recommended for studies focusing on interaction effects as the primary outcome, and Balanced Overlap designs incorporate some overlap between levels, making a trade-off between academically-ideal designs and improving performance for interactions. This left the two remaining options: Complete Enumeration, which follows all three of the generally accepted design principles, and Shortcut, which uses a less accurate tracking mechanism for level balance to build the design in a much shorter time compared to Complete Enumeration.

Sample size was another important factor in deciding which design to use. There is no consensus on accepted minimum sample sizes when generating stated choice data (Hensher et al., 2015), and there are multiple formulas proposed for finding sample sizes. Two assumptions have a wider basis (Orme & Chrzan, 2021): a general industry baseline indicates that at least 300 respondents is ideal or 200 respondents per analyzed subgroup, and the formula:

$$\frac{nta}{c} \geq 1000 \tag{4.8}$$

where n is the sample size, t is the number of choice experiments, a is the number of alternatives in the experiment, and c is the maximum number of levels for any attribute. Applying Equation 4.8 to this study, the estimated sample size would conservatively be anywhere between 84 and 125 respondents, using a range of 10 to 15 choice experiments, assuming the number of alternatives is 5 and the maximum number of levels is 4. A third assumption used by Sawtooth Software is to use a random-answer simulated set of respondents, and generate designs that show standard errors below 0.05 for main effects on attributes used across every alternative, and 0.10 for alternative-specific attributes. J. M. Rose and Bliemer (2013) suggest that designs that are S-efficient or D-efficient can substantially minimize the sample size required to obtain reliable estimates. S-efficient designs minimize the sample size required to gain significant parameter estimates, and D-efficient designs minimize variances and covariances across all estimates.

The design philosophy for this study was to maximize D-efficiency and minimize the standard error across parameters for specific sample size levels, using the simulated respondent base method. Because the survey area population is relatively small, the expected sample size was also relatively small, so it was important for the final design to have reasonably good estimates at small sample sizes. Table 4.7 summarizes a series of test runs using simulated data sets for the Complete Enumeration and Shortcut methods. First, two test cases were generated using the Shortcut method to test the difference between including 12 or 13 random experiments. These cases did not include IVTT attributes, but were still valuable for determining the impact of additional experiments, which showed minimal decreases in standard error but a larger improvement in D-efficiency. 13 random experiments were chosen, since the addition of one task would not have a very negative impact on respondent burden but would have a notable increase in D-efficiency. The next four runs measured the relationship between the number of survey designs (or versions) and the sample size. Sample sizes of 120 respondents and 300 respondents were used representing a lower-end and higher-end expectation of the final sample size, with the true sample size expected to be somewhere in between the two numbers. Under these scenarios, sample size had a much stronger improvement on the D-efficiency of the design and the standard error. With 120 respondents, the D-efficiency was slightly lower if there were 300 versions instead of 120 versions, and the standard error occupied a wider range, where the minimum was slightly lower but the maximum was slightly higher. The drop in efficiency was expected, since the respondent base would only be answering a portion of the total number of versions, so it is less likely respondents would be exposed to a balanced set of scenarios. With 300 respondents, the D-efficiency and standard errors were slightly improved when using 300 versions instead of 120. Because the sample size was expected to fall somewhere in between, it was decided to keep 120 versions and err on the side of caution.

Finally, tests were completed using Complete Enumeration. Complete Enumeration follows a more academically rigorous approach to experimental design, and Sawtooth Software recommends using Shortcut only if Complete Enumeration can not build a functional design. Three different design seeds were used, and the third case had the highest D-efficiency and competitive standard errors. In all cases, the standard errors would be a little too high with only 120 respondents, but would be well within the desirable range with 300 respondents, so a respondent base of 200 or more was considered sufficient to obtain acceptable standard errors. In the Complete Enumeration scenarios, the number of transfers variable did not have perfect balance. A prohibition was placed on the 0 transfer case appearing with transfer times over 0 minutes, so the 0 transfer case appeared less often in the choice experiments than the other cases. Because a usable design was still able to be generated, Complete Enumeration was still chosen, but interaction effects between the number of transfers and transfer time were not able to be estimated due to the prohibition.

The final result was a SP section with 1 fixed and 13 random experiments. Figure 4.4 shows a sample experiment. The order of alternatives was randomized to minimize order bias between participants. Because IVTT may not be as intuitively useful as the total amount of time travelling, total time was presented in the experiments instead, using a composite of IVTT, wait time, walk time, number of transfers, and transfer time. It was decided not to include both estimates in the table at the same time to minimize burden due to the large number of experiments each respondent would need to complete. Respondents

Table 4.7: Summary of design test runs in Lighthouse Studio

Design	Tasks	Versions	N	D-Efficiency	SE (min)	SE (max)
Shortcut (test)[a]	12	120	300	416.04739	0.03317	0.07378
Shortcut (test)[a]	13	120	300	455.38912	0.03178	0.07093
Shortcut	13	120	120	172.20565	0.04983	0.11447
Shortcut	13	300	120	173.82193	0.04920	0.11535
Shortcut	13	120	300	433.25650	0.03171	0.07423
Shortcut	13	300	300	436.21948	0.03150	0.07123
Complete Enum. (1)[b]	13	120	120	174.24134	0.05027	0.11410
Complete Enum. (1)[b]	13	120	300	436.11873	0.03165	0.07273
Complete Enum. (2)[b]	13	120	120	171.96680	0.05003	0.11394
Complete Enum. (2)[b]	13	120	300	433.07433	0.03175	0.07363
Complete Enum. (3)[b]	13	120	120	174.25270	0.04996	0.11684
Complete Enum. (3)[b]	13	120	300	437.86970	0.03188	0.07055

[a] Null IVTT variables included
[b] Imperfect level balance for 0 transfer case

could estimate the in-vehicle time by subtracting the other components if desired, and a description of each of the times was provided at the bottom of each experiment page to help respondents determine the relationship between each time attribute. Reliability was also explained on each page to help respondents interpret the presented values and understand why a deviation in travel time might occur.

The SP section assumed a traditional trip-based approach, which comes with well-known limitations. In practice, trips can form parts of 'tours' or trip chains, where multiple smaller trips are made between when a person leaves returns home. The purpose of other trips in the chain can influence the mode taken for the assessed trip. For example, a person taking their child to school before work or getting groceries after work may be more inclined to drive, even if the standalone work trip is conducive to other modes. These travel patterns are captured by more complex activity-based modelling approaches (Systematics et al., 2012), with the caveat that these can be more challenging to ask in choice-based surveys, particularly with smaller populations. Trip-based models are still used in other current research and practice (Section 2.3.2), and were chosen as the intended output and the design philosophy behind this survey in order to balance survey complexity with respondent uptake.

If these were your only options, which would be your best and worst choices?

(1 of 14)

Mode	Taxi/Uber	Transit-integrated ridesourcing	Cycling	Transit (GRT bus and ION)	Driving
Total time	11 min	48 min	11 min	44 min	6 min
Reliability	+/- 1 min	+/- 1 min	+/- 2 min	+/- 1 min	+/- 1 min
- Wait time	5 min	30 min	--	3 min	--
- Walk time	--	0 min	--	5 min	--
- Number of transfers	--	3	--	1	--
- Transfer time	--	0 min per transfer	--	30 min per transfer	--
Cost	$30.00	$8.00	--	$5.00	$15.00 parking
	Best	Best	Best	Best	Best
	Worst	Worst	Worst	Worst	Worst

- **Total time:** the time spent from start to end, which includes:
  - **In/on vehicle time**
  - **Wait time:** the time spent waiting for the first vehicle
  - **Walk time:** the **total** time spent walking (from home to the first stop **and** from the last stop to your destination
  - **Number of transfers** times the **transfer time**: the time spent waiting for transfers across the entire trip (e.g. 2 transfers with 5 minutes per transfer would be 10 minutes)
- **Reliability:** the uncertainty of the total time estimate based on external factors (good/bad traffic, congestion, few/many stops on the route)

Figure 4.4: Sample stated-preference experiment

4.1.5 Construct Survey Instrument (Pre-Stated-Preference)

It is preferred to have the respondent complete the SP section as early as possible since it was the most essential part of the survey. However, some questions need to be asked before the SP experiments. Following research ethics guidelines, consent needs to be given by the respondent upon reading the information letter at the very start of the survey. If the respondent is not in the target group, they should be filtered out before spending too much time on the survey. Respondents should be familiarized with the required terminology prior to taking the survey. Their existing travel patterns should be validated before they are exposed to the SP scenarios, so that their scenarios can best match their real-world situation as closely as possible, and their travel times can be used to calibrate the SP time estimates.

The first questions provided to the respondent surrounded consent and inclusion. Respondents must be provided with a set of standardized information about taking surveys, their responsibilities, and their rights, and the respondent must agree before continuing. Three questions were then asked to filter out non-target respondents. First, they must have been at least 16 years old. As identified in section 4.1.2, parents tend to make travel decisions for children. Children under 16 also require parental permission for participating in research, which would have been challenging to secure due to anonymous nature of the survey. Second, the respondent must have lived in the City of Waterloo, and had to identify the ward in which they lived. The ward was used as a crude filter to differentiate people who live in the study area (wards 1, 2, and 6). Because of how Canada Post routes are designed (discussed in 4.2), people may live in Waterloo and receive a postcard, but not live in the study area. It was decided to keep anyone's data who lives in the City of Waterloo, and optionally filter later depending on the response rate. Third, the respondent must have taken a trip that meets six criteria: the trip must normally be made outside of the COVID-19 pandemic, start at their home, end within the Region of Waterloo, not be to grade school, not be made by walking, and the respondent must have decision-making power over their mode choice. Trips outside of the COVID-19 pandemic better reflect regular trip patterns. Intracity trips were ideal since TIR is more applicable within cities and regions, and transit alternatives were simpler to generate. Removing the walking alternative followed the alternative refinement in section 4.1.2 and allowed for focusing on longer trips that were more competitive with driving, cycling, and transit. Respondents without the freedom to decide which mode they choose would likely be captive and give poor utility estimates that are less sensitive to the attributes. Removing grade school trips was required for similar reasons to the age boundary, because grade school trips are typically made by either school bus (if the student lives in a bused zone), by walking (if the student lives close to the school), or as a passenger (if the student lives in between or if the parent chooses to drive them). In these cases, the student typically does not choose their mode, and removing grade school trips allows school buses to be removed from the alternatives list. Respondents that did not meet the age, residency, and trip characteristic criteria terminated the survey.

Respondents were then provided a one-page explainer on TIR (Figure 4.5), which provided them with a concise and direct explanation of the main elements of the mode. Differentiating this mode from general fixed-route transit and private ridehailing was important for ensuring the respondents made accurate decisions in the SP section of the survey. Respondents were also asked if they were familiar with the 903 Flex service that had previously operated in the survey area, which determined both the general familiarity and use of the former service.

The next phase was the RP section. Since IVTT elements would pivot around a respondent's actual trips, it was decided to use an external API to calculate the trip times automatically. Google Maps and OpenTripPlanner were used in earlier stages of this research (Chapter 3), and were natural candidates. Google's APIs that drive Google Maps were chosen due to the relatively accurate travel time estimates across driving, cycling, and transit modes, and the ease of integrating them into the survey. The Google Directions API, which is one of the two Google APIs used in this research, has also been previously been used by Saxena et al. (2020) for automated collection during surveys. Google Cloud, which provides access to these APIs, is also free for projects with low numbers of API requests per month. Two advantages came from automatically calculating trip times for respondents. First, the risk of the respondent entering incorrect times or leaving the survey due to the manual steps required is greatly reduced, which had been identified as an issue in prior studies (Yan et al., 2019). Second, trip metrics for each trip can be quickly determined, including steps of the transit trip, which allows for measuring their existing preferred trip against trip alternatives.

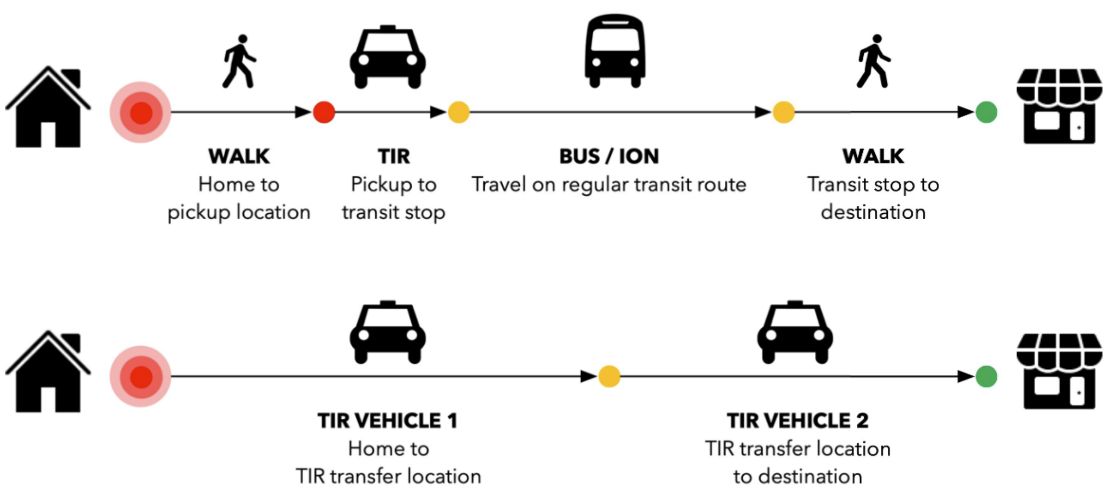
A front-end page was designed to translate a respondent's home, destination, and departure time to a series of travel times and characteristics (Figure 4.6). Figure 4.7 outlines the process for converting the respondent's data to a series of variables. Respondents were reminded of the guidelines for their trip, to ensure they picked an appropriate origin-destination pair. For privacy reasons, the home and destination addresses could not be stored in the survey, so a process was developed to ensure that data was kept as privately as possible while the respondent was on the page, and that no identifiable location data

You will be asked to choose between travel options that currently exist in your area, and a new mode: **transit-integrated ridesourcing (TIR)**.

TIR is a theoretical future travel option where Grand River Transit would operate demand-responsive service to extend the reach of existing transit service. The main elements of this service are:

- **Part of the transit network:** The service could be operated by a private company (like a taxi company) or Grand River Transit, but would function as part of Grand River Transit's fare payment system
- **Instant booking:** You can book it immediately through an app or by phone, just like you would a taxi or an Uber ride
- **Variable transfers:** Some system designs may take you to the nearest bus stop or a transfer point to shorten your walking time, while others may take you directly to your destination
- **Variable starting points:** Some system designs may pick you up at your door, while others may have "flexible stops" that you need to walk to, that are typically closer to your home than a bus stop
- **Shared rides:** Rides are shared with other passengers (meaning it may make additional stops), but the vehicles are car-sized

This service is most common in areas like yours with single-detached homes on crescents and cul-de-sacs, and is one way of extending the reach of transit in areas where buses can't operate. The following diagram depicts two examples of the many ways TIR systems could be designed. In some cases, the system is configured so that you only transfer between ridesourcing vehicles without buses.



Ensure you understand how this service differs from existing transit service, Uber, and taxi service before continuing.

Figure 4.5: Survey page explaining transit-integrated ridesourcing to respondents

was remaining once the respondent moved to the next question. Home and destination addresses were determined using the Places API using Autocomplete, and were temporarily stored in JavaScript as LatLng objects. A departure time was generated representing the typical time the respondent took the trip, to the nearest 15 minutes, and was stored as the next opportunity the trip would occur (e.g. the following Thursday at 3:30 p.m.). Once the respondent pressed 'Find travel times', the LatLng locations and departure time were sent to the Directions API to find transit trip components, and the Distance Matrix API for driving and cycling times. Text would update on the page for the respodnent to indicate that a time had been found, and the responses from the Directions and Distance Matrix APIs would be processed as variables and stored. The final suite of stored values is given in Figure 4.6 (b). Three status values were also included (transitStatus, driveStatus, cycleStatus) which indicated whether each trip was able to be found successfully for research purposes. From the transitStatus values, it was determined that headway was not regularly stored for GRT trips in Google's database, so the wait time was typically stored as 0 minutes and was subsequently not usable for further analysis.

After finding respondents' real-world estimated travel times, respondents indicated their preferred mode for their trip and the trip's purpose. Respondents that chose modes other than driving or passengers in private vehicles were asked a follow-up question to pick one or the other as their most likely car-based alternative, which was used as one of the alternatives in the SP section. A wide range of purposes were provided to respondents, as well as an 'other' field to type in their own cases, which could then be aggregated later as needed depending on how many trips were submitted under each purpose. It was decided to leave the purpose open to the respondent to gather work and non-work cases at the respondent's discretion. Respondents were also asked if their trips were for caring work (i.e., to help children or dependants), which would indicate the trip is primarily for helping another individual and not for the respondent's individual needs.

4.1.6 Construct Survey Instrument (Post-Stated-Preference)

Generally, it is desirable to leave demographic or personal questions until the end of the survey, since respondents are more likely to leave the survey early when more personal questions are asked (Qualtrics, 2020). The remaining questions for the survey were presented after the SP section. Questions in this part were either less immediate or were more sensitive, so are best saved until after the respondent has invested time in the remaining parts and has developed some trust in the survey's questions. The post-SP section consisted of four main parts: ownership, COVID-19, demographics, and feedback and appreciation.

A

0% 100%

In this survey, we will ask you questions about a trip you would normally make **outside of COVID-19**. To make the survey more applicable to your trip, we will generate driving and cycling times using your home and destination locations to personalize your survey.

Enter the home and destination location for a trip you have taken:

- from your home to another location **within Waterloo Region**
- that was **not** made by walking
- where you had freedom to decide how you would travel to your destination
- that was **not** for attending grade school (K-12) as a student

Choose a departure day and time that represents the **most likely** day and time you would consider making this trip.

Home: 626 Royal Fern Street, Waterloo, ON, Can

Destination: 842 Victoria Street North, Kitchener, ON,

Departure time: Thursday 3 : 30 p.m.

Find travel times

Drive times: Found

Cycle times: Found

We **do not** store or know your home and destination locations. These locations are input directly into Google Maps to generate driving and cycling times. You also do not need to enter your exact home address, you can enter another address near yours and the times should still be accurate. A transit trip will also be generated which will help us understand your existing transit situation.

B

GoogleRequest_driveTime	18
GoogleRequest_cycleTime	42
GoogleRequest_transitTimeWalk	8
GoogleRequest_transitTimeWait	0
GoogleRequest_transitTimeIVTT	46
GoogleRequest_transitTimeTransferAvg	8
GoogleRequest_transitNumTransfers	1
GoogleRequest_transitTime	62
GoogleRequest_departureDate	Thu Apr 22 2021 15:30:00 GMT-0400 (EDT)
GoogleRequest_transitStatus	Directions: OK. No headway found so wait time set to 0.
GoogleRequest_driveStatus	Distance Matrix: OK
GoogleRequest_transitRoute	13
GoogleRequest_cycleStatus	Distance Matrix: OK

Figure 4.6: Sample survey entry (A) and corresponding stored variables (B)

Figure 4.7: Simplified process for finding and storing travel variables using Google APIs

The ownership questions aimed to assess what respondents already own for travel purposes, which may influence their travel choices. Respondents were asked if they owned a bicycle, how many personal vehicles their household owns, and how they would most likely pay for a GRT fare. There were 10 options provided for the transit question, including unlimited-use passes (U-Pass, college, corporate, veteran, Ontario Works), discount passes (seniors, grade school students), fare cards (adult, reduced fare), or no card or pass, where respondents would have to pay by cash or ticket instead. If respondents indicated their household owns two or more vehicles, a follow-up question asked if the household would consider owning fewer vehicles if their area had improved transit or TIR. Respondents were also able to provide explanations for why they would not be willing to reduce their vehicle ownership in an open-entry box. A respondent that owns a bicycle was expected to be more open to choosing cycling, and a respondent that has access to a household vehicle was expected to be more open to choosing driving or being a passenger in a private vehicle. Respondents with transit cards of any kind were expected to be more open to taking transit, since they had previously decided to buy a card, and respondents with unlimited passes were expected to be less sensitive to transit fares, since the fare would not be felt immediately.

Although the survey was conducted during COVID-19 pandemic restrictions, respondents were asked to consider how they would travel outside of the pandemic. Even with this reminder, it is possible that respondents may have biases or influences for or against different modes because of how the pandemic influenced travel patterns. A 3-level Likert question asked whether respondents were more or less likely to take each of the five modes after the pandemic was over, to understand how opinions may change after the pandemic and to see if there was correlation between the most chosen modes and the modes people were more likely to take.

The last part of the Sawtooth-hosted part of the survey asked about demographics. Respondents were asked for their age, gender, and estimated gross household income, all of which are common demographic identifiers in transportation models. Bins were aggregated based on other sources' ranges to maintain privacy for respondents, while having enough specificity to be able to differentiate utility differences between groups within a demographic attribute. Age bins were aggregated from the census, which used bins of 5 years. Gender options included male, female, and a free-form other field to capture other gender identities including non-binary respondents. Income bins were based on a combination of census bins, which used variable bins with more specificity at lower incomes, the median and average household incomes in the region (around \$110 000), and the wealthier nature of some of the surveyed neighbourhoods.

It is also common to provide appreciation to respondents after they complete the survey. The appreciation portion of the survey is secondary to the academic contributions provided by the remainder of the survey, and is discussed further in Appendix E.

4.2 Dissemination

Survey dissemination was complicated by COVID-19. The original strategy was to deliver an online survey that would be advertised through GRT channels, in-person sessions at community centres, university/college posters, neighbourhood associations, and municipal and regional resident feedback email groups. Door-to-door outreach was going to be employed to improve the response rate of the survey once it was delivered. Because of pandemic restrictions by the time the survey was ready to be delivered, in-person outreach plans were cancelled. Additionally, there was some concern about the response rate that could be achieved using GRT's own channels.

A new strategy was developed that helped minimize COVID-19 contact challenges, and took advantage of opportunities from the lockdown. Instead of doing in-person sessions and contacts, postcards were delivered through Canada Post to all neighbourhoods in the study area, with a brief description of the survey, the appreciation for completing it, and a survey link and QR code (Figure 4.8). An advantage of the postcard method was that neighbourhoods could be included or excluded using postal routes, so that postcards were only delivered to people living specifically in the study area. A disadvantage of using postcards was the expense associated with it in comparison to purely online or labour-driven approaches like door-to-door contact, so efforts were made to minimize expenses while maximizing the benefits of the approach. The smallest postcard option was chosen (5 inches by 7 inches), since the printing was cheapest, and the cheapest direct mail option was chosen (Neighbourhood Mail) to minimize delivery costs.

Neighbourhood Mail is unaddressed and is targeted using postal routes. Postal routes do not perfectly line up with the study area, so routes were included or excluded based on the likelihood that the route was mostly capturing the correct residents. Houses and apartments along these routes were included, and farms and businesses were excluded. Figure 4.9 compares the chosen delivery routes with the intended study area. The missing areas on the west side of the map were almost all part of one larger mail route that extended far into the townships outside of the city boundary, with a considerable number of rural homes that would not meet the criteria to complete the survey. Some areas to the east of the study area were included because they were relatively small components of a route

PARTICIPANTS INVITED FOR TRANSIT SERVICE RESEARCH

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Board (ORE#42587).

UNIVERSITY OF WATERLOO | Department of Civil and Environmental Engineering

A

B

We are looking for residents in northwest Waterloo to fill out a survey on transit service options. As a participant in this study, you would be asked to fill out a 10-15 minute survey where you indicate your preferred mode of travel in a series of scenarios to a place of your choosing in Waterloo Region. This study will help transportation researchers understand the factors influencing mode travel in areas like yours.

Each person in your household who is 16 years old or older is invited to complete the survey. Other criteria for eligibility are outlined on the survey website.

In appreciation for your time, you may enter into a draw for:

- 1 of 10 PC, Sobeys, or Metro-Food Basics gift cards (valued at $50 each), or
- 1 of 10 Grand River Transit swag bags (valued at $10 each)

For more information about this study, please contact:

Prof. Chris Bachmann
Department of Civil and Environmental Engineering
519-888-4567 ext. 31303 | chris.bachmann@uwaterloo.ca

To participate in this survey, scan the QR code or visit:

uwaterlootir.sawtoothsoftware.com

Figure 4.8: Postcard mailed to residents with survey information and link (A: front, B: back)

that was mostly in the study area, or predominantly consisted of non-residential space, including parking lots and parks.

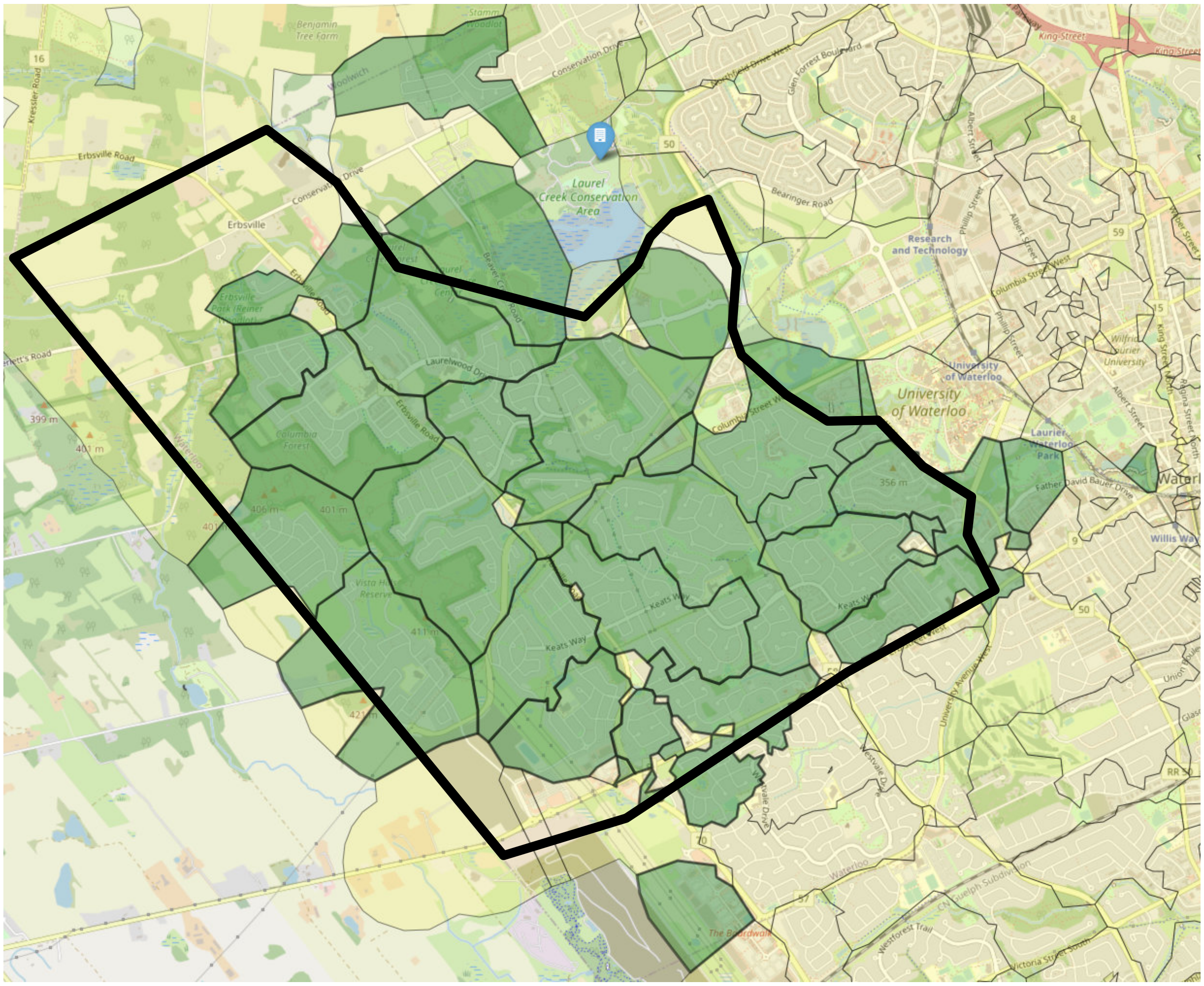


Figure 4.9: Chosen Canada Post delivery routes compared with the intended study area (Canada Post Corporation, 2020; OpenStreetMap contributors, 2019). North compass and scale not provided in the original map.

One of the previously identified challenges (Section 4.1.3) was achieving a good sample size. The TTS was used as a point of comparison since it is a similar type of survey with more resources. In the 2016 TTS, a sample test of different survey methods found no major response difference between unaddressed mail and addressed mail, which supported the decision to use Neighbourhood Mail, nor a major difference for people who received a detailed instruction sheet versus those that did not (A. Rose, 2018). While this may not apply in all areas or for all types of surveys, the TTS operates in within this area and surrounding regions. Therefore, the additional cost of addressed mail was not considered worth the potentially marginal improvement in sample size. Phone call follow-ups for incomplete survey responses were also used to improve response rates, but that option was not available in this survey due to the nature of how responses were anonymized and collected. In the corresponding TAZs, 1421 residents had completed the 2016 TTS, 70% of which completed it online and 29% by phone (Data Management Group, 2016). The expectation for this survey was a sample size much lower than 1421, since the TTS operates with much larger resources and formal government affiliation. The predicted sample size was expected to be closer to 200-600 respondents, based on mail engagement rates provided by Canada Post.

The final survey reached 10 968 households across 20 mail routes, and were delivered on the week of 3 May 2021. 14 neighbourhood and home associations in the area were also contacted to share the survey with their members. Some of these associations confirmed that they posted the survey on their Facebook groups, and this was confirmed by the participants' User-Agent strings from their web browsers.

4.3 Survey Statistics and Filtering

The survey ran from 30 April 2021 to 31 July 2021, with most respondents completing the survey in May, and no respondents participating after 8 July (Figure 4.10). 396 respondents interacted with the survey overall, representing a $\sim$3.6% engagement rate from the postcard and neighbourhood association outreach campaign, which is lower than the address-only sample of the TTS. Considering the TTS mail campaign is personalized to the resident's address and is formally affiliated with multiple government and transit agencies, the response rate for this survey, with only a University of Waterloo affiliation and a general postcard, was considered successful. 267 respondents completed the survey, 114 respondents started the survey, but did not finish, and 15 respondents were disqualified in the filtering questions at the start of the survey (10 for not having a qualifying trip, and 5 for not providing consent).

Of the respondents that did not finish, the most common departure points from the survey were the home-destination question in the RP section (46 respondents), the filtering questions at the start of the survey (34 respondents), at various points across the SP section (20 respondents), and the page explaining TIR (10 respondents). There are some possible explanations for why the home-destination question was a common drop-off point. First, although the question was clear about home or destination addresses not being stored (only the travel times and general transit characteristics were stored), respondents may have felt uncomfortable due to privacy concerns. Second, this was the first question in the survey that required text-entry, which may have resulted in a higher than expected cognitive load compared to a survey with only radio buttons. Third, the respondent needed to consider a trip using the six trip criteria from the filtering questions (home-destination trips, within the Region of Waterloo, not by walking, freedom to decide how to travel, and not attending grade school, and assume it's made outside of COVID-19). It is possible that some respondents found this experiment onerous or could not think of a trip easily that met these criteria, even though most criteria were asked earlier in the survey. For the filtering questions, the most likely reasoning for respondents leaving was self-disqualification upon realizing they likely would not qualify after answering the questions.

The device the respondents were using to answer the survey may have also contributed to the number of incomplete surveys. 205 respondents engaged using an Android phone or iPhone (mobile respondents), and the remaining 191 respondents used either a tablet or desktop computer (large-screen respondents). 73 mobile respondents did not complete the survey (36%) while only 41 large-screen respondents did not complete the survey (21%), indicating that mobile respondents were more likely to not finish the survey. This could be due to either mobile respondents expecting shorter engagement time or finding the survey more onerous to complete while on a small screen. Questions with considerably higher shares of departures from mobile respondents were the filtering questions (24 mobile versus 10 large screen), the page explaining TIR (8 mobile versus 2 large screen), and the SP section (13 mobile versus 6 large screen). While the true reasoning for departures is unknown, some theories can be proposed. The filtering questions required scrolling through three questions, and some respondents may have opened the link to the City of Waterloo's ward map and left the survey. The page explaining TIR, while explained as concisely as possible, still had considerable text and a diagram that may have not have been as easy to read for some mobile respondents. The SP section required the respondent to swipe between alternatives, using Sawtooth Software's default responsive survey formatting, which they may have found more tiring than the large-screen respondents that had all experiments visible at once. Surprisingly, the home-destination question in the RP section had a roughly even share of departures between mobile and large-screen respondents, indicating departures on this question may have been more due to the nature of the question than device interaction challenges.

As part of the filtering process, respondents were asked which ward they lived in (Figure 4.11). Ward 1, 2, and 6 were the target wards since they overlapped with the 903 Flex service area. Of these wards, Ward 2 overlapped most strongly. The high share of Ward 2 responses and considerable share of Ward 1 and 6 responses meant most responses should represent the survey area. Enough responses were pulled from Wards 1, 2, and 6 to calibrate mode choice models (Section 5.2.1), so the 267 complete responses were filtered to 232 responses for subsequent analysis.

The 232 remaining responses were reviewed for random responses and to understand non-traders who did not change their best and worst alternatives in any experiment. Random responses were evaluated based on a previously established technique for cleaning responses through Sawtooth Software surveys (Orme, 2019). A batch of 300 randomized responses were generated, and the root-likelihood of the randomized responses were compared against the actual respondent set. The 95th percentile value for the random respondents was 0.314, and the respondent with the minimum root-likelihood had a value of 0.323; thus no responses were removed based on randomness. Finally, non-traders were reviewed. 26 of the remaining respondents did not switch their best choice (3 transit, 12 auto, 11 cycling), and 14 did not switch their worst choice (1 transit, 6 private ridehailing, 7 cycling). Only two of these respondents did not switch both their best and worst choices. Although modes were ordered differently for different respondents, the modes would appear in the same order within a respondent's experiments. It is therefore challenging to know whether these two respondents were 'straightlining' or just had strong attachment to these modes, and it is possible they may have been simultaneously highly captive to their best mode and strongly against their worst mode. Further investigation revealed both respondents also had very fast SP completion times (less than 40% of the median completion time) and total survey completion times, so they were removed from further analysis, leaving 230 total responses. This final set of 230 respondents was used for the remainder of the research. Some other respondents also answered fairly quickly, but there was not enough supplementary evidence to suggest they were oversimplifying their decision-making.

Similarly, the fixed experiment was used to determine if some respondents would consider modes other than auto or cycling. For people that chose auto or cycling as their best modes, they were either already non-traders or were often only choosing between those two modes. Similarly, for people who chose TIR, transit, or private ridehailing as their worst modes; they were typically choosing between those three modes across their other experiments. Surprisingly, in some experiments a few respondents chose a different mode as their worst mode. In both the best and worst cases, people with surprising mode choices in the fixed experiment versus their other experiments spent a similar amount of time on each experiment as other respondents did, so these decisions could be due to forgetting how they answered earlier experiments or other unobserved factors.

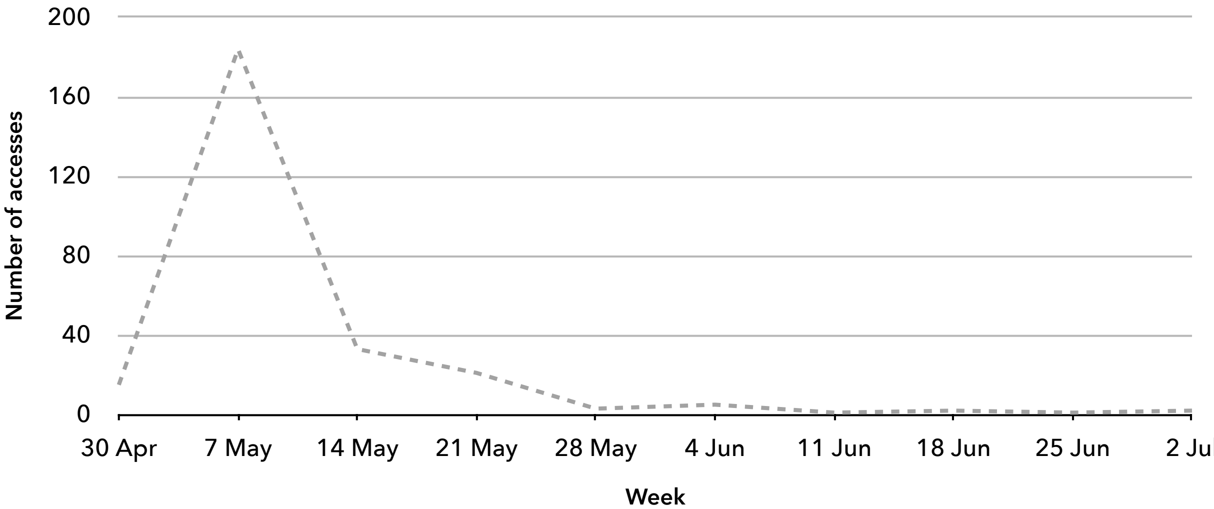


Figure 4.10: Survey accesses by week

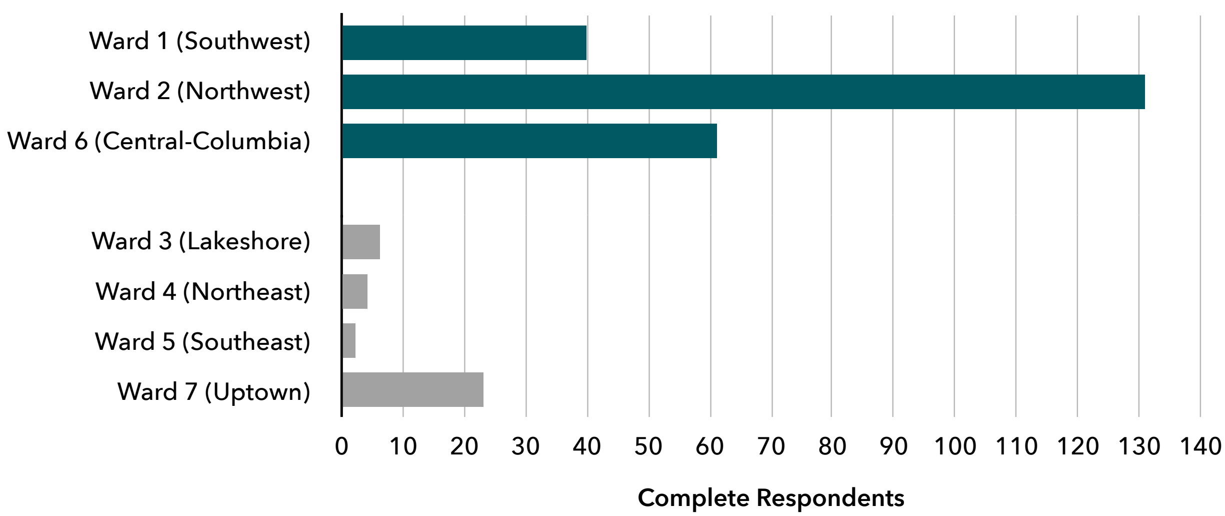


Figure 4.11: Respondents by ward (complete responses only), with desired wards highlighted

4.4 Results and Discussion

This section presents the primary findings of the pre- and post-SP sections of the survey. SP findings are discussed in Section 5.2.1.

4.4.1 Demographics

Figure 4.12 summarizes the demographics of the 230 remaining survey respondents by age, gender, and household income; and the estimated share using the 2016 Canadian census (adapted from Figure 4.3). Overall shares of male and female respondents were fairly equal, with a few respondents choosing not to answer or identifying as non-binary. Compared to the census estimates, respondents aged 25-34 were generally oversampled, particularly for female respondents, as were 16-24 year old female respondents, which resulted in undersampling for almost all other age groups. Similarly, respondents with household incomes between \$45 000 to \$69 999 and \$125 000 to \$149 999 were undersampled versus the census estimates while other income bins were similar to the estimates. Enough respondents were included in each bin that future model applications could effectively weight responses by socioeconomic variables.

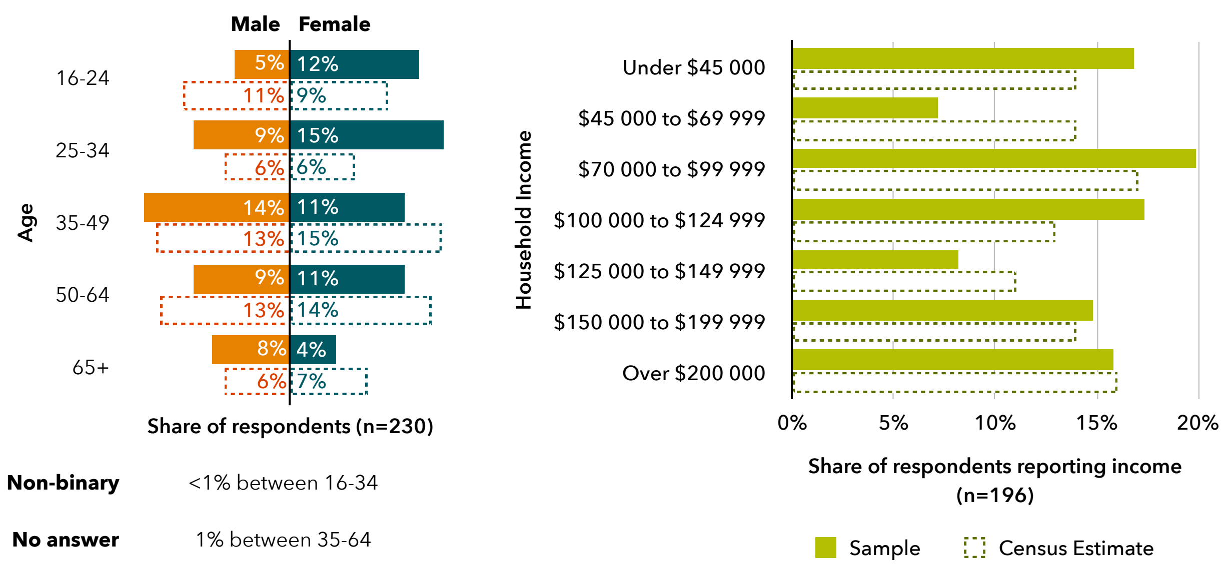


Figure 4.12: Age, gender, and income ranges for survey respondents and estimated share from 2016 census

Respondents were also asked in the survey if they had any familiarity with the 903 Flex service. Across wards, RPs, age bins, genders, and income brackets, most people (144 respondents) were unaware the service existed when it had been running. Of the people who were aware of it, a similarly small fraction of respondents across each segment had ever taken it (11 had taken it before versus 73 who were aware but had not).

4.4.2 Revealed Preferences

Respondents were asked to reveal a trip, and their typical mode and purpose for the trip. 137 respondents chose a driving trip (drivers), 66 chose a transit trip (transit riders), 11 chose a trip where they were a passenger in a private vehicle or in a private ridehailing vehicle (passengers), and 16 chose a cycling trip (cyclists). For trip purpose, 20 respondents chose home-based school (HBS) trips, 87 chose HBW trips, and the remainder chose home-based other (HBO) trips, which were predominantly shopping, entertainment, and visits. Caring trips were concentrated in the HBO category (14% of HBO trips), and the remaining 2 caring trips were HBW trips. Figure 4.13 compares the time ratios of cycling and transit alternatives versus the driving alternatives, for each RP segment of respondents. A time ratio of 2 indicates a cycling or transit alternative was twice as long as the driving alternative. Most cycling alternatives were 1-2 times longer than the driving alternative, with cyclists tending to have the most competitive cycling alternatives and drivers having the least competitive. Transit trips mostly ranged from 2-4 times longer than the driving alternative, with transit riders having the most competitive transit alternatives and either cyclists or passengers having the least competitive, depending on the length of the alternative trip. The time ratios for each segment suggest that the time competitiveness of each trip alternative has an influence on which mode respondents in this area typically chose for their travel.

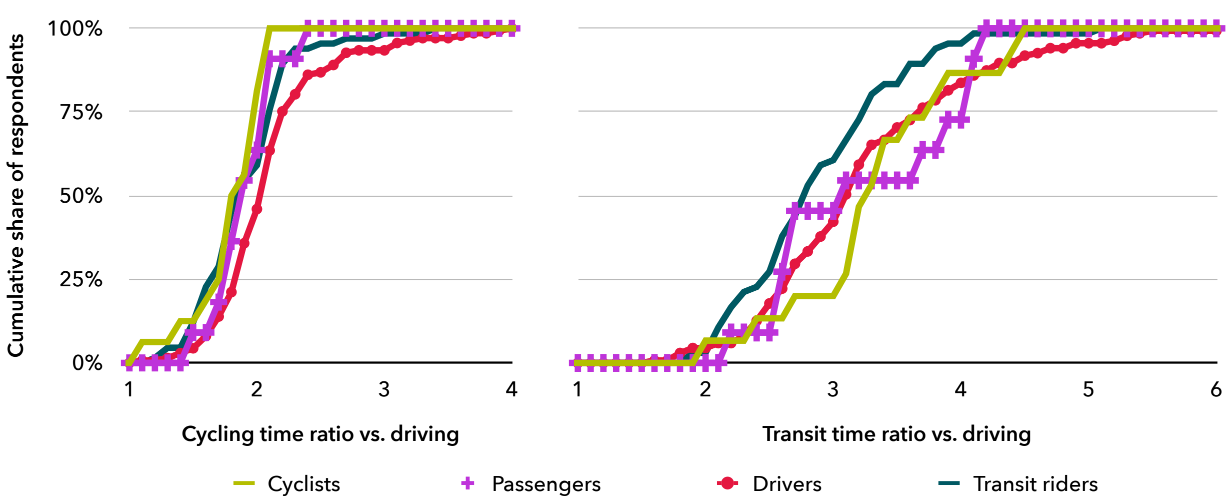


Figure 4.13: Time ratios for cycling and transit alternatives compared to driving alternatives, by respondents' revealed-preferences

Figure 4.14 compares the total walking time, number of transfers, and average time per transfer for transit alternatives for each RP bin. Walking time was typically a combination of access and egress time, but could also include walking between transfer points in some cases. Walk times were binned into under 5 minutes, which guarantees that both access and egress were 5 minutes or less, 5-10 minutes, where the average of access/egress would be 5 minutes, 10-20 minutes, where the average of access/egress would be 10 minutes, and over 20 minutes, where the walk time would be onerous for most users. As expected, transit riders had the most competitive combined access and egress times. Respondents across the remaining bins were generally split between 5-10 minutes or 10-20 minutes for the bulk of their alternatives, which in design guidelines have been shown to be large drop-off points in utility and transit mode share (Ontario Ministry of Transportation, 2012). Most respondents would have had no transfers in the transit scenario, although transit riders had slightly more direct alternatives and drivers had slightly less. Although the passenger respondent base was small, they had the highest number of 2-transfer cases. No respondents had a 3-transfer case or higher. When considering the average time spent per transfer, transit riders again had more desirable transfer cases, with most transfers falling under 10 minutes on average. Drivers and cyclists had the worst average times per transfer, with most transfers falling above 10 minutes on average, and some drivers having average transfer times over 20 minutes.

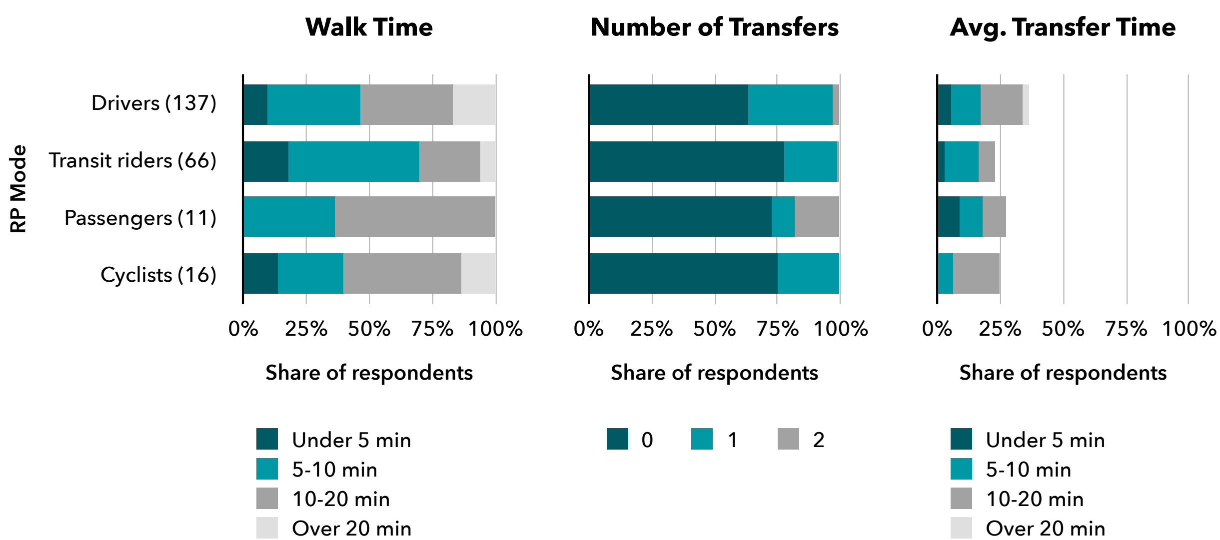


Figure 4.14: Walk times, number of transfers, and average transfer times for transit alternatives, by respondents' revealed-preferences

Figure 4.15 shows different segments of vehicle and transit pass ownership by the RP modes identified by respondents. Most respondents have at least one car in their household.

Almost every driver or transit rider has at least one household car, which is less common for passengers or cyclists. Most drivers have two household cars, and most transit riders have one. Similarly, outside of passengers, most respondents personally own a bicycle. Outside of drivers, most respondents also have at least one form of fare card or pass for the transit system. Surprisingly, just over half of the transit riders surveyed had any form of fare card or pass, most of whom were using fare cards. Respondents with no cards or passes indicated they would use cash or tickets if they needed to take transit.

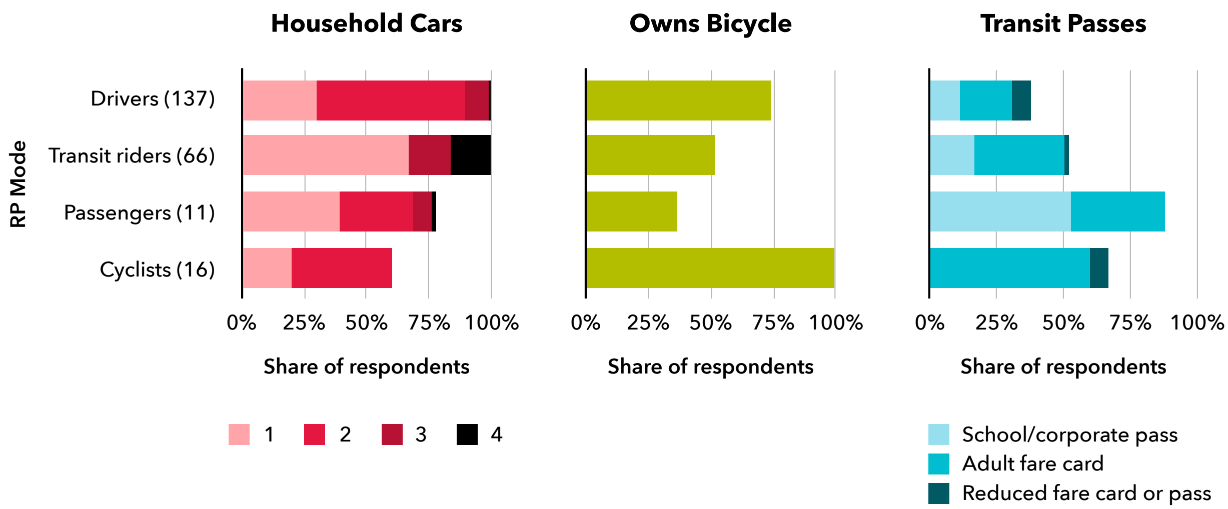


Figure 4.15: Vehicle and pass ownership by respondents' revealed preferences

131 respondents indicated their household owned multiple vehicles. 62 of these respondents indicated they were willing to sell at least one of their vehicles. Of the respondents who were willing to sell, the most common barriers were dissatisfaction with transit attributes (primarily access/egress, schedules, and travel time), far travel distances for work or leisure, and issues around scheduling and sharing with other household drivers. Respondents that were not willing to sell also primarily cited far travel distances and scheduling and sharing issues, but also had general satisfaction from the convenience and flexibility of driving.

The willingness of almost half the respondents with multiple vehicles to reduce their car ownership is promising, since car ownership tends to be a primary driver in increasing the auto mode share (Kitamura, 1989). While transit agencies do not have complete control over the reasons people choose to use cars, some of the barriers would be addressable by transit agencies. Access and egress time and distance, frequencies, schedules, and total travel time are in some ways addressable by the agency, particularly in the area where this survey was administered. Naturally, some agencies may struggle do this in low-density areas where the ability to pay for provisioning the service becomes harder. For residents with long travel distances, improved connectivity with intercity transit may be helpful for addressing some of their hesitance in shifting to transit. It is unclear whether transit pass ownership had a large impact on which modes people habitually chose in this area or if it is a consequence of taking transit frequently.

4.4.3 COVID-19

Figure 4.16 bins preferences for different modes after COVID-19 by the modes identified by respondents in their RP section. For auto, cycling, and TIR, most respondents across each bin indicated no change in preference due to COVID-19. Across all bins, respondents with a change in preference for auto or cycling were more likely to choose those modes after COVID-19, whereas respondents with a change in preference for TIR were less likely to choose it after COVID-19. Shares for TIR were unexpectedly similar for each bin, which may be because respondents had minimal exposure to this mode previously. Transit had mixed preferences after COVID-19: no change was the most common response in each of the bins, but cyclists were less likely to consider taking transit after COVID-19, while transit riders and passengers leaned toward more likely. Private ridehailing was clearly the most negatively impacted mode, with almost no respondents being more likely to choose it after COVID-19, and at least a third of respondents in each bin being less likely to choose it.

Understanding how respondents perceived these modes after COVID-19 has two benefits. First, the findings contribute to the growing body of literature that aims to understand how COVID-19 temporarily or permanently may change people's perceptions of different modes. If long-term travel patterns are impacted after the pandemic subsides, then these findings provide evidence of the underlying behavioural responses. If travel patterns eventually return to normal, then the findings will help understand how people may react in future pandemics or public health emergencies, not only from a direct mode share perspective, which would be evidenced by observed travel patterns, but from a mental perspective, indicating modes where people have negative perceptions because of the pandemic.

Second, the SP experiments asked residents to consider how they travel outside of the pandemic, but it is possible that their perspective of how they would travel was biased to some degree because of the situational factors at the time they completed the survey. A positive bias toward a mode after COVID-19 may indicate more preference in the experiments than they would otherwise have, and similarly a negative bias could indicate less preference than they would otherwise have. The general increased likelihood for taking

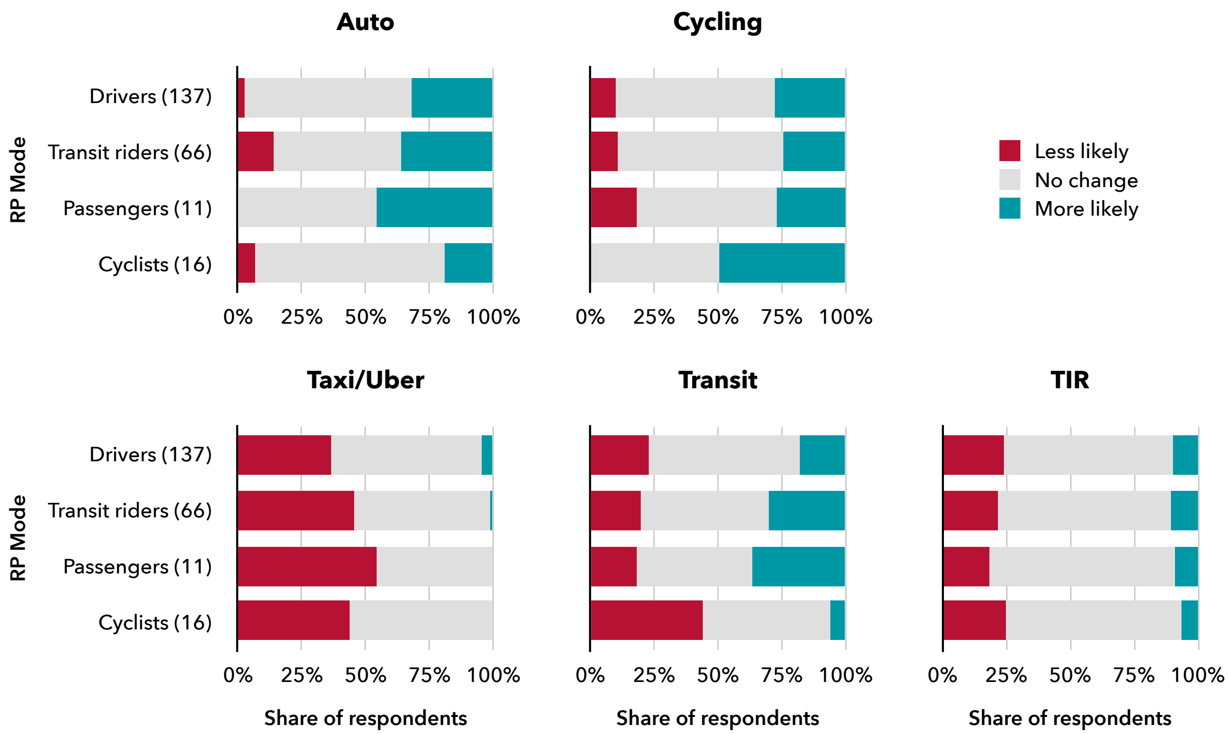


Figure 4.16: Likelihood of choosing a mode after COVID-19 by respondents' revealed-preferences

auto and cycling after COVID-19, and general decreased likelihood for private ridehailing, may be due to the isolated versus shared nature of those modes, respectively. Auto and cycling are generally completely unshared modes, or at least are shared within a household unit, whereas taxis and Ubers are shared with drivers in a small vehicle. Transit and TIR are also shared modes, but preferences may have been less strong against these modes since some or all of the trip is in a larger vehicle. It is also possible that due to the positive correlation between how modes were perceived in the SP experiments with the likelihood of choosing the mode after COVID-19 (Section 5.2.1), respondents may have subconsciously correlated future likelihood with their existing preference for the mode.

4.5 Conclusions of RP-SP Survey

This survey aimed to capture the demographics of a suburban population with high interest in transit with low levels of existing service. Respondents were screened by age, ward, and trip type to ensure their demographics matched the decision-making capability, location, and medium to long distance trip that was being assessed. A total of 230 respondents were used for the remainder of the research, filtered from 267 complete responses. These responses were demographically similar to the 2016 census in the same area, indicating a generally similar fit and validity of the base of respondents. The dataset of responses provides a unique set of variables aimed at better understanding transit-integrated ridesourcing, uniquely combining cost, important time attributes, and common alternatives (driving, passenger, cycling, and ridehailing), which have not all been included together in recent transit-integrated ridesourcing surveys. The dataset (Terry & Bachmann, 2022) may also provide useful to other researchers aiming to conduct other research using the results of the survey.

While the SP portion and mode choice findings are analyzed in the following chapter, the surrounding parts of the survey provided interesting initial findings. Comparing respondents' chosen modes against their real-world alternatives, people tended to choose modes that were the most competitive, even without necessarily having full knowledge of the travel times for their alternatives. Specifically, cyclists had the most competitive cycling time ratios, and transit riders had the most competitive transit time ratios. These findings confirm travellers are behaving rationally, at least with respect to travel time. Most respondents in the area had no transfers for their transit trips, and no respondents had more than 2, so the decision to cap the number of transfers for transit and TIR in the SP portion at 3 was reasonable.

Unsurprisingly, drivers had the highest share of car ownership and the highest share of multiple cars per household, and cyclists were the only RP bin with complete bicycle ownership. However, barely half of self-identified transit riders used any form of fare card or pass, which may indicate that there is a considerable population for which increased transit ridership may not be correlated with pass ownership. Many respondents indicated COVID 19 did not impact their views of transit or TIR meaningfully, suggesting there is future potential for these modes as the pandemic subsides. Transit agencies would also benefit from stronger marketing of their TIR pilots, since many respondents were not aware of the previous pilot that ran in their neighbourhoods.

Chapter 5

System Evaluation

The final contribution of this research extends the findings of the RP-SP survey in Chapter 4 to quantitatively evaluate different TIR system types. A mode choice model was estimated using the SP results of the survey to determine sensitivities to modes and their attributes. Elasticities for attributes were determined and applied in a sensitivity analysis, which assessed predicted impacts under different system types and policy scenarios.

Mode choice models in transportation tend to use classical logit models with linear attributes. This model advances mode choice literature by incorporating Bayesian estimation, non-linear time and cost attributes, and transit-integrated ridesourcing, which have not been combined in previous models. This combination of characteristics allows for measurement of sensitivity to transit-integrated ridesourcing across combinations of individual respondents at smaller sample sizes, and for measuring differences between major attribute levels. The model may be transferable to other areas using established transferability techniques. The marginal effects and elasticities produced by the model are of interest to researchers interested in transit-integrated ridesourcing. The mode share analysis of different system configurations, and the resulting understanding of the impact of attributes on those configurations, has allowed for the first design guidance applicable to real-world transit-integrated ridesourcing projects.

5.1 Methods

5.1.1 Model Estimation

Mode choice models can be generated using survey panel data. The most common model is the MNL model (Train, 2009), which assumes systematic utility functions (e.g., Equations 4.1 to 4.5) with random error terms that are independent and identically distributed (i.i.d.) Gumbel. The probability of choosing an alternative k (P_k) under MNL is given by,

$$P_k = \frac{e^{V_k}}{\sum_j e^{V_j}} \tag{5.1}$$

where V_k is the utility of alternative k and V_j is the utility of each alternative j in the choice set. This assumption is made for mathematical convenience but leads to the independence from irrelevant alternatives (IIA) property and associated limitations (e.g., proportional shifting). The MNL model also has no ability to account for preference and scale heterogeneity (Hensher et al., 2015). Mixed logit models attempt to improve on the MNL model in specific applications, in part by assuming each systematic utility parameter is drawn from a distribution of values, allowing for some distribution of preferences across the population.

Mixed logit models can be estimated using classical statistics or Bayesian statistics, and the Bayesian form is often referred to as Hierarchical Bayes (HB) (Sawtooth Software, 2021). HB models consist of two parts: lower-level MNL models for each respondent in the sample (consisting of their preference coefficients), and an upper-level distribution which informs the lower-level MNL models. The upper-level uses a multivariate normal distribution with the form,

$$\beta_i \sim Normal(\alpha, D) \tag{5.2}$$

where β_i is the vector of coefficients for respondent i, α is the vector of means of the coefficients across all respondents in the model, and D is a matrix of variances and covariances across individuals. The lower-level model uses the same form as the standard MNL (Equation 5.1).

Estimation is done through sequential iterations: β and D are used to estimate α, β and α are used to estimate D, and α and D are used to estimate β. This procedure is explained in detail in the technical paper published by Sawtooth Software (2021). An effect of this type of model is that lower-level individual models are influenced by the distribution of all respondents, which can be calibrated to allow for lower-level models to adhere more or less strongly to the upper-level distribution. Bayesian estimation avoids the need to maximize a simulated likelihood function and enables consistent and efficient estimates under more relaxed conditions, but it is more challenging for a modeller to determine if convergence has been achieved (Train, 2009). Huber and Train (2001), and later, Elshiewy et al. (2017) showed that both classical and Bayesian estimation should be able to produce similar results for finding individual-level utilities.

Three draft mode choice model specifications were generated using Lighthouse Studio: a classical linear MNL model, a Bayesian mixed logit model with primarily linear coefficients (i.e., linear mixed logit), and a Bayesian mixed logit model with non-linear coefficients (i.e., part-worth mixed logit). The linear MNL model was provided for comparison to traditional mode choice models in transportation that use classical estimation. The Bayesian specifications were used to determine if any attributes in the model have non-linear effects on utility.

Each of the models were prepared using similar techniques. Survey responses were checked for speeder behaviour, including straight-lining or pattern responses, and non-trader behaviour, where respondents stick with one alternative, which can influence mode constants (S. Hess et al., 2010). Furthermore, in the mixed-logit models, individual respondents' root-likelihood (RLH) were compared against a set of 1 000 random computer-generated respondents to ensure their responses were not random. The 230 responses analyzed were from respondents that completed the survey and self-identified as living in one of the three wards that overlapped with the study area. For the mixed logit models, 10 000 draws were pulled to reach convergence during estimation, and another 10 000 draws were used to estimate coefficients for the respondents. All models also used the best and worst tasks: worst tasks are automatically coded as a negative response, so were treated as an inverse of a best task. In the linear MNL and linear mixed logit models, all attribute levels were coded linearly except for the mode constants. No attributes were constrained to have negative or positive coefficients, but well-known relationships like price and time negativity were checked to ensure they met real-world expectations. In the part-worth mixed logit model, attribute levels did not need to be coded into the software. Utilities for non-linear attribute levels were automatically scaled to sum to 0 within attributes before estimation using effects coding.

The mean estimate and t-stat for each attribute were generated for the linear MNL model. Using a 95% confidence interval, t-stats that fell within -1.96 and 1.96 indicated that the variable was not found to be statistically significant. For the mixed logit models, three parameters were generated for each model attribute. The mean value, which represents the estimated α, is equal to the average of the β coefficients from the individual (lower-level) MNLs and is the utility estimate for the upper-level model. The 95% confidence interval indicates the upper bound (97.5th percentile) and the lower bound (2.5th percentile) of the possible values for the mean. For part-worth attributes, if multiple levels within an attribute have overlapping confidence intervals, then the attributes must be tested further to assess the likelihood that the values fall on one side of the other level's mean estimate. Estimates for one level's α are compared to the estimates of α for the other level in each draw from the mixed logit estimation process. The share of draws where the α of one value is less than the α of the other value indicates the confidence that the first level is significantly less than the other (Orme & Chrzan, 2021). The individual standard deviation is also calculated, which is the standard deviation of β coefficients for the lower-level MNLs, indicating the level of heterogeneity in the β coefficients among respondents. Upon estimation, two measures of fit were evaluated. Percent certainty, or McFadden's rho-squared, indicates where the log likelihood lies between a completely chance model (the null model, with a percent certainty of 0.000) and a perfect fit (a log-likelihood of 0, with a percent certainty of 1.000). The log likelihood and percent certainty was automatically generated for the linear MNL model. Individual log-likelihoods were converted from the individual respondents RLH for the other models, then summed across all respondents to find the total log-likelihood.

Using the linear and part-worth mixed logit models, a final mixed logit model was generated based on the part-worth model. This final model converted the part-worth attributes that were not found to have non-linear relationships to linear attributes, and removed attributes that were not significant at a 95% confidence interval.

Segments for different ages, genders, household incomes, and destinations were generated and compared with the final model. Age and gender bins were retained from those included in the survey. Household income was aggregated into two bins: households with under \$100 000 in income and households with \$100 000 or greater. Destination was aggregated from the multiple trip purposes provided in the survey. For home-based trips, trips were separated into home-based work (HBW), home-based school (HBS), and home-based other (HBO).

Although respondent utilities are often demographically weighted in logit models, Sawtooth Software does not provide the ability to weight respondent utilities when using Bayesian estimation. This restriction is supported by prior research from Sawtooth Software that indicated there were minimal effects on the utilities (Howell, 2007). Weighting was considered in later mode share simulations (Section 5.1.2) of different TIR configurations.

5.1.2 Model Validation and Calibration

After estimating the mode choice model, the model was validated using real-world mode shares and calibrated by adjusting the alternative-specific constants (ASCs) and the scale factor. As identified in Chapter 4, SP models tend to be good for determining trade-offs, but poor at replicating real-world equilibria due to the choice of attributes tested and the decision-making of respondents when completing surveys versus making real-world decisions (Hensher et al., 2015). By adjusting the SP model to replicate RP mode shares, analyses can be conducted with the model that should result in reasonably accurate estimates of real-world changes in mode share. This process consisted of five steps. First, real-world estimates were determined, providing target values that the SP model should replicate by the end of the process. Second, a representative base trip was designed with attributes close to the RP median for each mode, in order to find the base SP shares before calibration. Third, respondents were weighted to match their RP declared mode choice with survey data from TTS. Fourth, the scale factor and alternative-specific constants (ASCs) were adjusted to ensure that when TIR was added, it would have an accurate mode share. Finally, TIR was added to determine the initial mode share for scenario analyses.

The most reliable estimates for real-world mode shares come from the TTS, which was previously used in the survey design phase to determine the most popular modes (Table 4.1 in Chapter 4). Because the survey, and by extension, the resulting model used a narrower field of potential trips, the TTS statistics were updated to reflect the boundaries of the study. Specifically, trips were included in the mode share estimates from the TTS if the origin was in one of the survey TAZs, the destination was anywhere in the Region of Waterloo, and the trip was made by someone aged 16 years or older. Trips were then filtered by purpose to ensure any grade-school trips were removed. The second set of shares used was the RP shares that respondents provided within the survey.

While trips in the survey area are fairly heterogeneous, a single trip was used for validation and calibration of the SP results. The trip, which forms the base case, has attributes falling near the median value among all the trips provided in the RP part of the survey. A comparison of the attributes of the base case and the median is provided in

Appendix F. The SP shares under the base case, TTS shares, and RP shares are shown in Figure 5.1. If SP shares matched the TTS shares, no further steps would be required. In this case, without calibration, the SP shares over-represent transit and cycling and under-represent ridesharing and auto, compared to the TTS shares.

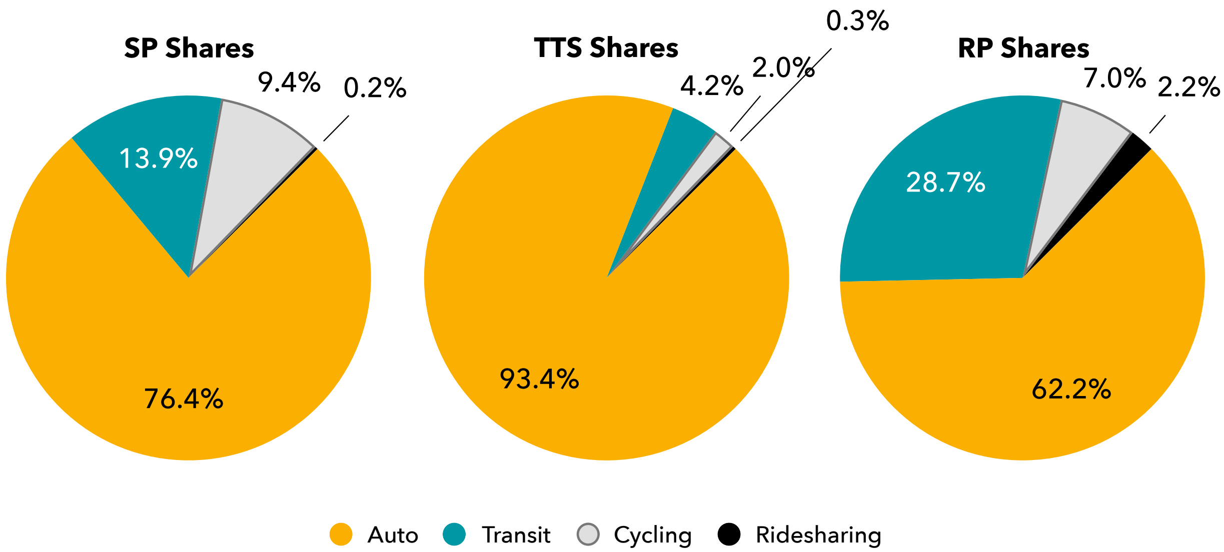


Figure 5.1: SP shares under base case, TTS shares for the associated TAZs, and RP shares from survey respondents

Three techniques were used to adjust the SP shares to match the TTS shares: weighting, adjusting the scale factor, and adjusting the ASCs. Recognizing that the RP modes provided by respondents will not perfectly align with their SP preferences, adjusting respondent weights is one way to ensure that respondents who are suspected to be over-represented or under-represented are appropriately scaled in the model. The scale factor (λ) represents the relative scale for the parameters of the SP model when compared to the RP model. This also equals the ratio between the size of the SP variance compared to the RP variance. There are established ways to accomplish scaling with classical MNL models, including the nested-logit 'trick' (Hensher et al., 2015), which may not be as simple to compute for Bayesian models where individual-level models are still maintained. Guidance from Sawtooth Software recommends practitioners not adjust their models, but if they chose to do so, to change the scale factor (identified as the 'exponent') to achieve shares closer to the target values (Orme, 2006). Then, ASCs can be adjusted to account for any remaining individual changes needed to match shares.

The first step was re-weighting respondents to achieve closer shares to the target. Respondents were binned to compare the shares in SP, RP and the TTS. Unlike the survey chapter, auto passengers were binned with drivers, because both respondent categories use the auto mode. Auto passengers were also not binned separately because only 6 respondents chose ‘passenger in a private vehicle’ as their RP mode, requiring a very large weighting (∼4.8) to match the share of auto passengers in the real-world. Weights were calculated by dividing the RP share by the TTS share, to ensure that each bin has the same weight in the model as the corresponding share in the TTS. While the auto mode has a weight almost 11 times the size of the ridehailing weight, which is higher than typically recommended (Sawtooth Software, 2022), the final weights are considered valid due to the sheer dominance of auto travel in the survey area. Tests of the flexibility of the model (by applying extremely high scale factors to the model to force a higher auto share) revealed that scale factor alone would not be able to provide an auto share over 90%, indicating that people who strongly prefer cycling or transit are over-sampled in the respondent base. Demographic weights were also tested (as proposed in Section 4.4), but actually skewed the SP model more disproportionately toward cycling and transit, so were not considered in the final model. Applying the RP weights to the SP model resulted in a series of shares closer to the TTS shares, but that still required further adjustment.

The second step was finding the appropriate scale factor (λ), which was done in tandem with the third step (adjusting ASCs). While some SP models can be used for sensitivity analysis without adjusting for RP shares (a method originally considered for this analysis), the presence of a new mode (TIR) in the SP case means the ASCs for the existing modes need to be accurate to ensure TIR is not over- or under-weighted once it is added. The method used to adjust the scale factor and ASCs was to find the value of λ that minimized the required ASC adjustments to reach the correct shares on average. ASC adjustments were calculated by Lighthouse Studio when the software was provided a scale factor value. The mean absolute error for the ASCs for auto, cycling, transit, and ridehailing was the metric minimized to find the final λ, which was equal to:

$$MAE = \frac{|Adj_A| + |Adj_C| + |Adj_T| + |Adj_{RH}|}{\lambda} \tag{5.3}$$

which is the sum of the absolute values of the adjustments divided by the scale factor λ. This is mathematically equivalent to whichever λ resulted in the ASC adjustment for ridehailing being 0, because ridehailing had the highest absolute change in mode share for each unit change in λ, compared to other modes. Because of how small ridehailing’s share is in the real-world, being able to accurately predict it relative to other modes was considered valuable. The final scale factor was 0.5897, which falls in the general range identified by practitioners for surveys designed through Lighthouse Studio (Sawtooth Software, 2022).

Table 5.1 shows the respondent count, weighting, shares, adjusted ASCs for each mode to shift from the model shares at $\lambda = 0.5897$ to the TTS shares, and the final share once transit-integrated ridesourcing is added. After finding the ASC adjustments, TIR was added using the 903 Flex parameters as a base (discussed in Section 5.1.4), resulting in a starting case where TIR has a 0.98% share. This share is higher than what was observed in the TIR pilot in Chapter 3, based on the number of observed trips, but the model assumes residents have perfect knowledge of the choice sets. The survey results indicated that most residents were unaware of the service (Section 4.4.1), which may have been a contributing factor to the lower real-world share.

Table 5.1: Respondent count, weighting, adjusted shares, and alternative-specific constant adjustments

Mode	Model Share (SP)	Count	RP Wt.	Model Share (RP Wt.)	Model Share ($\lambda = 0.5897$)	ASC Adj.	Post Adj. Share	Final Share
Auto	76.44%	143	1.503	86.27%	83.19%	1.433	93.44%	92.76%
Cycling	9.70%	16	0.291	5.18%	6.22%	-0.980	2.03%	2.01%
Transit	14.40%	66	0.148	8.43%	9.80%	-0.453	4.24%	3.95%
Ridehailing	0.60%	5	0.137	0.11%	0.79%	0.000	0.30%	0.29%
TIR	–	–	–	–	–	0.000	–	0.98%

5.1.3 Model Application: Marginal Effects and Elasticities

Using the validated and calibrated model, marginal effects and elasticities were calculated to determine the impact each attribute has on the base case trip. Marginal effects and elasticities are a common way of reporting model results in literature (Hensher et al., 2015). Elasticities represent the percent change in quantity per percent change in an attribute. In this research, the quantity is represented by mode share. The two main types of elasticities are point elasticities and arc elasticities. Point elasticities measure the percent change in mode share from one of the two endpoint attribute levels over which the change is being measured, while arc elasticities are measured from the midpoint of the two attribute levels. Arc elasticities are useful when the point elasticities at each endpoint are not similar, and are used throughout this research. The arc elasticity is given by:

$$E_{i,i+1} = \frac{\delta Q_{i,i+1}}{\delta x_{i,i+1}} \times \frac{\bar{x}_{i,i+1}}{\bar{Q}_{i,i+1}} \tag{5.4}$$

where E is the elasticity between levels i and $i+1$, Q is the mode share (quantity), x is the attribute being changed (often price), $\bar{Q}$ is the mean of the mode share at points i and $i+1$, and $\bar{x}$ is the mean of the attribute levels x_i and x_{i+1}.

Marginal effects are easier to visually interpret because they represent the absolute change in quantity per unit change in an attribute. Marginal effects are calculated by:

$$M_{i,i+1} = \frac{\delta Q_{i,i+1}}{\delta x_{i,i+1}} \tag{5.5}$$

where M is the marginal effect between levels i and $i+1$, and the other variables are the same as they are in Equation 5.4. Marginal effects are reported in this research in units of mode share change (as a percent) per unit of the attribute being changed. For example, if a transit fare increased from \$1.00 to \$2.00, and the mode share for transit decreased from 3.0% to 2.5%, the marginal effect would be -0.5% mode share per \$1.00 increase in fare price, or simply -0.5. Marginal effects are specifically reported in absolute units, not in relative units. In this case, marginal effects represent a change in mode share, which is a percentage, but if the number of trips were chosen as the quantity unit, then marginal effects would be measured in the change in the number of trips per unit of the attribute.

In classical logit models, marginal effects and elasticities are generally the same at any attribute level for linear attributes. This is because classical logit models are solving for one 'individual', which represents the aggregate views of the respondents that provided their trade-offs to the modeller. Hence, there is only one set of mode shares to be adjusted and therefore one relationship of utilities to manipulate. In Bayesian logit models, because an individual choice model is estimated for each respondent, mode shares are calculated at each combination of attribute levels by *averaging* the mode shares of each weighted individual respondent. For an individual, a shift from one attribute level to another may cause a different proportional change in mode share compared to another individual, so the marginal effects and elasticities may differ depending on where they are estimated between two levels, even if they are connected via a linear relationship. For simplicity, marginal effects and elasticities used the survey endpoints for linear attributes (i.e., for IVTT ratio), and were calculated for each interval of attribute levels for non-linear attributes (e.g. from 0 transfers to 1 transfer, then from 1 transfer to 2 transfers). Marginal effects and elasticities were only calculated for the base case (instead of the full suite of trip cases in Section 5.1.4).

5.1.4 Model Application: Trip Cases

Different types of trips that might be made using TIR were then evaluated under different system configurations. Figure 5.2 depicts each of the trips and Table 5.2 lists the concepts for each trip case. Origin and destination locations are given in Appendix F.

Trip case 1a and 1b represent the peak and off-peak variants of the median trip, where all attributes fall near the median value. Trip cases 2a and 2b represent trips with a similar length to trip cases 1a and 1b, but worse transit access. The IVTT ratio, access time, egress time, number of transfers, and average transfer times are higher in the transit alternative, and IVTT ratio and egress time are higher in the TIR alternative compared to trip cases 1a and 1b.

Trip cases 3 and 4 represent long trips. Trip case 3 uses a long trip with many transfers close to fixed-route transit. The IVTT ratio is similar to trip cases 2a and 2b, but there are more transfers, shorter access/egress times, and middling average transfer times. Trip case 4 uses a trip that has some of the most undesirable characteristics for intraregional travel, and was designed to test the least transit and TIR friendly boundaries of the TIR. The wait time, combined access/egress time, IVTT ratio, number of transfers, and average transfer time are higher in trip case 4 than in any other case.

Many respondents had RP trips with high access/egress times but low IVTT ratios and short distances. Although distance is not considered in the model, trip case 5 uses a trip that replicates the high access/egress times and low IVTT ratio of those trips. Trip case 1a has some of the most transit and TIR friendly attribute levels, and trip case 5 allows for a competitive best-case scenario where the IVTT ratio is lower and number of TIR transfers is lower, but the combined access/egress time is higher.

Using the typology developed in Chapter 3, trip cases 1a and 1b are inconvenient indirect feeders, trip cases 2a and 2b are double-ended remote trips, trip case 3 is an indirect transit replacement, and trip cases 4 and 5 are single-ended remote trips. These trip types cover most of the popular types from the 903 Flex, except for trips without transit like non-transit trips and direct feeders. Therefore, trip case 6 was designed to use a trip where there is no competitive transit alternative available. The trip goes between a former 903 Flex virtual stop and a bus stop, so is considered a direct feeder with an access/egress time of 0 minutes. Trip case 6 could be hypothesized as a best-case scenario for TIR, because there is no transit and the TIR trip is very competitive.

Table 5.3 outlines the transit and TIR settings used for each trip case. These settings are used as the default values for each trip case.

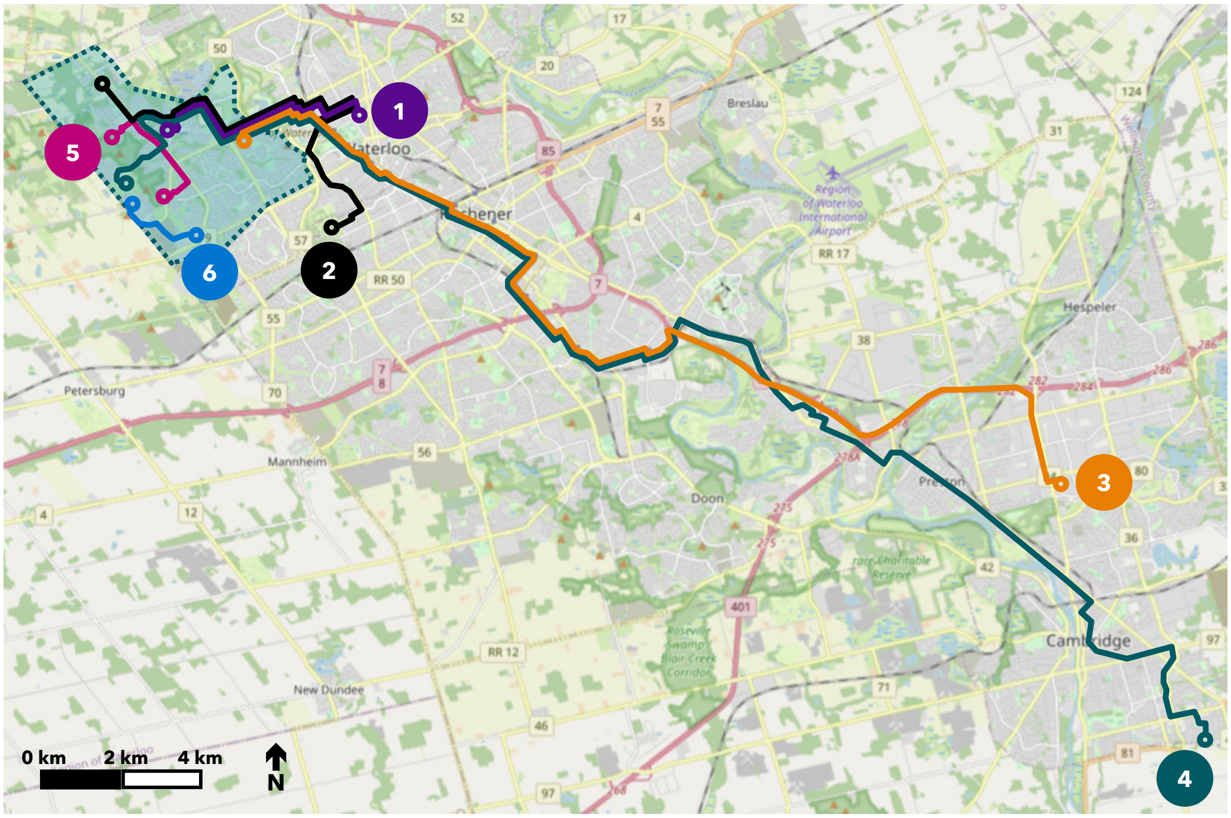


Figure 5.2: Transit trip cases for system evaluation and 903 Flex survey area

Table 5.2: Concept for each trip case

Case	Concept	Dist. (km)	Transit Proximity	Schedule
1a	Median	6.5	Near	Peak
1b	Median	6.5	Near	Off-peak
2a	Median remote	9.5	Far	Peak
2b	Median remote	9.5	Far	Off-peak
3	Long	29	Near	Peak
4	Long remote	39.5	Far	Off-peak
5	Short with low IVTT	3	Far	Peak
6	No transit alternative	3	N/A	N/A

Table 5.3: Trip case transit and transit-integrated ridesourcing settings

Case	Mode	Wait (min)	Access (min)	Egress (min)	IVTT Ratio	Transfers	Avg Transfer Time (min)
1a	Transit	7.5	7	3	1.5x	0	0
	TIR	5	1	3	1x	1	7.5
1b	Transit	15	7	3	1.5x	0	0
	TIR	5	1	3	1x	1	15
2a	Transit	7.5	15	13	2.1x	1	15
	TIR	5	0	13	1.7x	1	7.5
2b	Transit	15	15	13	2.1x	1	7.5
	TIR	5	0	13	1.7x	1	15
3	Transit	7.5	3	1	2.1x	2	12.5
	TIR	5	0	1	2.1x	2	12.5
4	Transit	30	19	9	2.5x	3	15
	TIR	5	5	9	2.4x	3	21.5
5	Transit	7.5	11	5	1x	0	0
	TIR	5	4	0	1x	0	0
6	TIR	5	0	0	1x	0	0

5.1.5 Model Application: Configuration Scenarios

TIR configuration scenarios were designed to cover three categories of changes to TIR systems: operational adjustments, permitted demand patterns, and changes in monetary costs. Scenarios are rooted in the system types found in the literature review (Tables 2.4 and 2.5 in Chapter 2). This subsection discusses each scenario and the changes made to the trip case variables. While settings for most modes are fairly simple, some of the TIR settings specific to each case require further explanation and are outlined in Appendix G. Scenario results were calculated using the Share of Preference format (i.e., the standard logit equation) in Lighthouse Studio's simulator mode.

Table 5.4 presents the scenarios with operational adjustments. Operational adjustments involve small-scale differences in levels of service quality. Since additional stops were removed as a survey attribute (Table 4.4 in Chapter 4), additional stops can be modelled by adjusting IVTT ratios. The 'more stops' scenario adds 0.5x to each case's IVTT ratio, representing additional stops slowing the service down due to either more popularity or a lower vehicle-to-rider ratio. On the other hand, the 'IVTT same as auto' scenario considers the extreme case where no stops are made along any leg of the trip. The 'synced transfers' case explores the trade-off between wait time and transfer time. Instead of picking up the user as quickly as possible and taking them to the next leg of the trip at a time that may not sync with a transfer, the driver times the pick-up time to ensure that the rider arrives within 5 minutes of the scheduled transfer, resulting in longer wait times compared to a non-synced case. Transfer time was reduced to 2.5 minutes for the first transfer point (the maximum transfer time divided by 2) and the transfer time adjustment between the original time and 2.5 minutes was added to the wait time. The average transfer time was recalculated assuming the remaining legs had their original transfer times, if there was more than one transfer.

The next scenarios explored include different permitted demand patterns, which relate to the spatial attributes of system types. Table 5.5 presents the scenarios with different permitted demand patterns. In the many-to-many scenarios, it is assumed the service covers the entire region (i.e, that there are no service zones). Three variants are analyzed where TIR does pick-ups and drop-offs at fixed-route stops, at virtual stops, or provided door-to-door service. In all three cases, the IVTT ratio is dropped to 1x, since there is no fixed-route transit with mandatory stops. Wait times are increased to 10 minutes to reflect the expected longer waits for service since the service area is larger and trips are open to hundreds of locations across the region. By nature of the many-to-many structure, there are no transfers. The difference between the three variants is the walk time: for fixed-route stop service the walk time is adjusted to the walk time for the transit alternative, for virtual stop service the walk time is not changed from the starting case (i.e., the 903 Flex case), and for door-to-door service the walk time is changed to 0 minutes.

The 'nearest fixed stop' scenarios in Table 5.5 considers a transit-supportive variant where TIR feeds the rider directly to the closest fixed-route stop on their transit alternative trip. In the access variant, this service is only offered from their origins to the access stop. In the access and egress variant, the destination end also has feeder service, and is synced to have a TIR vehicle waiting (a 0-minute transfer). In both variants, the IVTT ratio and average transfer time is recalculated using the TIR and transit legs. The number of transfers at minimum is the same as the number of transit transfers. If the origin or destination of the case's trip is within a 5-minute walk, no service is offered to the nearest stop, and therefore no transfer is required at that end of the trip.

Two more scenarios consider less common permitted demand patterns. In one scenario, a many-to-few service similar to one of Innisfil Transit's permitted demand patterns was modelled, where service is only provided to or from the major transit hubs in the Region of Waterloo (listed in Appendix G). A 30-minute transfer penalty applies to taking another TIR trip once at one of the hubs to discourage users from using the service as a somewhat inconvenient many-to-many service. For the first leg, the virtual rider in each case takes

Table 5.4: Scenarios for different operational adjustments

					TIR
	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)
More stops	+0.5x	—	—	—	—
IVTT same as auto	1x	—	—	—	—
Synced transfers	—	+Transfer time adj.	—	—	2.5*

* Cases with more than 1 transfer only had the first transfer adjusted to 2.5 minutes

Table 5.5: Scenarios for different permitted demand patterns

					TIR
	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)
Many-to-many (fixed)	1x	10	Transit walk time	0	0
Many-to-many (virtual)	1x	10	—	0	0
Many-to-many (door)	1x	10	0	0	0
Nearest fixed stop, access	Inc.[a]	—	0-5[b]	Transit transfers +0-1[b]	Var.[a]
Nearest fixed stop, access and egress	Inc.[a]	—	0-5[b]	Transit transfers +0-2[b]	Var.[a]
Many-to-few, 30 min transfer	Var.[c]	—	0 (access), Var. (egress)[c]	0 or 1[c]	30 or transit wait[c]
Zonal service, 5 km zones, door-to-door	1x	—	0	1 per whole 5 km	2.5

[a] IVTT ratio and transfer time average recalculated to account for TIR and transit portions (IVTT ratio always increases)
[b] Service not provided on the access or egress leg if the walk time is under 5 minutes
[c] Under many-to-few, the second leg of the trip may be via transit or via TIR

service to the hub that is closest to their destination. For the second leg, the rider chooses whichever trip has a higher likelihood of getting to their destination faster: either waiting for the 30 minute penalty and taking TIR again from the hub, or waiting for fixed-route transit and taking it to their destination. In another scenario, 5 km zones apply to the entire region with many-to-many door-to-door service. Thus, every 5 km the rider needs to transfer to another TIR vehicle that arrives within 5 minutes.

Table 5.6 lists a series of scenarios exploring changes in monetary costs. Zonal, sectional, and flat upcharge fare scenarios are explored representing different ways of treating TIR based on fare types typically used in public transit (Vuchic, 2004). Zonal fares have a base fare plus a fee for each zonal boundary crossed. Sectional fares (or 'distance-based fares') have a base fare plus a fee for each unit of distance travelled. Flat upcharge fares charge a flat fare on top of the base fixed-route transit fare. Fare regimes for zonal and sectional are chosen so that the maximum fare is \$8.00, which is the upper end of the fare range assessed in the SP survey. The zonal demand pattern is used for the zonal fare case to explore how zonal pricing might change the desirability of a zonal system. Scenarios for free transit, free TIR, and the combination of the two are analyzed, with the latter scenario exploring the impacts on all modes when both services are free and allowing comparison with the individual scenarios. Scenarios at each parking fee level above \$0.00 are explored to compare each level's impact to other studied scenarios. Finally, at the \$15.00 parking level, three extra scenarios are considered: first, combining it with only free transit-based alternatives; second, with free transit-based alternatives and a more expensive ridehailing fee; and third, free transit-based alternatives with many-to-many door-to-door service.

Table 5.6: Scenarios for different monetary costs

	RH	Auto	Transit						TIR
	Rate ($/min)	Park. ($)	Fare ($)	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare ($)
Zonal service and pricing	—	—	—	1x	—	0	1 per whole 5 km	2.5	1 + 1 per transfer
Sectional	—	—	—	—	—	—	—	—	0.2 + 0.2 per whole km
Flat upcharge	—	—	—	—	—	—	—	—	5
Free transit	—	—	—	—	—	—	—	—	0
Free TIR	—	—	0	—	—	—	—	—	—
Free transit and TIR	—	—	0	—	—	—	—	—	0
$1.00 parking	—	1	—	—	—	—	—	—	—
$3.00 parking	—	3	—	—	—	—	—	—	—
$15.00 parking	—	15	—	—	—	—	—	—	—
+ free transit and TIR	—	15	0	—	—	—	—	—	0
+ free transit and TIR, $2.50/min ridehail	2.5	15	0	—	—	—	—	—	0
+ free transit and TIR, many-to-many (door)	—	15	0	1x	10	0	0	0	0

5.2 Results

5.2.1 Mode Choice Model

Table 5.7 presents the estimated utilities for the linear MNL, linear mixed logit, part-worth mixed logit, and final mixed logit models. For all non-linear attributes, the coefficients are reported as zero-centred (i.e., utilities above zero represent more preference for that level within the attribute, and utilities below zero represent less preference for that level within the attribute, compared to the average).

Table 5.7: Model results for linear multinomial logit, linear mixed logit, part-worth mixed logit, and final mixed logit specifications

Attribute / Level	Linear MNL		Linear Mixed			Part-Worth Mixed			Final Mixed		
	Mean	t-stat	Mean	95% CI	σ	Mean	95% CI	σ	Mean	95% CI	σ
TIR	-0.58	-17.29	-3.84	-4.71, -3.02	5.48	-2.55	-3.03, -2.07	3.10	-2.02	-2.42, -1.64	2.38
Transit (T)	-0.49	-14.64	-3.30	-4.26, -2.31	6.49	-2.19	-2.76, -1.60	3.86	-1.64	-2.11, -1.20	2.97
Taxi/Uber (RH)	-1.59	-45.90	-10.78	-12.21, -9.27	7.76	-6.20	-6.76, -5.64	3.25	-4.77	-5.22, -4.32	2.46
Auto (A)	1.91	56.25	13.19	11.70, 14.57	7.09	7.97	7.29, 8.64	3.88	6.17	5.63, 6.70	3.04
Cycling (C)	0.74	20.88	4.73	3.51, 5.95	8.15	2.98	2.23, 3.73	5.01	2.26	1.68, 2.85	3.83
IVTT ratio (T/TIR)											
1x auto	-0.41	-12.12	-2.73	-3.30, -2.21	1.81	1.63	1.34, 1.91	0.98	-1.23	-1.45, -0.99	0.82
2x auto						-0.11	-0.36, 0.17	0.61			
3x auto						-1.52	-1.77, -1.26	1.06			
IVTT deviation (A)											
+/-5%	0.00	0.38	0.02	-0.04, 0.07	0.16	-0.36	-0.70, 0.02	0.48	–	–	–
+/-15%						-0.06	-0.47, 0.36	0.74			
+/-25%						0.21	-0.26, 0.73	0.61			
+/-50%						0.21	-0.20, 0.57	0.63			
IVTT deviation (T/TIR/RH)											
+/-5% auto	0.00	1.05	0.02	-0.05, 0.09	0.27	0.00	-0.25, 0.23	0.68	–	–	–
+/-10% auto						-0.14	-0.38, 0.11	0.61			
+/-15% auto						-0.17	-0.41, 0.08	0.71			
+/-20% auto						0.31	0.05, 0.62	0.72			
IVTT deviation (C)											
+/-5%	-0.01	-1.41	-0.06	-0.15, 0.02	0.24	0.21	-0.34, 0.58	0.77	–	–	–
+/-10%						0.07	-0.34, 0.40	0.88			
+/-15%						-0.23	-0.58, 0.05	0.47			
+/-20%						-0.05	-0.52, 0.46	0.49			
Wait time (T/TIR/RH)											
3 min	-0.03	-14.39	-0.19	-0.25, -0.13	0.21	1.20	0.93, 1.48	0.95	0.85	0.59, 1.10	0.69
5 min						1.06	0.78, 1.35	0.76	0.80	0.59, 1.02	0.63
10 min						-0.12	-0.38, 0.13	0.77	-0.01	-0.22, 0.19	0.55
30 min						-2.14	-2.48, -1.81	1.15	-1.64	-1.92, -1.41	0.94
Walk time (T/TIR)											
0 min	-0.04	-15.33	-0.24	-0.30, -0.18	0.23	1.93	1.56, 2.31	1.30	1.58	1.30, 1.86	1.06
5 min						1.23	0.84, 1.58	0.87	0.92	0.64, 1.18	0.69
10 min						-0.58	-0.95, -0.20	0.87	-0.50	-0.75, -0.25	0.61

continued on next page

Table 5.7: (continued)

Attribute / Level	Linear MNL		Linear Mixed			Part-Worth Mixed			Final Mixed		
	Mean	t-stat	Mean	95% CI	σ	Mean	95% CI	σ	Mean	95% CI	σ
30 min						-2.58	-2.92, -2.22	1.08	-2.00	-2.27, -1.75	0.90
Transfers (T/TIR)											
0	-0.42	-15.76	-2.78	-3.11, -2.44	1.71	3.15	2.61, 3.69	1.40	2.39	2.09, 2.68	1.12
1						0.43	0.16, 0.77	0.58	0.43	0.17, 0.72	0.51
2						-1.20	-1.53, -0.80	0.78	-0.97	-1.20, -0.75	0.66
3						-2.38	-2.79, -1.98	1.14	-1.85	-2.13, -1.57	0.85
Time per transfer (T/TIR)											
0 min	-0.06	-22.84	-0.45	-0.52, -0.37	0.31	3.79	3.24, 4.32	1.52	2.91	2.60, 3.22	1.09
5 min						1.85	1.49, 2.19	1.20	1.45	1.13, 1.74	0.99
10 min						-1.15	-1.54, -0.81	0.85	-1.02	-1.26, -0.77	0.70
30 min						-4.48	-5.01, -4.04	1.59	-3.34	-3.70, -2.98	1.26
Parking cost (A)											
$0.00	-0.14	-22.18	-1.06	-1.20, -0.90	0.58	3.75	3.04, 4.40	1.37	2.89	2.41, 3.39	0.87
$1.00						2.29	1.84, 2.83	1.00	1.85	1.45, 2.26	0.87
$3.00						0.27	-0.22, 0.69	0.80	0.16	-0.27, 0.50	0.65
$15.00						-6.31	-6.95, -5.65	2.09	-4.90	-5.37, -4.45	1.47
Fare (T)											
$0.00	-0.11	-4.97	-0.54	-0.80, -0.29	0.94	1.46	0.98, 2.01	0.87	0.90	0.60, 1.22	0.68
$2.00						0.25	-0.12, 0.69	0.75	0.16	-0.13, 0.44	0.51
$3.50						-0.65	-0.93, -0.35	0.70	-0.27	-0.55, 0.00	0.52
$5.00						-1.06	-1.47, -0.71	0.92	-0.79	-1.16, -0.45	0.46
Fare (TIR)											
$0.00	-0.09	-6.85	-0.58	-0.74, -0.40	0.66	1.48	0.99, 1.84	1.02	0.87	0.52, 1.13	0.74
$1.00						0.79	0.41, 1.19	0.90	0.51	0.17, 0.89	0.70
$3.50						-0.61	-1.06, -0.07	0.73	-0.05	-0.41, 0.27	0.65
$8.00						-1.66	-2.03, -1.29	1.10	-1.33	-1.77, -0.90	0.68
Fare (RH)											
$1.00 per min	-0.23	-19.35	-2.35	-2.72, -1.99	1.72	5.87	5.12, 6.52	2.02	4.36	3.96, 4.81	1.55
$2.50 per min						1.26	0.90, 1.71	1.16	1.16	0.66, 1.62	0.92
$5.00 per min						-2.31	-2.77, -1.82	1.24	-1.73	-2.15, -1.36	0.98
$10.00 per min						-4.83	-5.48, -4.31	1.76	-3.78	-4.30, -3.34	1.41
Sample size (n)	230		230			230			230		
LL	-5956.79		-1689.02			-1427.31			-1815.81		
LL (null)	-9624.44		-9624.44			-9624.44			-9624.44		
% Cert.	.3811		.8245			.8517			.8113		

IVTT deviation was not significant under any of the models. Under linear MNL, the t-stat was between -1.96 and 1.96. Under linear mixed logit, the 95% confidence interval of mean estimates overlapped with 0, and draw tests indicated that none of the attributes reached 90% confidence to be above or below 0. Under part-worth mixed logit, the confidence intervals for every level overlapped with at least one other level, and draw tests identified that none of the levels reached 95% confidence to be higher or lower than all the other levels in the attribute except for 20% deviation for shared modes (transit, TIR, and taxi or Uber), which was significantly different enough from two of the three other levels. Because these attributes were not significant, they were removed from the final mixed logit model.

For all remaining attributes, each of the three draft models indicated a statistically significant linear or non-linear relationship. Individual coefficients fell within a wider range of values for mode constants versus any other attributes, which is evident from the larger individual standard deviations for these levels versus any other attribute or level set, due to the heterogeneity of modal preferences. Specifically, cycling had the highest degree of variation, which was expected since some respondents felt very positively about cycling while others did not. The constants for TIR and transit have considerable overlap at the 95% confidence interval, indicating that these modes are viewed similarly. Other modes have no overlap with each other, which signifies a clearer order in preferences for other modes in comparison to TIR and transit.

Figure 5.3 compares the part-worth mixed logit model with a linearized equivalent. The linear approximation was constructed from endpoints of the part-worth model, which was easier to overlap with the part-worth utilities than applying the linear model directly. The IVTT ratio multiplier for transit and TIR over auto shows a clear linear relationship, with the part-worth utility being nearly indistinguishable from the linearized equivalent. Taxi and Uber fares show the greatest deviation, with a clear non-linear relationship between levels. Wait time shows minimal differences between the utilities at the 3 minute and 5 minute levels, indicating that on a whole the population did not consider them to be meaningfully different. Most other attributes primarily deviate at one of the midpoints and have somewhat linear relationships between the midpoint and the endpoints. For the purposes of the final mixed logit model, attributes were kept non-linear except for the IVTT ratio multiplier over auto, since it showed a highly linear relationship.

Table 5.8 shows how the mean estimates of the final model specification vary across different demographic and characteristic segments in the sample. Segmented models were generated for age, gender, household income, and destination. Some respondents chose not to reveal their gender or household income, and were removed from these segmentation models. For gender, non-binary respondents were also removed because only two respondents identified as non-binary, which were not enough responses to represent how non-binary residents would differ versus a broader population. While the absolute value of utilities can not be directly compared between segments, the changes of level utilities within an attribute can be compared for each segment. This table also only presents the mean values, which does not represent the full distribution of estimated means corresponding to individual respondents. Recall that the estimated utilities for each segment are influenced

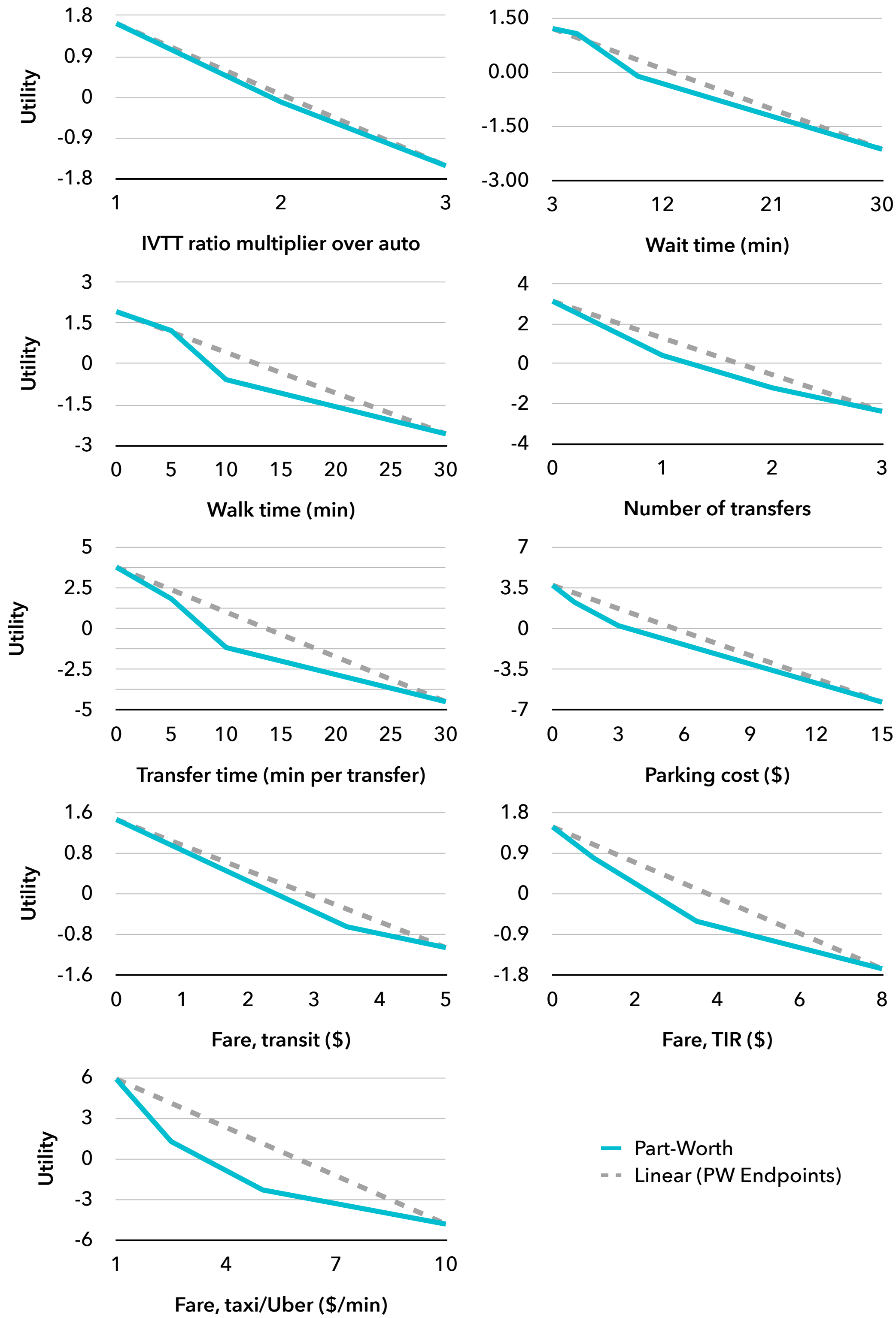


Figure 5.3: Plots comparing part-worth utilities and linear representations connecting between part-worth endpoints

by the upper-level distribution that considers all segments, so real-world differences among segments may be even more pronounced.

The ordering of mode constants did not change with any segmentation, with auto always being the most preferred mode, followed by cycling, transit, TIR, and finally taxis and Uber vehicles. Auto and cycling were also always preferred more than average and the other modes were preferred less than average. Older groups tended to have near equivalent preferences for TIR and transit. Respondents who were younger, female, had lower household incomes, or were taking an HBS trip preferred TIR and transit, although had a stronger preference for transit over TIR compared to other segments. Compared to other modes, cycling was more preferred when respondents were younger, male, had lower household incomes, or taking an HBS trip.

For time attributes, wait time generally had the lowest impact and transfer time had the highest impact on utility, for all segments. Female respondents had a higher sensitivity to changes in wait time and at low levels compared to male respondents, but lower sensitivity to changes in walk time and the number of transfers at low levels. Preference for 3-minute wait times and 5-minute wait times were fairly close in all segments, and in some segments 5-minutes showed an average higher preference than 3 minutes, which is likely due to overlapping confidence intervals for the mean estimates. It is more likely that respondents in these groups do not perceive changes in utility when shifting from 3-minute to 5-minute waits. Respondents who were younger or taking an HBS trip were less sensitive to shorter walk times and transfers, but more sensitive to longer walk times. Respondents who were female or had higher household incomes were less sensitive to 5-minute transfer times, but every group had roughly the same proportional drop in utility with 10-minute transfer times.

For cost attributes, parking cost and taxi and Uber fares had the highest impact. Taxi and Uber fares having a high impact was expected since they had the highest absolute range of fares, but parking cost having a similarly high impact was not expected since it peaked at only $15.00. Changes in parking cost and taxi and Uber fares caused fairly similar proportional drops in utility across all segments. For transit fares, seniors were more sensitive to the shift from free transit to $2.00 fares, and respondents taking an HBS trip were less sensitive to the shift from $2.00 to $3.50 fares. TIR fares had the highest variation among segments. Respondents aged 16-24 years old or taking HBS trips preferred $3.50 trips over $1.00 trips in the model, although the difference was not large and, similarly to the wait time case, may indicate that these respondents were indifferent to the difference in price at these levels. Conversely, the difference between free TIR and

Table 5.8: Means across age, gender, household income, and destination segmented models

Attribute / Level	Total	Age					Gender		HH Inc. ($)		Destination		
		16-24	25-34	35-49	50-64	$\geq$65	F	M	Low	High	HBS	HBW	HBO
n	*230*	*41*	*56*	*59*	*47*	*27*	*122*	*103*	*86*	*110*	*20*	*87*	*123*
TIR	-2.02	-1.39	-2.16	-2.17	-2.18	-2.08	-1.76	-2.43	-1.46	-2.56	-1.36	-2.33	-1.91
Transit (T)	-1.64	-0.68	-1.74	-1.64	-2.15	-2.00	-1.28	-2.23	-0.85	-2.25	-0.52	-2.04	-1.54
Taxi/Uber (RH)	-4.77	-5.54	-4.53	-4.83	-4.73	-4.01	-4.91	-4.59	-4.87	-4.61	-4.88	-4.53	-4.91
Auto (A)	6.17	4.98	6.03	6.14	7.00	6.87	6.00	6.39	5.01	6.81	4.34	6.22	6.43
Cycling (C)	2.26	2.63	2.40	2.50	2.06	1.21	1.96	2.86	2.17	2.62	2.42	2.68	1.94
IVTT ratio (T/TIR)	-1.23	-1.03	-1.29	-1.28	-1.31	-1.11	-1.16	-1.32	-1.04	-1.38	-1.04	-1.41	-1.12
Wait time (T/TIR/RH)													
3 min	0.85	0.86	0.96	0.79	0.87	0.71	0.90	0.84	0.82	0.93	0.83	0.94	0.80
5 min	0.80	0.70	0.86	0.80	0.77	0.88	0.76	0.86	0.76	0.86	0.77	0.93	0.72
10 min	-0.01	-0.11	-0.01	0.01	0.01	0.06	-0.09	0.05	-0.12	0.05	-0.15	-0.05	0.04
30 min	-1.64	-1.46	-1.81	-1.61	-1.65	-1.64	-1.58	-1.75	-1.45	-1.85	-1.45	-1.82	-1.55
Walk time (T/TIR)													
0 min	1.58	1.24	1.65	1.62	1.63	1.75	1.51	1.69	1.45	1.78	1.28	1.80	1.47
5 min	0.92	0.93	0.91	0.86	1.04	0.83	0.96	0.90	0.77	1.02	0.90	1.02	0.85
10 min	-0.50	-0.30	-0.49	-0.53	-0.64	-0.47	-0.49	-0.51	-0.40	-0.60	-0.30	-0.64	-0.42
30 min	-2.00	-1.87	-2.07	-1.96	-2.04	-2.11	-1.98	-2.08	-1.81	-2.21	-1.88	-2.17	-1.90
Transfers													
0	2.39	2.06	2.47	2.46	2.49	2.38	2.32	2.52	2.07	2.72	1.87	2.68	2.26
1	0.43	0.45	0.37	0.48	0.47	0.35	0.40	0.49	0.36	0.48	0.59	0.48	0.37
2	-0.97	-0.88	-0.95	-1.07	-0.94	-0.95	-0.93	-1.04	-0.84	-1.08	-0.89	-1.04	-0.93
3	-1.85	-1.63	-1.88	-1.87	-2.02	-1.77	-1.79	-1.97	-1.58	-2.11	-1.57	-2.12	-1.70
Time per transfer (T/TIR)													
0 min	2.91	2.61	3.04	2.92	3.01	2.88	2.87	3.02	2.74	3.15	2.53	3.16	2.80
5 min	1.45	1.25	1.59	1.45	1.49	1.38	1.34	1.63	1.16	1.70	1.15	1.59	1.40
10 min	-1.02	-0.91	-1.15	-1.01	-1.05	-0.93	-0.97	-1.12	-0.92	-1.18	-0.86	-1.20	-0.93
30 min	-3.34	-2.95	-3.49	-3.36	-3.46	-3.33	-3.24	-3.53	-2.97	-3.67	-2.82	-3.54	-3.27
Parking cost (A)													
Free ($0.00)	2.89	3.19	2.77	2.85	2.91	2.68	2.94	2.83	2.88	2.85	3.03	2.81	2.92
$1.00	1.85	1.97	1.79	1.79	1.99	1.68	1.90	1.79	1.75	1.87	1.75	1.73	1.95
$3.00	0.16	0.05	0.25	0.14	0.14	0.22	0.15	0.17	0.16	0.19	-0.08	0.23	0.15
$15.00	-4.90	-5.21	-4.82	-4.79	-5.04	-4.58	-4.99	-4.78	-4.79	-4.92	-4.69	-4.77	-5.02
Fare (T)													
Free ($0.00)	0.90	1.00	0.90	0.83	0.90	0.91	0.93	0.83	0.88	0.85	0.71	0.86	0.96
$2.00	0.16	0.09	0.24	0.22	0.16	0.02	0.15	0.21	0.19	0.17	0.12	0.21	0.14
$3.50	-0.27	-0.24	-0.34	-0.30	-0.23	-0.20	-0.28	-0.26	-0.22	-0.29	0.01	-0.34	-0.27
$5.00	-0.79	-0.85	-0.80	-0.75	-0.83	-0.73	-0.80	-0.78	-0.85	-0.73	-0.84	-0.73	-0.83
Fare (TIR)													
Free ($0.00)	0.87	0.96	1.06	0.77	0.77	0.72	0.90	0.82	1.09	0.77	1.05	0.90	0.82
$1.00	0.51	0.17	0.52	0.49	0.69	0.70	0.46	0.54	0.50	0.50	0.02	0.56	0.55
$3.50	-0.05	0.20	-0.13	0.00	-0.15	-0.21	-0.05	-0.03	-0.10	-0.04	0.19	-0.06	-0.09
$8.00	-1.33	-1.33	-1.45	-1.27	-1.32	-1.20	-1.31	-1.33	-1.49	-1.24	-1.25	-1.40	-1.29
Fare (RH)													
$1.00 per min	4.36	4.40	4.33	4.37	4.56	3.98	4.35	4.42	4.09	4.57	4.17	4.40	4.36
$2.50 per min	1.16	0.95	1.17	1.25	1.23	1.12	1.11	1.24	0.94	1.32	0.89	1.25	1.14
$5.00 per min	-1.73	-1.72	-1.76	-1.77	-1.78	-1.54	-1.74	-1.74	-1.56	-1.85	-1.64	-1.83	-1.68
$10.00 per min	-3.78	-3.63	-3.73	-3.86	-4.01	-3.57	-3.72	-3.92	-3.46	-4.03	-3.43	-3.82	-3.81

$1.00 was minimal for older respondents, while dropping back to a similar proportion to other segments at $3.50.

5.2.2 Marginal Effects and Elasticities

Table 5.9 shows the marginal effects and elasticities for the base case (trip case 1a). The marginal effects demonstrate relationships similar to those of the SP model's utilities (Tables 5.7 and 5.8). Direct elasticities and marginal effects, which are changes in a mode's share due to changes in the *same* mode's attributes, are identified in bold. All other values are cross elasticities and marginal effects, which are changes in a mode's share due to changes in *another* mode's attributes. Of note is the 3-5-minute wait time window in the transit, TIR, and ridehailing cases, which show unintuitive relationships (an increase in wait time resulting in an increase in mode share), which was attributed in the model results in Section 5.2.1 to an indifference among the respondent base between 3-minute and 5-minute wait times. Otherwise, the relationships are as expected. The greatest marginal effects are for parking, where adding a $1.00 parking fee from $0.00 results in a 4.07% loss to the auto share, and *each* additional $1.00 increase in parking fees results in further 2.8-3.2% losses in auto share. Other large marginal effects include the IVTT ratio for transit, which had a 1.33% loss in transit share for each 1x increase in the ratio, and adding one transfer from the zero transfer case, which results in a drop of 1.41% mode share for transit and 1.31% mode share for TIR. Because of ridehailing's small starting share, few attributes had ridehailing marginal effects over 0.01%. Changing the per-minute rate had the greatest effect, with an expected drop in 0.15% share for every $1.00/min increase between $1.00/min and $2.50/min. Similarly, because cycling had no direct attributes in the model, only attribute levels that caused very large changes in utility overall have a larger marginal effect. Parking costs has the greatest impact, with the $0.00-$1.00 region predicting a 1.51% increase in cycling share, and every $1.00 increase after that predicting a 0.71-0.84% increase.

5.2.3 Operational Adjustments

Figure 5.4 shows the absolute changes in mode shares when the TIR service has many more stops (a higher IVTT ratio by 0.5x), the same IVTT ratio as auto (a ratio of 1x, which is perfectly direct), and synced transfers. In the 'IVTT same as auto' scenario, trip cases 1a, 1b, 5, and 6 are shaded because the base TIR cases are already set to a ratio of 1x (i.e, these configurations do not affect these trip cases). Similarly, in the synced transfers

Table 5.9: Case 1a marginal effects and elasticities for mode attributes (direct in bold)

Attribute	Mode	Min	Max	Marginal effects					Elasticities				
				A	C	T	RH	TIR	A	C	T	RH	TIR
IVTT ratio	Transit	1x	3x	1.13	0.04	**-1.33**	0.02	0.14	0.02	0.04	**-0.74**	0.12	0.27
	TIR	1x	3x	0.21	0.01	0.08	–	**-0.30**	0.01	0.01	0.04	0.02	**-0.86**
Wait	Transit	3	5	–	0.01	–	-0.01	-0.01	–	0.03	**0.00**	-0.08	-0.05
		5	10	0.16	0.01	**-0.18**	–	0.02	0.01	0.03	**-0.34**	0.12	0.12
		10	30	0.05	–	**-0.05**	–	–	0.01	0.02	**-0.35**	0.05	0.08
	TIR	3	5	-0.03	–	0.01	–	**0.02**	–	0.00	0.01	-0.02	**0.10**
		5	10	0.06	–	0.01	–	**-0.07**	0.01	0.01	0.02	0.03	**-0.64**
		10	30	–	–	–	–	**-0.01**	–	0.00	0.02	0.01	**-0.39**
	Ridehailing	3	5	-0.01	–	–	**0.01**	–	–	–	–	**0.13**	-0.01
		5	10	0.03	–	–	**-0.03**	–	–	0.01	0.01	**-1.08**	0.01
		10	30	–	–	–	–	–	–	–	–	**-0.70**	–
Walk	Transit	0	5	0.31	0.01	**-0.30**	–	-0.03	0.01	0.02	**-0.11**	0.03	-0.07
		5	10	0.35	0.01	**-0.38**	–	0.01	0.03	0.06	**-0.59**	0.13	0.09
		10	30	0.07	–	**-0.09**	–	0.01	0.02	0.03	**-0.58**	0.08	0.25
	TIR	0	5	0.05	–	0.01	–	**-0.06**	–	–	0.01	0.01	**-0.13**
		5	10	0.04	–	–	–	**-0.04**	–	–	-0.01	0.01	**-0.31**
		10	30	0.01	–	0.01	–	**-0.02**	–	0.01	0.05	0.02	**-0.85**
Transfers	Transit	0	1	1.27	0.05	**-1.41**	0.02	0.06	0.01	0.01	**-0.22**	0.03	0.03
		1	2	0.64	0.03	**-0.90**	0.01	0.22	0.01	0.02	**-0.65**	0.06	0.28
		2	3	0.20	0.01	**-0.26**	–	0.04	0.01	0.01	**-0.43**	0.02	0.08
	TIR	0	1	1.07	0.03	0.20	0.01	**-1.31**	0.01	0.01	0.03	0.03	**-0.40**
		1	2	0.32	0.01	0.16	0.01	**-0.50**	0.01	0.01	0.06	0.03	**-1.02**
		2	3	0.13	–	0.02	–	**-0.15**	–	–	0.01	0.02	**-0.95**
Transfer time	Transit	0	5	0.15	0.01	**-0.17**	–	0.01	–	0.01	**-0.20**	0.02	0.02
		5	10	0.08	–	**-0.13**	–	0.04	0.01	0.02	**-0.71**	0.05	0.27
		10	30	0.01	–	**-0.01**	–	–	–	–	**-0.24**	0.01	0.05
	TIR	0	5	0.25	0.01	0.05	–	**-0.31**	0.01	0.01	0.04	0.04	**-0.28**
		5	10	0.21	0.01	0.07	–	**-0.29**	0.02	0.02	0.13	0.11	**-1.70**
		10	30	0.01	–	–	–	**-0.01**	–	–	0.01	0.01	**-0.54**
Fare	Transit	$0.00	$2.00	0.66	–	**-0.76**	–	0.10	0.01	–	**-0.15**	0.01	0.11
		$2.00	$3.50	0.12	0.01	**-0.16**	0.01	0.02	–	0.02	**-0.11**	0.05	0.07
		$3.50	$5.00	0.50	0.03	**-0.58**	0.01	0.05	0.02	0.06	**-0.70**	0.09	0.20
Fare	TIR	$0.00	$1.00	0.38	0.02	0.15	0.01	**-0.55**	–	–	0.02	0.01	**-0.14**
		$1.00	$3.00	0.18	–	0.15	–	**-0.33**	–	–	0.08	0.01	**-0.50**
		$3.00	$8.00	0.07	–	0.02	–	**-0.10**	–	0.01	0.03	0.03	**-0.72**
Rate / min	Ridehailing	$1.00	$2.50	0.12	0.01	0.01	**-0.15**	0.01	–	0.01	0.01	**-1.44**	0.01
		$2.50	$5.00	0.01	–	–	**-0.02**	–	–	–	–	**-1.46**	–
		$5.00	$10.00	–	–	–	–	–	–	–	–	**-1.10**	–
Parking	Auto	$0.00	$1.00	**-4.07**	1.51	1.76	0.21	0.60	**-0.02**	0.27	0.18	0.27	0.23
		$1.00	$3.00	**-2.80**	0.84	1.17	0.16	0.63	**-0.07**	0.39	0.34	0.48	0.57
		$3.00	$15.00	**-3.20**	0.71	1.39	0.45	0.64	**-0.45**	0.68	0.76	1.15	0.87

Direct elasticities and marginal effects in **bold**, cross elasticities and marginal effects otherwise. Dash indicates a value that falls between -0.01 and 0.01.

scenario, trip cases 5 and 6 have no transfers to sync. Across all three scenarios, the change in mode share is less than 1% for any mode in any case, except for the more stops scenario, where cases 5 and 6 have a drop of 2% and 2.4% in TIR, respectively. Although the drop is higher for these cases in the more stops scenario, these trip cases also have a much higher base share for TIR. In other cases where the IVTT ratio is adjusted, the change in mode share is minimal. Even though the starting share of TIR is low in trip cases 3 and 4 (0.4% and 0.2%, respectively; other starting shares in Appendix F) and the IVTT ratio is over 2x, the share of TIR only increases by at most 0.2% when the IVTT ratio is reduced to 1x, so realistically does not make TIR a more competitive option. An interesting finding from the model is the synced transfers scenario, where transfer time is reduced to 2.5 minutes and the wait time is increased by the same amount. In the longer trips, there is no change in mode share, but in the shorter trips there is a positive shift toward TIR, confirming that the respondents in the model are more sensitive to transfer time than wait time.

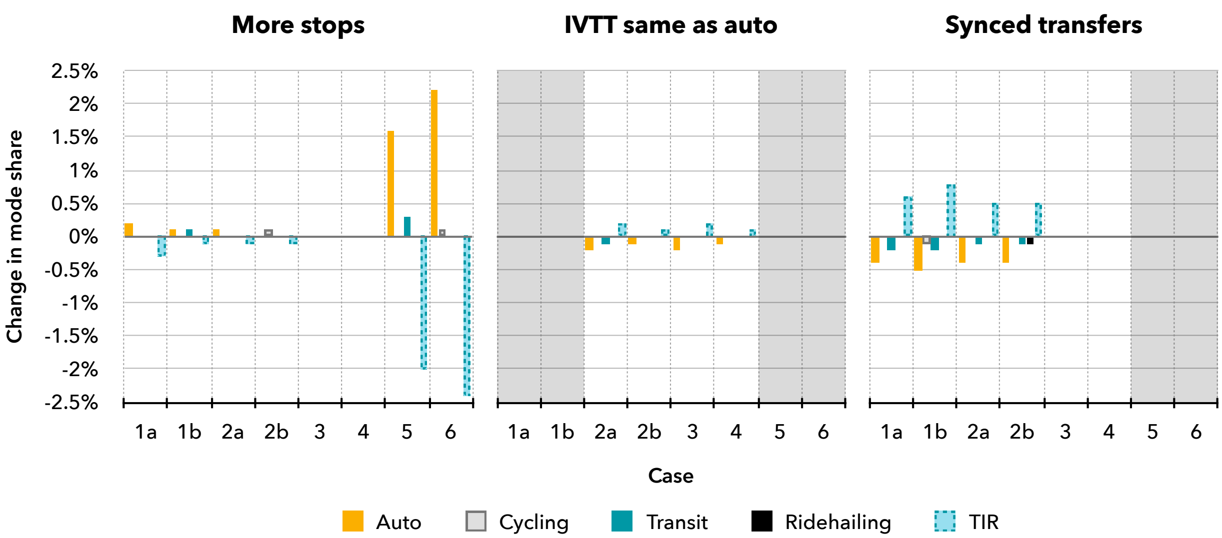


Figure 5.4: Changes in mode shares due to operational adjustments in transit-integrated ridesourcing

5.2.4 Permitted Demand Patterns

Figure 5.5 shows the changes in mode shares for three different many-to-many configurations: travel between fixed-route stops, travel between virtual stops, and door-to-door travel. For trip cases 1a-4, the TIR mode share increases, and in trip cases 5 and 6 the mode share decreases. For the latter cases, the decrease is because the trips were already direct but now have an increase in wait time from 5 minutes to 10 minutes. In cases 1a and 1b, where transit is more competitive, each configuration negatively impacts the share of transit. The fixed-route configuration has the lowest impact on TIR and auto and the door-to-door configuration has the highest impact. Although the impact on TIR and auto progressively increased from the fixed-route configuration to the door-to-door configuration, the impact on transit changes only minimally.

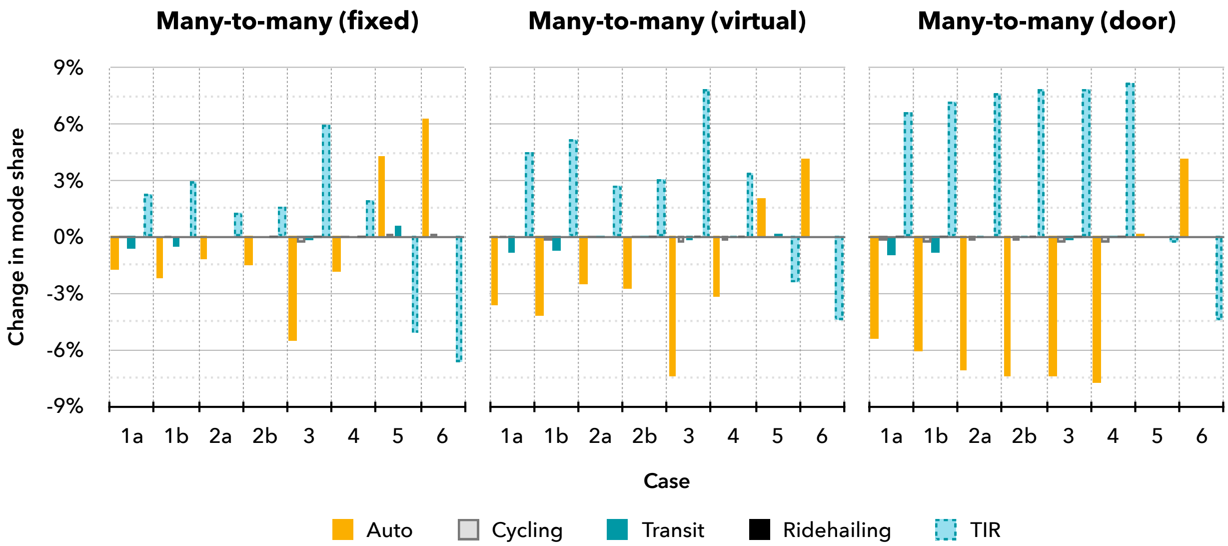


Figure 5.5: Changes in mode shares for many-to-many transit-integrated ridesourcing configurations

Figure 5.6 shows the changes in mode shares for the scenario where TIR takes the rider to the nearest fixed-route stop, both when only the access point has TIR and when both the access and egress points offer this service. Trip cases 1a and 1b only use TIR for the access side in both cases, because the trip ends too close to a fixed-route stop. Trip cases 3 and 6 have a complete drop in TIR, because case 3's trip is too close to existing fixed-route transit and case 6 has no transit alternative. Trip case 4 has more transfers than the survey's range covered, so this case's scenario uses extrapolation past the survey range boundaries. While extrapolation is not recommended past attribute level endpoints (Hensher et al., 2015), the findings for the transfer attribute in the high transfer cases are similar to the 3 transfer case. For the remaining cases, TIR mode share changes by the same amount for both the access and access/egress scenarios, except for trip case 5.

Figure 5.7 shows the changes in mode shares for the less common many-to-few and zonal service configurations. In the many-to-few configuration, trip cases 1a, 1b, 5, and 6 uses TIR for the first leg of the trip, then uses fixed-route transit for the second leg since it is faster than waiting for the transfer penalty to end. The trips for trip cases 2a, 2b, and 4 assume the rider waits for the 30-minute transfer penalty before directly going to the final destination, since it is faster than any alternative, and trip case 3 conveniently

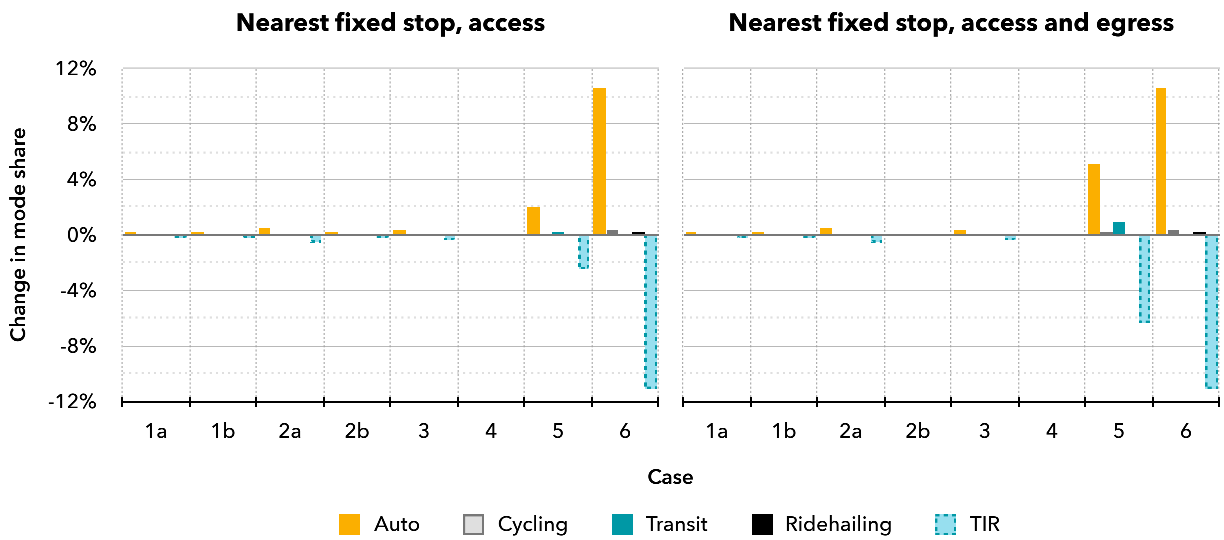


Figure 5.6: Changes in mode shares for transit-integrated ridesourcing configurations connecting to the nearest fixed-route stop

ends at one of the many-to-few locations, so it has no transfers. Consequently, trip case 3 shows a high increase in TIR share at the expense of auto, and to a lesser extent, transit and cycling. Trip case 4 shows a very slight increase for TIR, and trip cases 5 and 6 show a high decrease. In the extra case where an extra stop was added in the middle of the former 903 Flex area, only trip case 5 uses the stop, and there is a slightly less negative impact on TIR with the extra stop.

For zonal service, results for trip cases 3 and 4 again extrapolate past the attribute endpoints on the transfer attribute since the trips for these trip cases have five and seven transfers, respectively. Trip cases 1a-2b's trips have one transfer and trip case 5 has no transfer. In all trip cases, there is an increase in TIR share at the expense of auto, primarily. While this seems unexpected due to the high number of transfers, the elimination of access/egress time (due to door-to-door travel) may have outweighed any losses due to transfers.

5.2.5 Changes in Monetary Costs

The final scenarios analyze changes in monetary costs for all modes. The first set of scenarios consider transit-like pricing scenarios (Figure 5.8), including zonal, sectional, and flat upcharge pricing. As expected, shorter trips show a small increase in preference for TIR (around 0.5%) compared to the flat fare zonal service, while longer trips show a small decrease. In general, across all trip cases there is still a net increase in preference for

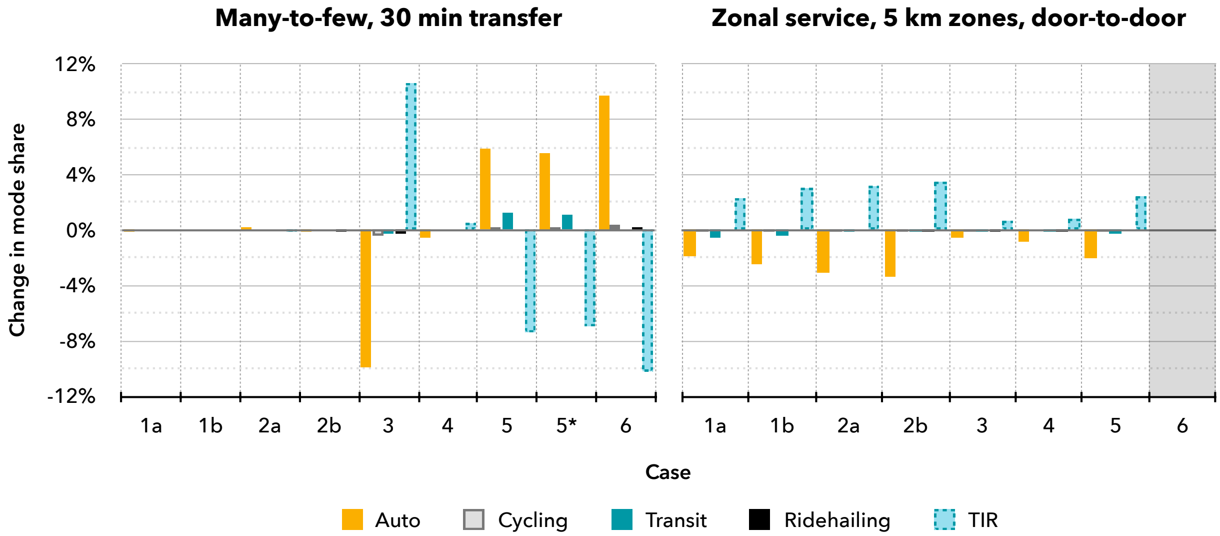


Figure 5.7: Changes in mode shares for less conventional transit-integrated ridesourcing configurations

TIR using zonal systems, even with zonal pricing that reaches \$8.00 for the ride in longer trip cases. Sectional pricing results in slightly cheaper fares for shorter trips and similar fares to zonal for longer trips. In the flat upcharge scenario, the \$5.00 fare for TIR (\$1.50 higher than fixed-route transit) results in a small drop (20-30% lower mode share than the base case) for all trip cases, which is more pronounced for trip cases 5 and 6 because of the larger starting share of TIR.

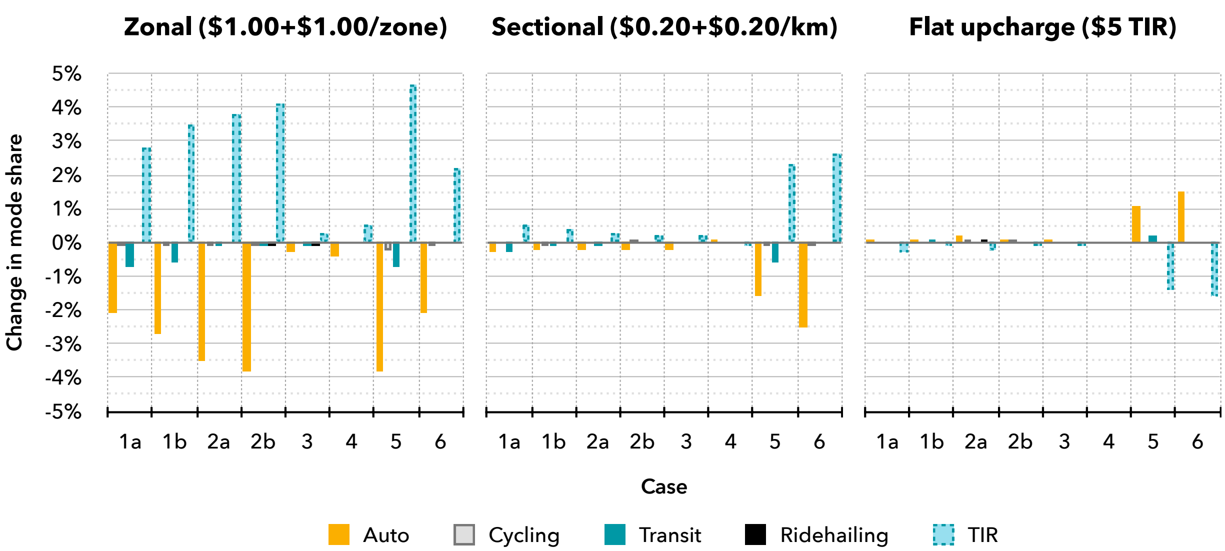


Figure 5.8: Changes in mode shares for zonal, sectional, and flat surcharge pricing scenarios for transit-integrated ridesourcing

Figure 5.9 shows the next set of scenarios, which consider free transit and/or free TIR. In the free transit case, trip case 6 is not evaluated because no transit trips are available. In the other trip cases, transit increases primarily at the expense of auto. Depending on which other modes are more popular in each case, those other modes also lose some share (TIR in cases 1a-2b and 5, ridehailing in cases 2b and 3, cycling in case 1b). In the free TIR case, the share of TIR doubles in trip cases 1a-4 (which all have starting shares of 1% or less), and increases by less pronounced but still large margins in trip cases 5-6. In some cases where transit has a higher starting share, the share of transit decreases by a up to 1%. Specifically, in case 1a, the drop in transit (0.5%) is close in magnitude to the drop in auto (0.8%), indicating that for this case there is potential to disproportionately negatively impact transit share in an attempt to pull more people from auto. In the scenario where both modes are free, transit and TIR experience no losses in mode share under any case, indicating that for ridership purposes, this is a benefit for both modes. In cases 1b, 5, and 6, cycling has a 0.1-0.2% drop, which is a relatively small impact compared to the starting shares (1.8-2.1%).

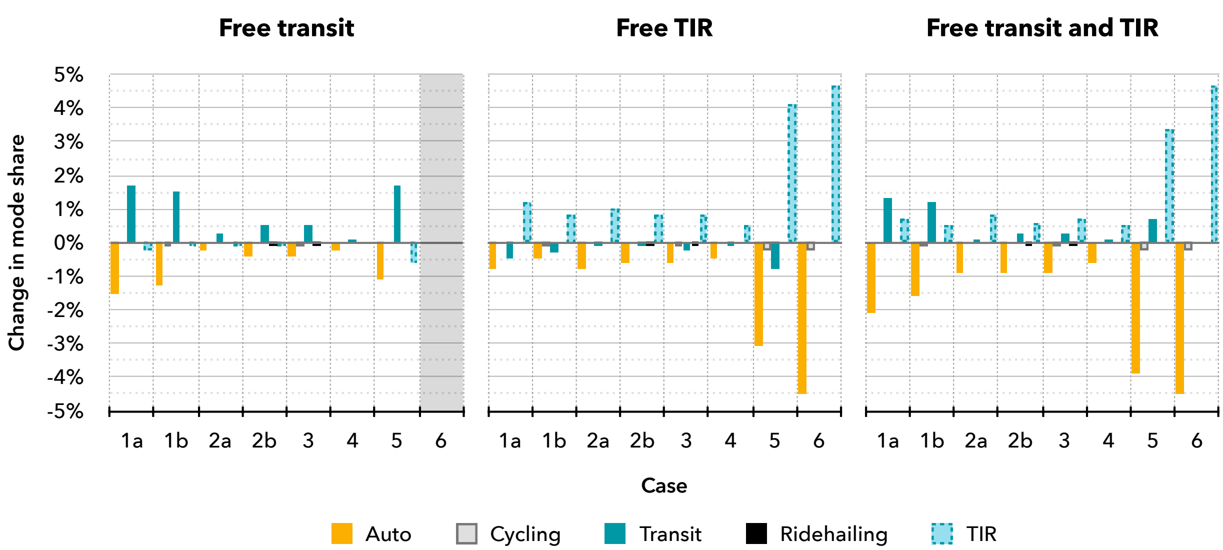


Figure 5.9: Changes in mode shares for free transit and transit-integrated ridesourcing

Figure 5.10 shows the changes in mode shares due to different parking fee levels. By far, parking has the single-largest impact on the share of TIR and auto mode share. At $1.00 parking, every case has a drop in auto share from 2.7-6.0%. Every other mode benefits across all cases. In cases 1a and 1b, cycling and transit share the majority of mode share increases. In cases 2a-4, cycling is the single-largest beneficiary. For cases 5 and 6, TIR has the largest benefit, and where transit is available, it has a similar increase in share to cycling. At only $1.00 parking, the benefit to cycling and ridehailing is larger than any other studied scenario, and the impacts on auto, transit, and TIR vary around the average to larger end of changes. At $3.00 parking, the impacts polarize more strongly, with TIR showing massive benefits in mode share in cases 5-6 of over 10% at the expense of auto, and cycling and transit showing higher shares in the other cases. At $15.00 parking, auto loses 32-61% of its share across all cases, and the other modes further entrench their growing shares in the cases they respectively were leading in in the $1.00 and $3.00 parking scenarios. This is the only scenario where auto drops below a 50% share. Although cycling, transit, and ridehailing have the best positive impacts with $15.00 parking, TIR does not always have its highest measured mode share in this scenario: cases 1b-4 have higher TIR shares in other scenarios (many-to-many door-to-door service and many-to-few).

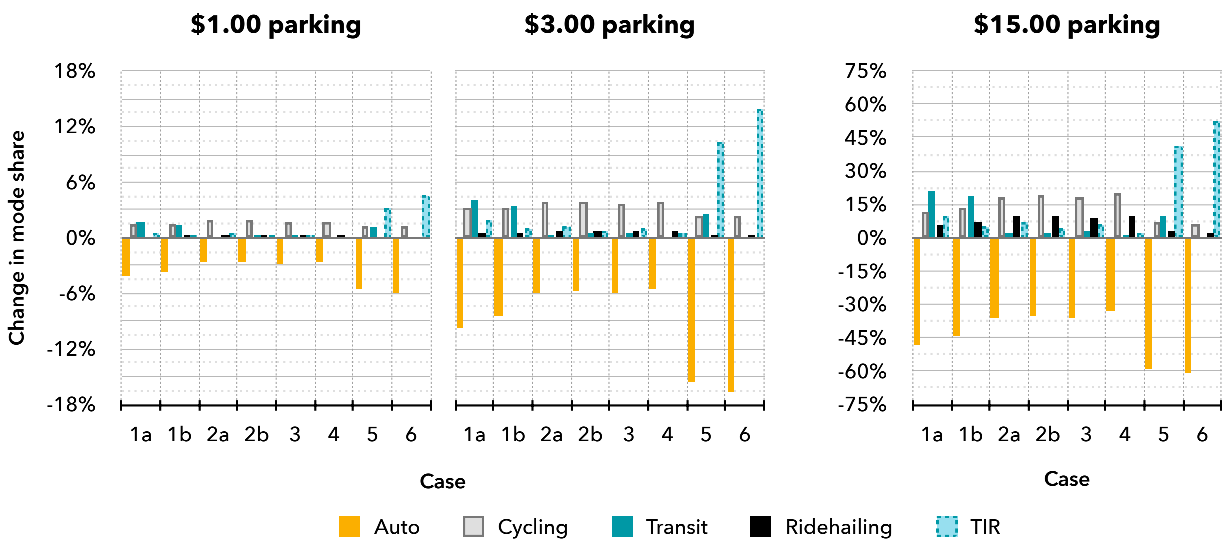


Figure 5.10: Changes in mode shares with different parking fees

Finally, three further scenarios are considered that incorporate the $15.00 parking attribute. Figure 5.11 shows the change in mode share *from the $15.00 parking scenario*. When free transit and TIR are included, transit has a much higher absolute increase than the free transit and TIR scenario without $15.00 parking, while TIR has minimal further gains. When comparing the first two scenarios, which only differ by the inclusion of a more expensive ridehailing rate ($2.50/min vs. $1.00/min), ridehailing has a large drop in share, over half of which shifts to auto with the remainder going somewhat evenly to the other modes. A composite scenario combining free transit, TIR, and many-to-many door-to-door service on top of $15.00 parking is also considered, which pushes the auto share lower than all other scenarios. In this scenario, TIR has a share between 50-62% for all cases. Cycling and transit are minimally impacted for case 5, but sees much larger drops (between one-third and one-half the free transit and TIR case with $15.00 parking).

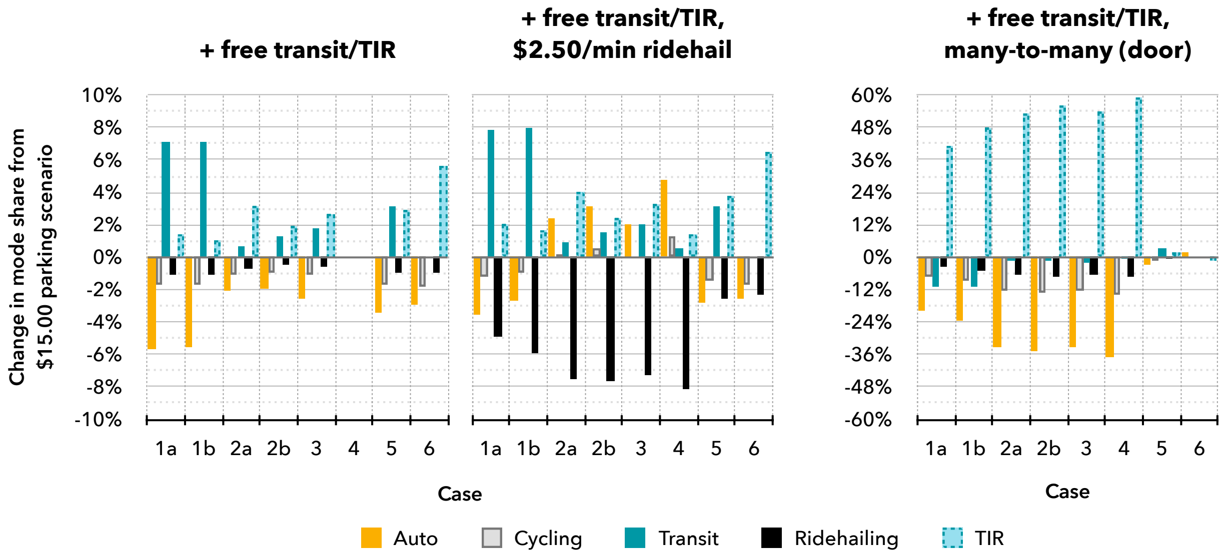


Figure 5.11: Changes in mode shares for with $15.00 parking fees and additional pricing changes for other modes

5.3 Discussion

Bayesian models are uncommon in transportation, particularly for traditional transportation mode choice modelling. As a result, the findings of this model are challenging to directly compare with other transportation models, since the coefficients and other calculated shares are determined differently than in classical models. IVTT ratio specifically is challenging to compare since it was measured differently than in many other studies, as a ratio of transit or TIR IVTT versus auto IVTT. Compared to a previous review of transportation elasticities, the transit fare sensitivities fall in the range of previously determined values, and the transit access/egress values fall between the range of previous train and bus elasticities (Hensher, 2008), indicating that on a whole the elasticities and marginal effects may be within a realistic range.

Although non-linearity is not often discussed in transportation literature, the findings across the attribute utilities, marginal effects, and scenario analyses suggest that there is value in considering the non-linearity of many transportation attributes. By considering where the largest drops in mode share occur for different attribute levels, transit agencies and municipal transportation planners can set targets for networks that minimize the likelihood of reaching a level with higher proportional drops in mode share, and worry less about negligible mode share drops. For example, this model suggests no great benefit in a 3 minute wait time versus a 5 minute wait time for transit, TIR, or ridehailing. Similarly, replacing free parking with a $1.00 parking fee has a bigger proportional impact than each additional extra \$1.00 increase (an auto decrease of 4% versus 2.8-3.2%), so even introducing a small parking fee with TIR service may cause a notable mode shift.

Even at the \$1.00 level, the mode share impacts across all modes are similar to the middle to upper end of impacts experienced in other scenarios, which demonstrates the power of direct pricing on the auto mode. Part of this is due to the dominance of auto in the existing shares: since it started at 86-97%, depending on the trip case, even a drop of a few percent causes a more dramatic change in mode shares in other modes than a drop in transit or TIR does. At higher parking levels, the dominance of other modes in some cases is extreme: in the more TIR friendly cases (5 and 6), the combined transit and TIR shares are over 60%. Although parking fees are able to produce strong responses from the model in specific cases, other cases with worse transit or TIR service (2a-4) have more resilient auto shares that would require additional changes to push the share of auto below 50%, since the alternatives to auto were not nearly as quick or desirable. It should be noted that even in these less desirable cases, TIR still has a mode share high enough to likely be worth operating from a ridership perspective, with a 2.2% share at worst.

Although the IVTT ratio has a relatively large marginal effect on the transit case, it is not as strong on TIR, likely due to the smaller starting shares in case 1a. While the negative impact of higher ratios is felt strongly in cases with higher starting TIR shares (cases 5 and 6), cases with less competitive TIR options do not have very large increases in TIR share when reducing the ratio to 1x. Operationally, synchronizing one of the transfers (decreasing one transfer's time and increasing wait time by the same amount) has a more positive effect for TIR for trips that are closer to the median.

Part of the intention of exploring preferences was to understand how preferences would impact ridership of different system type attributes (Table 2.4). Directness was not fully explored since it was assumed in the design of the survey (Section 4.1.2) that TIR would be shared by default. Preferences for combinations of access/egress distance, zonal patterns, and permitted demand patterns were still able to be predicted based on the model results. Use of different permitted demand patterns have, in some cases, very large impacts to the mode shares of each trip case. In the many-to-many case with no service zones, apart from wait time related issues for cases 5 and 6, other cases show very high increases in mode share for TIR (1-6% for fixed-route stops, 2.5-8% for virtual stops, 6-8.5% for door-to-door service). The many-to-few system, which also has no zones but has more restricted trip patterns than the 903 Flex, only benefits cases where the passenger would be going to one of the transfer hubs (~10% increase in case 3) or be taking a long trip where multiple transfers are required (~0.5% share increase in case 4). Some shorter trips are less desirable under the many-to-few system (~7-10% share decreases in cases 5-6). The addition of zonal service across the entire region, which has a considerable number of transfers in the longer trip cases, still results in an increase in TIR mode share when using door-to-door service (1-4%). The caveat with using a many-to-many system, particularly one with door-to-door pickups, is the potential for high costs, lower reliability, and erosion of fixed-route ridership that is cheaper to service. Lower reliability would be likely due to the much higher number of origin-destination pairs that could be serviced, pushing the service further from operating along route-like paths to servicing riders on an ad-hoc basis. The elimination of zones, which benefits longer trips, would also add time to servicing riders in more remote locations in the region.

In the nearest fixed stop cases, where TIR operates only a transit-supportive feeder, the expected share of TIR is lower and in some cases is not available because there is no transit alternative for the trip. The corresponding increase in fixed-route transit service is often not as high as the drop in TIR or the increase in auto, indicating that while a feeder-only service is an admirable goal in terms of supporting a fixed-route network, it may not achieve all of the goals of the system and, in some cases, may just cause people to continue taking auto modes.

The sustainability of making any of these choices should also be considered. Although these impacts were not directly measured as part of the model, inferences and caution concerning environmentally preferable modes, ridership, coverage, and utility may be made based on the findings. From a ridership perspective, a transit agency would want to ensure that their service has maximized ridership. The marginal effects and scenarios indicate that a free many-to-many service with no zones but controlled wait times and synced transfers in an environment with expensive parking and free transit would have significant uptake in TIR. Although the share of fixed-route transit is lower with door-to-door service, the increase in TIR share appears to overtake the losses in fixed-route transit. If the agency was more concerned about ensuring fixed-route transit still had a strong mode share, using a less competitive many-to-many system (like a fixed-route stop or virtual stop variant) would have higher shares of fixed-route transit while still having more riders take TIR than in the starting cases. The virtual stop variant is a good middle ground that benefits transit-poor residents more than transit-rich ones (since the TIR stop for transit-rich users is often the transit stop near their home), which better solves the issue of transit-poor residents having worse transit alternatives. From a coverage standpoint, TIR offered through virtual stops or door-to-door service would be the best option, since it would ensure everyone is within desirable walking distances (generally considered 400 m or 5 minutes) from transit or TIR.

From an environmental perspective, there are nuances between alternatives, but generally cycling is preferable, since it is an active transportation mode with a small physical footprint. Auto is discouraged, even with electric vehicles, since it has a large physical footprint and requires much more infrastructure to service the same number of people. Fixed-route transit, ridehailing, and TIR fall in the middle, within which fixed-route transit most efficiently moves large numbers of people. Therefore, combinations that prioritize cycling, then transit, then TIR and ridehailing, then auto would likely lead to better environmental outcomes. $15.00 parking, with no other changes, had the highest cycling share and a competitively low auto share, with higher transit, TIR, and ridehailing shares than the base cases. Including free transit and TIR continues to shift the share away from auto and only minimally from cycling and ridehailing, suggesting that the pricing alone could lead to very high environmental improvements.

Agencies should be careful to weigh the costs of additional service (particularly TIR) against the ridership benefits to ensure that enough people join the system to justify the increased levels of service. Systems with small zones (e.g., 903 Flex-like systems, direct feeder service) may more easily to provide lower wait times and more consistent service than systems with very large, region-wide zones. Configurations that greatly shift fixed-route transit to TIR would also reduce the cost efficiency of the fixed-route service, which may be more expensive for an agency to operate depending on how many people come to transit or TIR from other modes. Pricing mechanisms that greatly improved the ridership, like higher parking fees, could potentially also be used to help pay for improved transit service.

Finally, a comparison of the tested configurations to the original 903 Flex system is worth exploring. The 903 Flex operated using a many-to-many system with virtual stops, restricted to a specific zone with shared trips, with no transfer integration and a free transfer (with no additional charge). The appeal of the 903 Flex system's configuration was expected to be higher than it was in the pilot phase for some shorter trips. The lack of familiarity most respondents had with the system (Section 4.4.1) suggests that one of the biggest shortcomings in its existing configuration was a need for better awareness and marketing. The model and scenario results suggest that synced transfers, the removal of zones, and door-to-door service, could all improve the ridership of TIR to some degree, with potentially negative impacts on existing fixed-route service. Some of these changes, particularly region-wide many-to-many service of any kind, would be expected to increase the ridership considerably compared to the real-world service, shifting expected mode share of TIR closer to 10%. However, most of these changes were small in comparison to auto deterrents like parking, which could be combined with other changes specific to TIR to greatly expand the boundary of possible ridership growth. Although parking fees alone did not always expand TIR to a greater degree than other changes, the combination of parking fees with other changes resulted in a synergistic effect on TIR mode share. The much greater impacts of directly applying costs to auto versus tweaking transit and older forms of DRT has been observed even in older literature (D. B. Hess, 2001), where parking again had greater predicted impacts than other operational changes would be expected to have.

5.3.1 Limitations

By the nature of how SP surveys are designed, there are attributes that weren't considered in the survey and consquently the final model. Notably, because of the low significance of the reliability attribute, cycling was only represented by an ASC. The primary focus of this model is on TIR, and ensuring that attributes associated with TIR could be properly adjusted as needed. Hence, attributes specific to other modes were less necessary. Other factors that may have been useful for cycling specifically, but were not included due to the extra complexity of the choice sets provided to respondents, were weather impacts, seasonality, and quality of nearby cycling infrastructure. Cycling would be expected to have a much lower share in the winter than in the summer, in rainy conditions versus sunny conditions, and in areas with no dedicated infrastructure versus areas with cycle tracks (Flynn et al., 2012; Henao et al., 2015; Saneinejad et al., 2012). The restrictions set on the types of trips that could be made may also limit the impacts of the model findings: walking trips in particular are a competitive mode for very short trips, and for the cases covering much shorter scenarios (5 and 6, which were around 3 km long), walking may have had a non-zero share.

Market awareness and how well respondents understand each mode in real-world situations should also be considered when interpreting the results. Respondents are not likely to fully consider each of the five modes for every trip they make, and as a result modes that they were open to in the survey may not be fully considered or evaluated in real life. Lighthouse Studio allows for using a survey variable as a flag for product awareness, which can be used to scale the results (Sawtooth Software, 2022). One question in the survey asked about whether respondents were aware of or had taken the 903 Flex, and using this variable as a flag for product awareness was briefly explored. It was decided in the end to consider how respondents would choose each mode assuming they had full awareness of the alternatives, which is the regular assumption in discrete choice modelling. The importance of properly advertising new modes should be appreciated by transit agencies looking to try any new TIR systems, considering the low previous awareness of 903 Flex in the survey (Chapter 4).

Similarly, there are other barriers to choosing modes that could not be captured in the final survey. While transit-integrated ridesourcing was fully explained to respondents in the survey (Figure 4.5), older respondents may have challenges understanding the nature of how the mode operated due to a lack of familiarity with modern mobile apps and the booking process for similar modes like private ridesourcing. Safety is often a concern, particularly for shared modes, which may impact the response to transit-integrated ridesourcing in this survey. While COVID-19 was not directly found to have an impact on transit-integrated ridesourcing in Chapter 4, lingering effects from the pandemic like concerns over sanitation and airflow may still be factors that impact this mode.

A small caveat was indicated on some of the scenario analyses due to extrapolation being needed to calculate the mode shares. Specifically, the zonal service cases and the nearest fixed-route cases required more transfers than was in the model for cases 3 and 4 due to the length of these trips. While the results shown in the scenarios should still be relatively accurate, it is important to identify that extrapolating variables past the model boundaries can only give some prediction of what will happen based on the relationships from within the boundaries.

Assumptions had to be made about how to scale the RP modes to ensure that they reflected real-world shares and so TIR was introduced at the proper starting share. It is generally recommended not to adjust the ASCs for new modes like TIR, since no RP data can be used to calibrate the constant (Hensher et al., 2015). There may be other assumptions about the scale factor and relative ASCs for other modes that may have resulted in different shares of TIR.

Finally, the model results may require interpretation to be applicable to other regions. Municipalities and agencies can use a simpler approach, where major thresholds are transferred qualitatively from this research and the results of the analysis are used to infer which changes cause greater or lesser impacts on mode share, and to what relative magnitude. More complex approaches, like transfer scaling, are well detailed in literature and could also be applied to assess new transit-integrated ridesourcing systems in the planning stages (Systematics et al., 2012).

5.4 Conclusions of System Evaluation

Transit agencies are looking to ridesourcing as a possible extension of their fixed-route networks, and while it has been piloted in existing transit networks, little was known about how residents perceive TIR. In this chapter, a Bayesian mixed-logit model was constructed with the results of the survey from Chapter 4. This is the first TIR model that includes real-world attributes for time and cost with a full suite of competitive alternatives and estimated on a representative population. A series of trip cases were built representing trips with multiple combinations of attributes, to provide appropriate coverage of the types of trips that may be taken by residents in this area. With a fairly representative sample of the population, this study found that respondents had similar preferences to TIR as they do for fixed-route transit, both of which had much higher preferences than private ridesourcing options or taxis, even when accounting for their wariness of different modes due to COVID-19. The part-worth model revealed that the gap between 5-10 minutes for wait times, transfer times and walk times has the strongest drop in utility of the assessed time windows, so configurations of TIR may be most desirable if these times can be kept to 5 minutes or less. Marginal effects for the most representative base case confirmed these windows had the largest expected drop in mode share for TIR.

The single largest impact in the model was the introduction of parking fees, especially at higher parking fee levels. Only by changing parking fees was auto able to be reduced below 80% share under any case. Parking fees alone did not greatly benefit TIR, but highly benefited cycling, fixed-route transit, and ridehailing. Offering many-to-many service, particularly using door-to-door travel, was one of the most effective ways to improve the share of TIR, but this had some negative impacts on fixed-route transit. Thus, there are multiple options to consider depending on the aims of the agency. The most effective way to reduce auto share and elevate the most environmentally sustainable modes (cycling and fixed-route transit) would likely be to introduce direct costs like parking fees on auto and reduce the cost of fixed-route transit, which combined had greater impacts than most other combinations of alternatives. Agencies should consider exploring other direct pricing schemes for auto (like congestion or vehicle kilometres travelled (VKT) pricing) to most effectively reduce the share of auto and provide a more competitive environment for other modes to increase their shares. Other areas may also consider applying the model (e.g., using transfer scaling) so their agencies can assess their own planned transit-integrated ridesourcing systems before implementation.

Chapter 6

Conclusions and Recommendations

On-demand transit has been explored in previous decades for low-density areas like suburbs, where fixed-route transit is expensive to provide on a per-rider basis due to lower ridership. In previous decades, there has been considerable effort to try DRT systems like DART, but they found limited success, in part due to the long advance booking times. With the advent of TNCs offering ridesourcing, the possibility of an immediate app-based DRT mode like transit-integrated ridesourcing may have more success in attracting ridership in car-dependent areas. While a large body of literature has given attention to the impacts of private ridesourcing, there has been little attention to ridesourcing that is specifically provisioned as a shared mode through the public transit system.

This thesis expanded this body of literature through three phases. First, a typology was developed to explain spatial competitiveness with fixed-route transit, and was applied through a full analysis of a recent transit-integrated ridesourcing pilot. Second, a RP-SP survey was developed that contrasted transit-integrated ridesourcing with a list of common alternatives, exploring the sensitivity respondents had to different time and cost attribute levels. Third, a model was estimated and applied to a series of sample trip cases to determine how ridership would be expected to change for different configurations of transit-integrated ridesourcing.

6.1 Summary of Chapters

Chpater 1 introduced the concepts of shared mobility and transit-integrated ridesourcing. Chapter 2 followed with a review of former DRT services. This context emphasized the developments preceding ridesourcing-based DRT. Recent Canadian transit-integrated ridesourcing systems (since 2015) were reviewed to provide context to the common vehicle types, platforms, permitted demand patterns, fares, and hours of operation. Because of the rapidly evolving nature of transit-integrated ridesourcing and how recently many of these pilots started, this was the most complete summary of Canadian transit-integrated ridesourcing systems to date. Common permitted demand patterns and system attributes were determined from existing systems, DRT algorithms, surveys, and models; culminating in a summary of system types and their expected impact on passengers. A primary motivator for this research was the gap in the literature of how people perceive newer, more immediate forms of DRT like transit-integrated ridesourcing.

Chapter 3 analyzed all 4536 trips from the 903 Flex pilot in the Region of Waterloo, which operated from 2018-2019. Trips were characterized using a new trip typology, which sorted trips into 1 of 10 types based on proximity to transit. Transit, walking, and cycling alternatives were generated for each transit-integrated ridesourcing trip using OpenTripPlanner using GTFS feeds, using the origin and destination from the transit-integrated ridesourcing ride. Users were classified into frequent, average, or infrequent users based on how often they used the service, and were separately analyzed to determine differences in trends between user classifications. Changes in weekly ridership, trip types, pick-up times, trip magnitude, headways, and payment methods were explored to determine if there were trends over the four main periods of operation.

Chapter 4 introduced the RP-SP survey that was conducted from 30 April to 31 July 2021 in the same area where the 903 Flex previously operated. The design of the survey was described through the starting demographics, selection of alternatives and attributes, expected utilities, and formal design. The pre-SP portion, which included automated RP collection, and the post-SP portion, which included demographics questions, were also reviewed. Strategies for how to disseminate the survey were discussed, resulting in the final decision to use postcards targeted to residents living in the former 903 Flex area. 267 respondents completed the survey, from which 230 responses were used for analysis. Analysis of the survey in this chapter included demographic comparisons against the census, travel time competitiveness of cycling and transit alternatives, perceptions of modes due to COVID-19, vehicle and pass ownership, and a breakdown of RP trip times. Users were classified based on the mode they chose for their RP trip (drivers, transit riders, passengers, and cyclists), and findings were broken down by these 4 categories to see how findings changed for each group.

Chapter 5 extended the findings of the survey, describing the development of a Bayesian, non-linear, mixed logit mode choice model. The model allowed for estimating sensitivities to modes and their attributes. Linear and non-linear variants of models were estimated, and the utilities for each attribute were compared to test for non-linearity. A final model was estimated using a mixture of statistically significant linear and non-linear attributes. The model was segmented by age, gender, household income, and destination (HBS, HBW, and HBO). The model was then validated using real-world mode shares and calibrated using a representative trip as a base case. From that base case, marginal effects and elasticities were calculated. Seven further trip cases were developed to test boundaries of attribute level combinations based on real-world trips that could be taken from the study area. A series of system configuration scenarios were applied to the eight trip cases to determine how mode shares would be expected to change in the system types identified in Chapter 2.

6.2 Key Findings

The review of DRT literature, transit-integrated ridesourcing systems, and existing preferential research (Chapter 2) led to four major conclusions:

- The immediate response and ease of access for transit-integrated ridesourcing, in comparison to the booking process of traditional DRT, requires renewed research to understand how preferences may have changed with the advent of ridesourcing-style booking.
- Transit agencies have poor guidance on the best ways to integrate transit-integrated ridesourcing in a way that encourages positive mode shifts and effective increases in ridership.
- Current research tends to focus on ridesourcing as a competitive alternative to transit (often through companies like Uber and Lyft), instead of exploring how transit-integrated ridesourcing could compete with or complement fixed-route transit.
- Existing mode choice models that consider transit-integrated ridesourcing (Tables 2.2 and 2.3) have limited attributes, alternatives, or demographics. A more general mode choice model that considers all types of travel in suburban areas is required to better understand the role of TIR.

Developing the trip typology for transit-integrated ridesourcing trips and exploring the spatial and temporal characteristics of the 903 Flex pilot (Chapter 3) led to three major conclusions:

- TIR trips can be characterized by their spatial attributes to determine their competitiveness with fixed-route transit systems. An automated process is used to characterize these trips and can be transferred to other areas conducting similar analyses.
- Trips taken during the 903 Flex pilot were largely complementary to the transportation network (primarily consisting of indirect feeders and remote trips) and progressed toward more transit-supportive trip types.
- Over 16% of trips competed with transit, and had the highest share during the free transit promotional period. Agencies should be cautious about duplicating services, to avoid pulling users from existing fixed-route infrastructure.

Designing and administering an RP-SP survey for transit-integrated ridesourcing in the former 903 Flex area (Chapter 4) led to four major conclusions:

- Respondents tended to choose the RP mode that was most competitive from a travel time perspective, even without necessarily having perfect knowledge of the alternatives' travel times.
- Respondents who chose driving had the highest share of car ownership and number of cars per household, and cyclists had the highest rate of bicycle ownership, but choosing transit did not correlate with owning fare cards or passes.
- COVID-19 did not impact perceptions of fixed-route transit or transit-integrated ridesourcing meaningfully, suggesting that drops during the pandemic are likely to bounce back afterwards. Auto and cycling had positive perceptions due to COVID-19, so the existing strong share of auto may be strengthened due to ongoing pandemic concerns or new pandemics in the future.
- Agencies should be aware of how effective their advertising is for new services, since most respondents were not aware the 903 Flex previously operated in their area.

Estimating the mode choice model from the survey data and applying it to a series of trip cases (Chapter 5) led to four major conclusions:

- Respondents had similar preferences for transit-integrated ridesourcing and fixed-route transit, both of which were preferred to private ridesourcing and taxis. Transit-integrated ridesourcing may, therefore, be viewed as an on-demand extension of existing transit service from a resident's perspective.

- The 5-10 minute windows for wait time, transfer time, and walk time were the most sensitive to drops in utility and mode share, so configurations of transit-integrated ridesourcing should be sensitive to times that fall in or above this range.

- Parking fees had a substantial impact on mode shares, greatly reducing the predicted share of auto and shifting that share predominantly to cycling, fixed-route transit, and ridehailing. Other direct costs on auto should also be explored to consider whether they have similarly large expected impacts on the overall mode share.

- Many-to-many demand patterns for transit-integrated ridesourcing and door-to-door travel resulted in larger increases in the transit-integrated ridesourcing mode share, with some negative impacts to fixed-route transit. Benefits of moving to more permissive demand patterns and closer stops should be weighed against the negative impacts on fixed-route transit to determine what is overall preferable for a given system.

6.3 Agency Recommendations

Throughout the analysis of transit-integrated ridesourcing pilots, a series of best practices formed that may help guide agencies planning transit-integrated ridesourcing services in suburban areas. For agencies with fixed-route alternatives, agencies should characterize on-demand trips in their network, to determine how spatially distant the trips are from existing fixed-route transit service. Using the typology:

- Transit replacements spatially satisfy the need of a rider, and require either temporal changes (e.g., shorter headways, faster in-vehicle times) or more directness in the local fixed route to encourage a shift to existing fixed-route transit. Agencies should consider the feasibility of these changes to these existing routes to further attract riders to fixed-route transit.

- Indirect feeders have one end that is far for most people to access for transit. Riders may be taking these to cut one leg out of their trip (e.g., the first bus in a multi-bus trip) or because their true destination is near the transit-integrated ridesourcing destination. Agencies should consider looking more closely at the true origins and destination of riders using indirect feeders to assess the reasoning for taking these trip types to understand how to appropriately address the missing gap in existing service.

- Inconvenient and remote trips are challenging to serve using existing fixed-route transit, because the stops are located far from the rider's origins and destinations. Inconvenient trips may be taken by more transit-averse people or those with mobility concerns, while transit-friendly people would likely be willing to take the existing fixed-route service. Remote trips have a very poor transit alternative that most riders likely do not consider as an alternative due to the high access/egress time. If the trips are single-ended, then only one side has access/egress challenges, but the rider is also choosing to not take a feeder trip to the nearest stop and take the bus route. Agencies should consider the temporal competitiveness of the bus route, and whether there are incentives for riders to skip the route altogether (e.g. the transit-integrated ridesourcing service can just take them to their true destination anyway for the same fare).

- Direct feeders and non-transit trips are not able to be spatially satisfied with existing fixed-route service. Agencies should monitor for high numbers of direct feeders and non-transit trips between specific origin-destination pairs, which may indicate potential for future fixed-route service in the future.

From the model findings:

- Agencies should explore synchronizing transfers between transit-integrated ridesourcing and fixed-route transit, which increases wait time but lowers transfer time. In the model, each minute of wait time was perceived less negatively than each minute of transfer time.

- Agencies should consider system improvements that make the highest marginal improvements for each attribute. Specifically:

  - There are diminishing returns for wait times below 5-minutes. Agencies that can reliably achieve a 5-minute wait time should allocate further efforts into other system improvements.

  - The decrease in utility per minute for transit-integrated ridesourcing for the wait time, walk time, and transfer time attributes is larger between 5 minutes and 10 minutes than any other range of attribute levels, and the decreases in mode shares in this range are also larger or competitive with the largest decrease. Agencies with times in this window could prioritize small improvements to these times (e.g., from 8 minute transfer times to 5 minute transfer times) to maximize benefits.

- The change from 0 transfers to 1 transfer similarly has the highest decrease in mode share. Agencies should consider whether transfer-free transit-integrated ridesourcing systems (like many-to-many) are viable in suburban areas, but be cautious of how it impacts fixed-route service (e.g., by only offering it in transit-poor areas).
- Introducing parking costs increase the shares of all other modes greatly, particularly transit and active transportation. Because of how dominant auto is in suburban areas, a small decrease in auto share can have a much larger proportional increase for other modes. Municipalities should consider introducing or increasing parking fees to best support transit and active transportation. Other direct costs for auto should be considered by the appropriate governments to further discourage driving.

6.4 Contributions

This thesis makes five major contributions to transit research. The first contribution (analytical) is the first comprehensive trip analysis of a transit-integrated ridesourcing service from start to finish. The detail in the trip database allowed for user-level behavioural changes to be measured across the lifecycle of the pilot. By assessing the complete spatial and temporal characteristics of the 903 Flex, future agencies considering transit-integrated ridesourcing may hopefully have more specific takeaways from the conduct of the pilot project.

The second contribution (methodological) is the trip typology developed for the pilot analysis, which characterizes the spatial competitiveness of transit-integrated ridesourcing trips in comparison with fixed-route transit. The typology may be of use to agencies looking to characterize trips made in their own pilot projects, to determine whether their on-demand service heavily overlaps with existing fixed-route service, and if changes to the fixed-route service (like increased headways or more direct routes) may benefit if trips meet the right characterization (i.e., if they are transit replacements).

The third contribution (analytical) is the design and implementation of an RP-SP survey, which was one of only a few preference surveys that includes a modern app-based version of transit-integrated ridesourcing. The survey results are novel due to the combined inclusion of cost and most other common alternatives (driving, passenger, cycling, ridehailing), which have not been included together in transit-integrated ridesourcing surveys. While not the first survey to use automated RP attribute collection, it is still rare to automatically collect RP attributes (in this case, directly from the Google APIs) instead of asking respondents to fully enter the attributes. The survey was also conducted in an area that was previously identified as an ideal candidate area for on-demand transit, previously had a pilot service to which any new system configuration could be compared, and covers a general population without any strong biases toward a specific age, gender, or income range. By asking a general population about their preferences across a wide range of attributes, the results of the survey are likely similar to other areas with similar land uses, transit access, and car dependence. The anonymized results will also be provided in a database of user preferences, which will be contribute to the larger body of transit-relevant datasets.

The fourth contribution (methodological) is the mode choice model developed using Bayesian estimation and non-linear time and cost attributes, and used to estimate transit-integrated ridesourcing mode shares. Few models have considered modern DRT service, and to date none of these models have used Bayesian estimation or non-linear attributes for time and cost. The model is uniquely able to consider how the combination of individual respondents shifts the mode share across different attribute levels, and the non-linearity allows for understanding the varied impacts of different levels in contrast with linear models, which assume increases in time or cost have the same per minute or per dollar impact. This model may also be transferable to other areas of interest, following one of the many transferability techniques established in literature (Systematics et al., 2012).

The fifth contribution (analytical) is the assessment of how mode share changes across different system configurations. Using the combination of non-linear attributes and individual-level models from Bayesian estimation, a unique analysis was conducted of how mode share may be impacted by various changes to transit-integrated ridesourcing systems, and how other modes can impact transit-integrated ridesourcing provision in suburban areas in Waterloo and other areas with similar characteristics. The use of non-linear attributes allowed for the identification of thresholds denoting sharp changes in perceived utility for the studied attributes.

6.5 Future Work

As with most research, there are opportunities to further extend what was completed in this thesis:

- **Trip typology in other areas and systems:** The trip typology in Chapter 3 was only applied to the 903 Flex pilot in Waterloo. Future research may explore applying this typology to a series of other new transit-integrated ridesourcing systems in Canada to compare the competitiveness of other systems with fixed-route transit, cycling, and walking.

- **Trip analyses with true origins and destinations:** The analysis in Chapter 3 made inferences on trip competitiveness by using 903 Flex origins and destinations, which are not the passenger's *true* origins and destinations (Figure 3.3). While the typology used is helpful for understanding the competitiveness of transit-integrated ridesourcing trips versus fixed-route transit trips, it may be possible to have more complete insights into the available alternatives for passengers if the complete trips are studied. For example, the 903 Flex trip database contains no transfers and all trips end within the service zone, but some passengers may have only used the 903 Flex for one leg of their trip, then transferred to another service (like fixed-route transit) for the remainder of their trip. There are opportunities in future research to work with agencies to conduct intercept surveys or use other techniques to determine the origins and destinations of the complete trips for trips taken in other transit-integrated ridesourcing systems that are still operating.

- **Seasonal, weather, and cycling infrastructure attributes in future transit-integrated ridesourcing surveys:** Respondents to the survey in Chapter 4 identified seasonality and weather as factors that would have impacted their mode choice. While this is most obvious for cycling, which is less popular in winter and adverse weather, transit-integrated ridesourcing options that require longer periods of walking may also be less desirable to some people in these conditions. The change in ridership of transit-integrated ridesourcing in these conditions is not certain, since this would also depend on how people respond to seasonality and weather in other modes like cycling. Recognizing that there are established categories for cyclists based on the quality of infrastructure (Geller, 2006), incorporating types of cycling infrastructure could also be a valuable attribute to add to test how cycling treatments would impact the trade-off between cycling and transit-integrated ridesourcing. Future research should consider ways to incorporate these factors into transit-integrated ridesourcing preferential surveys.

- **Walking as an alternative to transit-integrated ridesourcing:** Walking was removed from the survey in Chapter 4 to minimize decision fatigue in the SP experiments. While walking was considered the least competitive alternative compared to other modes that were kept in the survey, there is room to explore the competitiveness of transit-integrated ridesourcing to walking for shorter trips, like some of the trips identified in the 903 Flex pilot (Chapter 3).

- **Preferences in transit-free areas:** The survey in Chapter 4 and resulting model in Chapter 5 were conducted in an area with existing fixed-route transit. A possibility for future study would be to conduct a full analysis and survey in an area without a fixed-route transit alternative, since transit-integrated ridesourcing in these areas would not compete or integrate with fixed-route transit.

- **Direct costs for auto:** In the model developed in Chapter 5, parking costs were identified as the primary way to increase the shares of alternative modes (cycling, fixed-route transit, ridesourcing) and as a synergistic factor for increasing transit-integrated ridesourcing share in conjunction with other changes. Other direct costs for auto should be explored in future studies with transit-integrated ridesourcing, to determine if they would also have similarly sized impacts. Other options would allow for alternative ways to lower auto share if large increases in parking are too politically unrealistic in a specific area.

- **Alternative reliability metrics in transit-integrated ridesourcing:** In the model developed in Chapter 5, the reliability metric used was not found to be statistically significant. The specific metric used was a deviation in minutes from the provided IVTT, which was calculated as a percent change from the auto or cycling times. While this specific implementation of reliability was not significant in the model, other measurements of deviation or travel time reliability may be more successful. One option may include providing a series of IVTT estimates, as done in Alonso-González et al. (2020).

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Appendices

Appendix A

Ride Time Cleaning for 903 Flex

This section outlines the process for cleaning ride times in the 903 Flex dataset, which is used for Chapter 3. Of the 4536 rides in the dataset, 2828 rides did not have departure (pick-up) and arrival (drop-off) times that matched the reported ride time (i.e., the in-vehicle time). To find the available transit alternatives and conduct ride time comparisons, a cleaning procedure was developed and used to match the pick-up and drop-off times to the reported ride times. An inspection of the data suggested that the reported ride times were more reliably accurate, but the pick-up and drop-off times provided were not, so the reported ride time was assumed to be true and the pick-up and drop-off times were modified using a cascading series of educated assumptions. In cases where multiple times are provided by number, time 1 is the earliest time in the sequence and higher numbers indicate later times.

Four travel times were provided in the dataset: predicted pick-up time, actual pick-up time, predicted drop-off time, and actual drop-off time. Predicted times are when the operator believed the passenger would be picked up or dropped off. Each of these times were considered differently for analysis. Predicted pick-up time was used as the earliest time that a user may have wanted to take a trip. For comparison against other alternatives, predicted pick-up time was the time the user intended to start travelling (i.e., the start of 'wait time' for ridesourcing and transit, and the start of the trip for walking and cycling). Actual pick-up and drop-off times were used to find when a trip truly started and ended. Predicted drop-off was not used in the analysis, but was incorporated in the cleaning procedure to ensure accuracy in time cleaning. The calculated ride time which was compared with the reported ride time was set to the duration between actual pick-up time and actual drop-off time.

Table A.1 lists the cleaning cases considered and the actions taken to clean the data in each case. Actual pick-up time was considered the most essential time value for analysis, and was able to be left unchanged in 81% of cases. In the dataset, 1708 records had equal calculated and reported ride times (within a tolerance of 1 minute, cases 1a-1b). 593 of these trips had no changes applied (case 1a), 7 of which had no reported ride time to compare to. The other trips had a predicted drop-off time that was earlier than the predicted pick-up time (case 1b). The predicted pick-up time was set to equal actual pick-up time, since that was the next closest accurate value. Of the 2828 rides with mismatched trips, 1971 of them were edited using one of two quicker assumptive procedures. The first procedure was cases where the predicted times were logically ordered but the ride times mismatched (case 2). In this case, actual drop-off time was modified to be the actual pick-up time plus the reported ride time. The second procedure was cases where neither the predicted times were ordered correctly nor the ride times matched (case 3). This case was a combination of cases 1 and 2, so both actions from those cases were applied.

Table A.1: Ride time cleaning cases and counts (RRT: reported ride time)

Case	Total	Pick-up req.	Pick-up act.	Drop-off req.	Drop-off act.
1a	593	No change	No change	No change	No change
1b	1115	Pick-up act.	No change	No change	No change
2	364	No change	No change	No change	Pick-up act. + RRT
3	1607	Pick-up act.	No change	No change	Pick-up act. + RRT
4a	39	Time 1	Time 3	Time 2	Time 3 + RRT
4b	12	Time 1	Time 3	Time 2	Time 3 + RRT
4c	697	Time 1	Time 3	Time 2	Time 3 + RRT
4d	59	Time 1	Time 3	Time 2	Time 3 + RRT
5a	1	No change	No change	Pick-up act. + RRT	Pick-up act. + RRT
5b	3	No change	Time 1	Time 2	Time 1 + RRT
5c	36	No change	Pick-up req.	No change	Pick-up req. + RRT
5d	2	Time 1	Time 1	Time 2	Time 1 + RRT
5e	2	No change	No change	No change	Pick-up act. + RRT
6	6	No change	No change	Pick-up act. + RRT	Pick-up act. + RRT

The remaining 857 trips (cases 4a-6) went through a sequence of more specific procedures. In trips with 3 unique times (cases 4a-4d), the actual pick-up and drop-off times were the same, and the request times were different. The patterns included late requested pick-up and early requested drop-off (case 4a), early requested pick-up and late requested drop-off (case 4b), early requested pick-up and middle requested drop-off (case 4c), and middle requested pick-up and low requested drop-off (case 4d). Case 4c was the most common, and appeared in large sequential blocks, so was likely an issue with how RideCo was saving the data for each trip. None of the pairs of times formed a duration that was equal to the reported ride time, so drop-off time was set to the reported ride time plus the actual pick-up time as in other cases. The desired strategy of keeping actual pick-up time the same was not used in these cases since the times were rarely saved in a logical order. Requested pick-up was set to time 1, so that it would be earliest, and actual pick-up was set to time 3, assuming worst-case wait times for comparison against alternative modes. Trips with 2 unique times (cases 5a-5e) differed by high actual pick-up (case 5a), low requested times (case 5b), low requested pick-up (case 5c), low requested drop-off (case 5d), and high requested drop-off (case 5e). In each of these cases, the highest priority was keeping actual pick-up the same unless there was a logical disagreement (as in cases 5b-5d), in which cases it was set to the earlier of the times. The final case was trips where all 4 times were the same (case 6), where the drop-off times were modified to match the reported ride time.

Appendix B

Eliminated Attribute Levels

This section reviews the eliminated attribute levels in the survey. The initial set of attribute levels chosen is provided in Table B.1, with the eliminated or modified attributes indicated in **bold**.

Table B.1: Initial attribute levels chosen

Attribute	TIR	Transit	Private ridehailing	Cycling	Auto
In-vehicle time (min)	GAPI[a] (1x, 2x, 3x, **4x**)	GAPI[a] (1x, 2x, 3x, **4x**)	GAPI[a]	GAPI[c]	GAPI[a]
Wait time (min)	3, 5, 10, **15**, 30	3, 5, 10, **15**, 30	3, 5, 10, **15**, 30	–	–
Transfer time (min)	0, 5, 10, **15**, 30	0, 5, 10, **15**, 30	–	–	–
Walk time (min)	0, 5, 10, 30, **60**	0, 5, 10, 30, **60**	–	–	–
Fare / parking ($)	0, 1, 3.5, **6**, **12**	0, 2, 3.5, 5, **7**	GAPI[a] (1x, 2.5x, 5x, 10x)	–	0, 1, 3, **7.5**, 15
Number of transfers	0, 1, 2, 3, **4**	0, 1, 2, 3, **4**	–	–	–
Reliability	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 10%, 15%, 20%)	GAPI[c] (+/- 5%, 10%, 15%, 20%)	GAPI[a] (+/- 5%, 15%, 25%, 50%)

[a] Drive time determined from Google API
[c] Cycle time determined from Google API

For IVTT, the original maximum ratio was 4x, based on the highest ratio found in empirical tests of travel times in the region. The 4x case was removed due to concerns over auto dominance, and the maximum was reduced to 3x. Similar modifications were made to other attributes in cases where transit or TIR were not competitive enough in the experiments, and the assumption was made that at points between the old and new maximums (e.g., between 3x and 4x for IVTT), there would be minimal change in preference as people who had chosen transit or TIR at that point were already fairly captive, and people who had not chosen those modes would not be expected to switch modes.

For the remaining attributes, five levels were initially chosen to minimize the design size, and the least essential level was removed from each attribute to minimize the number of choice experiments needed, resulting in a maximum of 4 levels for each attribute in the final design. If the value was a midpoint, it was assumed that interpolation could be used between the preceding and following values. If the value was an endpoint, like in the IVTT case, then the same assumptions about captive respondents was made.

For wait time and transfer time, 15 minutes was removed since 5 and 10 minute cases were more interesting for analysis and were expected to be greater inflection points. For walk time, 60 minutes represented the real-world maximum for combined access or egress in the study area. 60 minutes was assumed to be highly undesirable, so 30 minutes was chosen as the new maximum, and it was assumed that people willing to walk 30 minutes would be a fairly small share of the respondent base.

$7.00 was initially chosen as the maximum transit fare because it was double the existing fare. $7.00 was removed to improve the desirability of transit in the experiments, because another fare already represented a value higher than the current fare, and because it was unlikely the GRT fare was going to reach that level in the foreseeable future. The TIR fares were chosen using a pivoting structure off of transit as inspiration ($0.00, Transit-$1.00, same as transit, Transit+$1.00, Transit+$5.00), representing different fare structures seen in TIR pilot projects ($0.00, $2.00, $3.50, $5.00, $7.00 transit fares resulted in $0.00, $1.00, $3.50, $6.00, $12.00 TIR fares). The $12.00 TIR fare was removed due to the loss of the top transit fare and to reduce auto dominance, and the $6.00 fare was replaced with $8.00, representing a Transit+$3.00 case in between the two original cases.

For parking, one of the middle parking fees ($7.50) was removed. No changes were made to private ridehailing fares or to the reliability metric.

The original range for the number of transfers in each experiment had a maximum of 4, representing the generally largest number of transfers empirically found in the region. Cases with 4 transfers were removed to make transit options more competitive. In an extensive literature review of people's perceptions of transfers, transfer times were found to be one of the main deterrents to taking transit (Chowdhury & Ceder, 2016), further supporting a lowered maximum number of transfers to minimize the impacts of transfer time.

Appendix C

Survey Software Selection

This section reviews the selection of the survey software. Four options were considered for building the experiment (Table C.1): Ngene, Qualtrics, Lighthouse Studio from Sawtooth Software, and R. Some R packages that were considered for design included AlgDesign and acebayes, which included some of the desired design functions. Surveys need to be designed and hosted, so options without hosting would additionally require a hosting platform. The design ethos for each option reflects how designs are constructed: model-first options use utility functions as the basis for generating the design, and attribute-first options use combinations of attributes as the basis. Qualtrics and R were removed earlier in the process: the appropriate Qualtrics packages were much more expensive than the alternatives, and generating designs in R had a higher learning curve with minimal benefit and no hosting. Lighthouse Studio offered an academic grant to graduate students that use their software for research, which brought the price to $0. Between Lighthouse Studio and Ngene, Lighthouse Studio was able to host and generate designs, while Ngene would still require a separate hosting account. It is possible to import Ngene designs into Lighthouse Studio, but Ngene would therefore need to be noticeably better than Lighthouse Studio's built-in functions to make this worthwhile. Both software aim to make a D-efficient surveys: Lighthouse Studio uses D-efficiency as one of the test metrics, and Ngene more explicitly designs surveys to be as D-efficient as possible. Lighthouse Studio was chosen in the end due to the lower cost and convenience of hosting and designing, and less restrictions on where the software could be installed.

Sawtooth Software also provides a second option, Discover, that was considered as an alternative to Lighthouse Studio. Lighthouse Studio is desktop software that works with a hosting platform, while Discover is a completely web-based platform. The main disadvantage with Discover was that it did not allow for free-format questions or customization of level labelling, which would not allow for the Google API integration or customizing levels around the Google-derived travel times. Therefore, between the two software options, Lighthouse Studio was confirmed as the software of choice.

Table C.1: Evaluation of stated-preference design software

Attribute	Ngene	Qualtrics package	Lighthouse Studio	R packages
Price	US$550	US$2000	free (academic grant)	free
Restrictions	1 licence, locked to computer	12-month subscription	until end of project	no licence
Hosting	No	Yes	Yes	No
Design ethos	Model-first	Attribute-first	Attribute-first	Either
Variability in designs	High	Unknown	Moderate	Low to moderate

Appendix D

Survey Questions

Before you start the survey, we want to check that you are eligible to continue.

1. Are you older or younger than 16 years old?
   - I am 16 years old or older
   - I am 15 years old or younger
2. Which City of Waterloo ward do you live in?
   - Ward 1 (Southwest)
   - Ward 2 (Northwest)
   - Ward 3 (Lakeshore)
   - Ward 4 (Northeast)
   - Ward 5 (Southeast)
   - Ward 6 (Central-Columbia)
   - Ward 7 (Uptown)
   - I live outside of the City of Waterloo

   If you aren't sure which ward you're in, you can look it up on the City of Waterloo website at www.waterloo.ca/en/government/city-council.aspx.
3. This survey addresses trips that you would normally make outside of the COVID- 19 pandemic. Trips must:
   - start at your home and end at another location in the Region of Waterloo
   - **not** be trips to grade school (K-12) as a student
   - **not** be trips where you would walk for the entire trip
   - be trips where you had freedom to decide how you travelled (in other words, you chose whether you biked, drove, took a taxi, etc.)

Have you made at least one trip that meets this criteria?

- Yes, I have made one trip that meets all four of these criteria
- No, I have not made a trip that meets all of these criteria

4. *Two paths depending on previous answers:*

   (a) *If respondent chose 'I am 15 years old or younger', 'I live outside of the City of Waterloo', or 'No, I have not made a trip that meets all of these criteria': Termination page due to not meeting criteria*

   (b) *All other respondents: TIR description page, Figure 4.5, continue to question 5*

5. The 903 Flex service that ran in your area from November 2018 to December 2019 was one possible configuration of transit-integrated ridesourcing. You may have had it installed on your phone and it would have had an app icon that looked like the image on the right.

   Did you use the 903 Flex service when it operated in 2018/2019?

   - Yes, I took at least one trip using the 903 Flex service
   - No, but I was aware of it
   - No, and I did not know about it

6. *(Also depicted in Figure 4.7)* In this survey, we will ask you questions about a trip you would normally make **outside of COVID-19**. To make the survey more applicable to your trip, we will generate driving and cycling times using your home and destination locations to personalize your survey.

   Enter the home and destination location for a trip you have taken:

   - from your home to another location within **Waterloo Region**
   - that was **not** made by walking
   - where you had freedom to decide how you would travel to your destination
   - that was **not** for attending grade school (K-12) as a student

   Choose a departure day and time that represents the **most likely** day and time you would consider making this trip.

   - Home: **text-entry field*
   - Destination: **text-entry field*
   - Departure time: **four selection menus for days, hours, minutes in 15 increments, and a.m./p.m.*

   Drive times: Not found yet/Found (depending on respondent progress)

   Cycle times: Not found yet/Found (depending on respondent progress)

We **do not** store or know your home and destination locations. These locations are input directly into Google Maps to generate driving and cycling times. You also do not need to enter your exact home address, you can enter another address near yours and the times should still be accurate. A transit trip will also be generated which will help us understand your existing transit situation.

7. Which travel option do you typically choose when making this trip?

    - Driving
    - Passenger in a private vehicle
    - Transit (GRT bus and ION)
    - Taxi or Uber
    - Cycling
    - Other (please specify) **text-entry field*

8. What is the purpose of your trip?

    - Daycare
    - Entertainment
    - Escorting a passenger
    - Post-secondary school
    - Shopping
    - Visits
    - Work
    - Other (please specify) **text-entry field*

    If you have many reasons for making this trip, pick the most common one.

9. Would you say this trip is care-related? (i.e., this trip is taken mostly to assist children or dependents?)

    - Yes, my main purpose is care-related
    - No, my main purpose is not care-related

    Some examples of care-related trips or caring work include escorting, buying food or other items, and other tasks you do primarily for others that depend on you like children or dependent adults.

10. *(If respondent did not choose 'Driving' or 'Passenger in a private vehicle')* You indicated that you don't normally make this trip using a private vehicle.

    For this trip, if you **had** to use a private vehicle (car, truck, etc.), would you be more likely to drive the vehicle or be a passenger in another person's vehicle?

    - More likely to drive a vehicle
    - More likely to be a passenger in a vehicle

This will impact whether ‘driving’ or ‘passenger in private vehicle’ is provided as an option in the survey.

–

Now, we will walk you through a sequence of situations where you are making the trip you previously entered.

You will consider five travel options in each scenario. The cost and time for each trip will change in each question for transit, TIR, and taxi/Uber. Consider the costs and times carefully before deciding. In each case, indicate which option you would choose **in this scenario** (your ‘Best’ option) and which option you would be least likely to choose (your ‘Worst’ option).

Some of the scenarios you see will not reflect how fast/slow your options are currently, but we want you to imagine that, in each scenario, these are your **only** options.

Definitions for some terms are provided below each scenario on every page. Remember that you can not go back to a previous scenario once you press Next.

Stated preference scenarios follow, tailored to each respondent, similar to Figure 4.4

–

We’re almost done. We have a couple more pages of quick questions for you about your demographics and other perspectives on transportation.

1. Do you own a bicycle?
   - Yes
   - No
2. How many personal vehicles does your household own? **text-entry field*
3. Do you have any of the following GRT fare passes or cards? (Or would you have one of these outside of the pandemic?) If you have more than one, choose the one you are more likely to use.
   - U-Pass (on a Waterloo WatCard or Laurier OneCard)
   - College pass (on a Conestoga ONE Card)
   - Corporate pass (through a TravelWise affiliated workplace)
   - Veteran’s pass
   - TAPP pass (through Ontario Works)
   - Senior’s reduced monthly pass
   - Elementary or secondary student reduced monthly pass
   - EasyGO fare card (adult fare)
   - EasyGO fare card (reduced fare for seniors, elementary and secondary students)

- I have none of the previous options, and would pay with cash or tickets

4. Are you more or less likely to take the following modes after the COVID-19 pandemic than you were before? **Respondents chose 'Less likely', 'No change', or 'More likely' for each mode*
   - Taxi/Uber
   - Cycling
   - Transit-integrated ridesourcing
   - Driving or passenger in a private vehicle **presented option depends on respondent's answer to question 10 in pre-SP section*
   - Transit (GRT bus and ION)

5. *(If respondent entered two or more vehicles for 'How many personal vehicles does your household own?')* You indicated your household owns multiple personal vehicles.

   If your area had improved transit or TIR, would your household consider owning fewer cars, trucks, and/or vans?
   - Yes, we would likely consider having less personal vehicles
   - No, we would want to keep all of our existing personal vehicles

6. *(If respondent entered two or more vehicles for 'How many personal vehicles does your household own?')* What is the primary reason your household would **not** be able or willing to reduce the number of vehicles you own? (max. 500 characters) **text-entry field*

7. Finally, we have a few questions about your demographics, which will help us use the results for modelling. How old are you?
   - 16-24
   - 25-34
   - 35-49
   - 50-64
   - 65 or older
   - Prefer not to answer

8. What is your gender?
   - Female
   - Male
   - Other **text-entry field*
   - Prefer not to answer

Where we use this: Gender may help determine if there are unexplained gender-based reasons why someone may choose to avoid or prefer a specific mode.

9. What is your estimated gross **household** income (before-tax)?
   - Under $45 000
   - $45 000 to $69 999
   - $70 000 to $99 999
   - $100 000 to $124 999
   - $125 000 to $149 999
   - $150 000 to $199 999
   - Over $200 000
   - Prefer not to answer

   Where we use this: Some previous studies indicate income is related to travel choices. This information will be used to determine whether these earlier studies apply to your neighbourhood.

10. Do you have any other comments before you end the survey? **text-entry field*

Appendix E

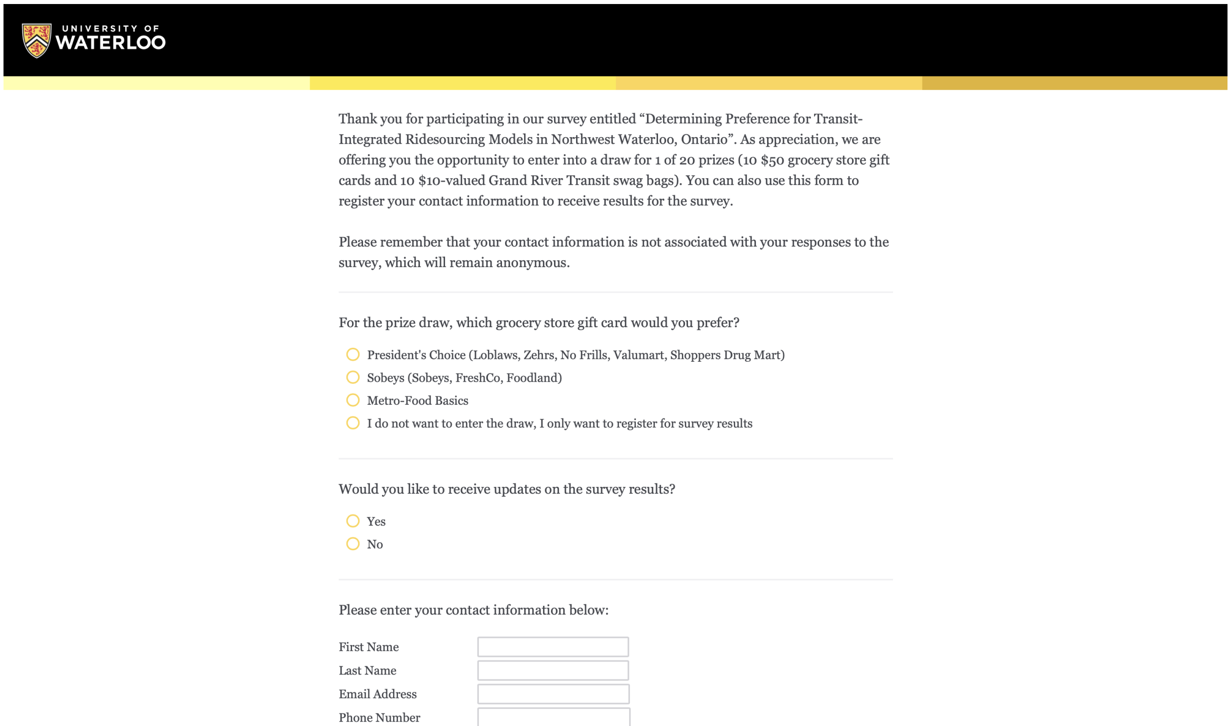
Survey Appreciation and Draw

This section outlines the survey appreciation and draw, which are secondary to the main findings of the survey, but are included here to complete the documentation of the survey design and implementation process.

Surveys often provide feedback and appreciation. Appreciation can be one way to thank people for completing the survey, and can manifest as a guarantee or chance for some form of remuneration. In this survey, a draw for appreciation was chosen instead of providing something to every respondent, in part because the uncertainty of the final size of the sample meant a draw would have a more stable budget. Gift cards and swag bags from GRT were the draw prizes. Grocery store gift cards were chosen as the draw prizes because they have the widest appeal. Loblaw, Sobeys, and Metro franchises were identified as the primary grocery stores in the area, so each were given as options for potential winners. 10 gift cards valued at $50 each were selected. GRT promised 10 swag bags later in the process, which contained promotional items including pens, buildable train models, and socks.

A Qualtrics survey was prepared to process the draw entries and mailing list subscriptions for people who were interested in the survey results (Figure E.1). At the end of the Sawtooth survey, a link was provided to send respondents to the Qualtrics survey. By using two separate surveys, their primary survey responses were fully detached from their name and contact information, so that their responses were not identifiable. Qualtrics was chosen for the feedback and appreciation survey because basic Qualtrics surveys are free for University of Waterloo researchers, and Qualtrics has more developed tools for ensuring valid email addresses and phone numbers are submitted than Sawtooth's online surveys. Respondents were asked for their preferred grocery store, in case they won a gift card, their preference for receiving survey updates when results were published, and their contact information so they can be reached for either the draw or results.

Techniques for securing the Qualtrics survey from fraudulent responses were considered. Built-in solutions that were employed included flagging suspected multiple entries, detecting bots with reCAPTCHA, and blocking the survey from search engine indexing. An additional method considered was to only accept responses if their previous page was the Sawtooth survey, to prevent link sharing. Unfortunately, web browsers pass HTTP


UNIVERSITY OF WATERLOO

Thank you for participating in our survey entitled “Determining Preference for Transit-Integrated Ridesourcing Models in Northwest Waterloo, Ontario”. As appreciation, we are offering you the opportunity to enter into a draw for 1 of 20 prizes (10 $50 grocery store gift cards and 10 $10-valued Grand River Transit swag bags). You can also use this form to register your contact information to receive results for the survey.

Please remember that your contact information is not associated with your responses to the survey, which will remain anonymous.

For the prize draw, which grocery store gift card would you prefer?

- President's Choice (Loblaws, Zehrs, No Frills, Valumart, Shoppers Drug Mart)
- Sobeys (Sobeys, FreshCo, Foodland)
- Metro-Food Basics
- I do not want to enter the draw, I only want to register for survey results

Would you like to receive updates on the survey results?

- Yes
- No

Please enter your contact information below:

First Name
Last Name
Email Address
Phone Number

Figure E.1: Qualtrics survey used for remuneration

```perl
my $datestring="";
$datestring = time();
$datestring = reverse $datestring;
$datestring = $datestring + 123456789;
return $datestring;
```

Figure E.2: Perl code for timestamping Qualtrics survey referrals

referrers differently from each other, and in test runs respondents could not always gain access to the Qualtrics survey depending on the browser they used. The decision was made to not include a referrer, and rely on a system using a check value (Figure E.2). The check value was a reversed version of the Unix time when the respondent opened the Qualtrics survey using a referral plus a modifier number to scramble the timestamp, which would result in unique identifiers for every time the Qualtrics survey was opened using the Sawtooth redirect. The check value was reviewed afterwards to ensure winning entries were valid and associated with a legitimate, unique entry. Using the check value, six responses were removed in the final draw, five because of re-entry (likely accidental or to update erroneous contact information in the initial entry) and one because it was a second person using the same survey entry, as verified by the timestamp.

The appreciation draw was administered after the end of the survey period. Three draws were administered: the first on 6 August 2021, the second on 30 August 2021, and the third on 7 September 2021. Each draw was conducted using the RANDBETWEEN function in Excel, where the random numbers fell in the same range as the respondent ID numbers. Numbers were re-rolled if there were duplicates or if the number had already been drawn in a previous draw. The first draw was used to pull 20 respondents from the list (10 for the gift cards and 10 for the swag bags). Winners were emailed and given until 23 August to reply. Two gift card winners and one swag bag winner did not reply, so three more entries were pulled in the second draw. The second draw winners were emailed and given until 6 September to reply. One of the gift card winners in the second draw did not reply, so one more entry was pulled in the third draw. Draw winners received their gifts on 9 August, 30 August, 7 September, or 14 September depending on the agreement made with the winner.

Appendix F

Evaluation Trip Cases

Table F.1 compares the attributes for case 1 (a and b) against the median values reported in the RP trips. Because headways weren't provided when trips were pulled from Google's API, the wait time of the RP trips is unknown. However, inspection of the trips revealed that the most popular transit alternatives were weekday morning peak trips on Route 13 (Laurelwood), so the same trip was used to generate an alternative for case 1. The first and third quartile values are also provided to indicate the range of values around the median.

Additional information follows concerning trip cases that was not required for the analysis, but may be of interest. All peak trips were generated in the future from the time of analysis using Wednesday, 3 August 2022 at 8:00 a.m. as the departure date and time, and all off-peak trips were generated using Sunday, 7 August 2022 at 1:00 p.m. as the departure date and time.

- Case 1:
  - **Origin (neighbourhood):** 540 Willow Wood Drive - east of Woodrow Dr at Willow Wood Dr (Laurelwood)
  - **Destination:** Willison Hall (Wilfrid Laurier University)
  - **Route:** 13
  - **Nearest 903 Flex stop:** Woodrow / Willow Wood
- Case 2:
  - **Origin (neighbourhood):** Erbsville Rd at Regal Pl (Erbsville)
  - **Destination:** Westmount Golf and Country Club
  - **Routes:** 13, then 12
  - **Nearest 903 Flex stop:** Regal / Erbsville
- Case 3:
  - **Origin (neighbourhood):** Beechlawn Dr at Stillmeadow Cir (Beechwood)

  - **Destination:** Cambridge Centre
  - **Routes:** 201, then 301, then 302
  - **Nearest 903 Flex stop:** Beechlawn / Stillmeadow

- Case 4:
  - **Origin (neighbourhood):** Sundew Park (Vista Hills)
  - **Destination:** Paul Peters Park
  - **Routes:** 13, then 301, then 206, then 54
  - **Nearest 903 Flex stop:** Sundew / Walking Fern

- Case 5:
  - **Origin (neighbourhood):** Interlaken Park (Clair Hills)
  - **Destination:** Spice Bush St at Red Osier Rd
  - **Route:** 13
  - **Nearest 903 Flex stop:** Freiburg / Keats Way

- Case 6:
  - **Origin (neighbourhood):** Avens St at Wild Calla St (Vista Hills)
  - **Destination:** Westside Marketplace
  - **Route:** N/A
  - **Nearest 903 Flex stop:** Avens / Wild Calla

Starting shares for each of the trip cases are given in Table F.2.

Table F.1: Case 1 attributes versus median attributes

Attribute	Case 1	Median (25%-75%)
Auto time (min)	12	11 (8-14)
Cycle time (min)	19	20.5 (15-29)
Wait time (min)	a: 7.5, b: 15	Unknown
Walk time (min)	10	10 (7-16.75)
Transit IVTT (min), ratio	18, 1.5x	17 (9-25), 1.4x (1.1x-1.9x)
Transit transfer time (min)	0	0 (0-6.25)
Transit number of transfers	0	0 (0-1)

Table F.2: Starting shares for each trip case

Mode	1a (%)	1b (%)	2a (%)	2b (%)	3 (%)	4 (%)	5 (%)	6 (%)
Auto	92.8	93.8	96.2	96.4	96.4	97.0	87.0	86.9
Cycling	2.0	2.1	2.1	2.1	2.2	2.2	1.8	1.8
Transit	4.0	3.3	0.5	0.6	0.7	0.3	3.2	0.0
Ridehailing	0.3	0.3	0.3	0.4	0.4	0.4	0.2	0.2
TIR	1.0	0.5	0.8	0.5	0.4	0.2	7.8	11.1

Appendix G

Evaluation Scenario Settings

Settings for auto, ridehailing, transit, and cycling are identified in Chapter 5. In some cases, simulator settings for transit-integrated ridesourcing require more explanation than can be easily provided by a table, and these are outlined in this appendix. The hubs used in the region for the many-to-few case are also provided.

In many-to-few systems, travel is generally oriented toward major destinations that people want to travel to, and can access from any other location in the system. While there are no many-to-few systems in the Region of Waterloo, there are major transit hubs identified by GRT that were used as destination hubs for the theoretical many-to-few system in Chapter 5. Figure G.1 shows the hub locations throughout the region, which were based off of the major transfer locations identified in GRT's system map and the two downtown locations without a hub, and an additional location (hub 13) used in a modified version of Case 5 that was at a popular destination in the 903 Flex pilot:

1. Conestoga Station
2. University of Waterloo Station
3. The Boardwalk
4. Uptown Waterloo (Waterloo Public Square Station)
5. Downtown Kitchener (Frederick Station)
6. Sunrise Centre
7. Fairway Station
8. Sportsworld Station
9. Stanley Park Mall
10. Conestoga College (Doon Campus)
11. Cambridge Centre Station

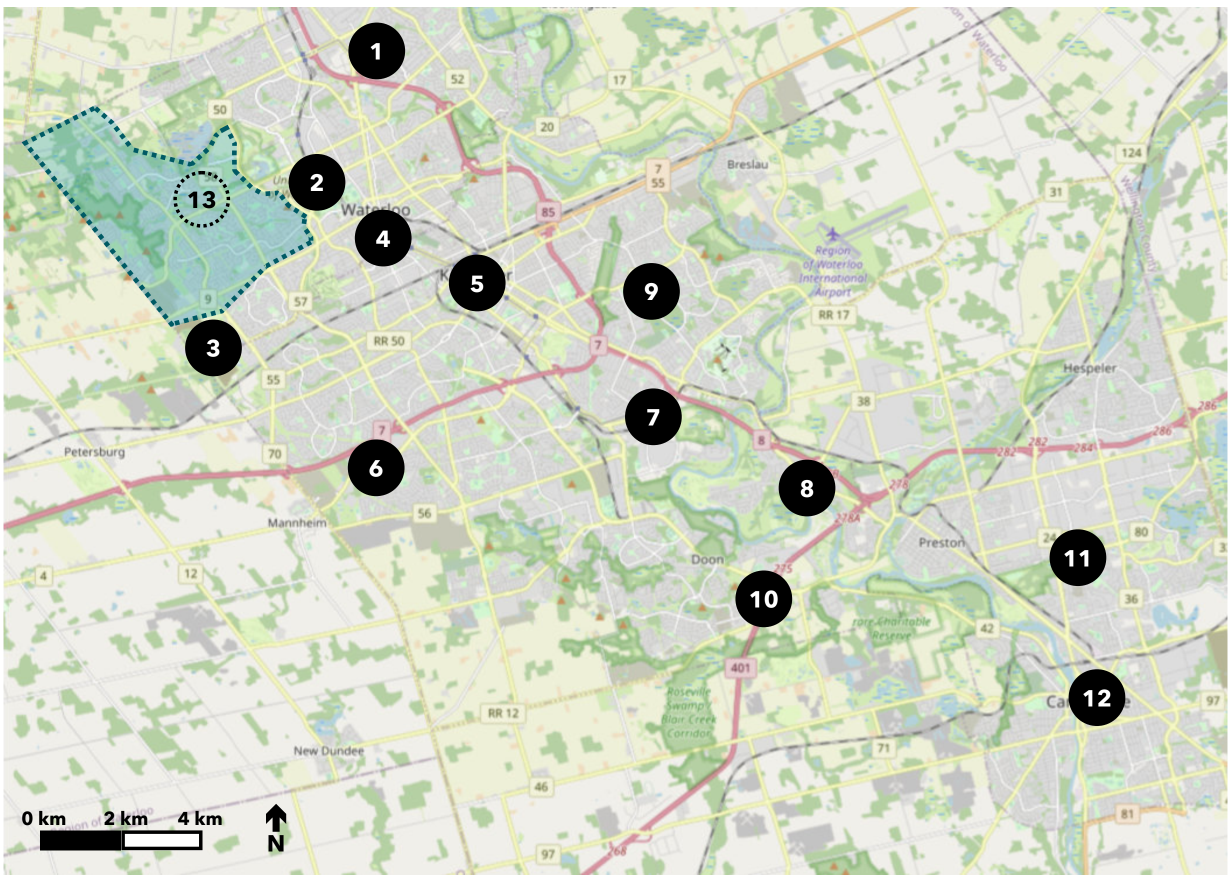


Figure G.1: Many-to-few hub locations

12. Ainslie Terminal
13. Columbia / Fischer-Hallman

In the many-to-few analysis, riders were taken to the closest hub to their destination. The transfer hubs used were:

- University of Waterloo Station (cases 1a, 1b)
- The Boardwalk (cases 2a, 2b, 5, 6)
- Cambridge Centre Station (case 3)
- Ainslie Terminal (case 4)

Table G.1 lists the settings for the transit-integrated ridesourcing alternative under each scenario in Chapter 5. For the many-to-many fixed-route stop scenario, case 6 has no transit trip so uses the nearest fixed route stops as the access and egress points for the service.

Table G.1: Transit-integrated ridesourcing settings for operational adjustment scenarios

Scenario	Case	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare
More stops	1a	1.5x	5	5	1	7.5	3.5
	1b	1.5x	5	5	1	15	3.5
	2a	2.2x	5	15	1	7.5	3.5
	2b	2.2x	5	15	1	15	3.5
	3	2.6x	5	0	2	12.5	3.5
	4	2.9x	5	15	3	21.5	3.5
	5	1.5x	5	5	0	0	3.5
	6	1.5x	5	0	0	0	3.5
IVTT same as auto	2a	1x	5	15	1	7.5	3.5
	2b	1x	5	15	1	15	3.5
	3	1x	5	0	2	12.5	3.5
	4	1x	5	15	3	21.5	3.5
Synced transfers	1a	1x	10	5	1	2.5	3.5
	1b	1x	17.5	5	1	2.5	3.5
	2a	1.7x	10	15	1	2.5	3.5
	2b	1.7x	17.5	15	1	2.5	3.5
	3	2.1x	10	0	2	9.75	3.5
	4	2.4x	30	15	3	12	3.5

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Scenario	Case	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare
Many-to-many (fixed)	1a	1x	10	10	0	0	3.5
	1b	1x	10	10	0	0	3.5
	2a	1x	10	30	0	0	3.5
	2b	1x	10	30	0	0	3.5
	3	1x	10	5	0	0	3.5
	4	1x	10	30	0	0	3.5
	5	1x	10	15	0	0	3.5
	6	1x	10	10	0	0	3.5
Many-to-many (virtual)	1a	1x	10	5	0	0	3.5
	1b	1x	10	5	0	0	3.5
	2a	1x	10	15	0	0	3.5
	2b	1x	10	15	0	0	3.5
	3	1x	10	0	0	0	3.5
	4	1x	10	15	0	0	3.5
	5	1x	10	5	0	0	3.5
	6	1x	10	0	0	0	3.5
Many-to-many (door)	1a	1x	10	0	0	0	3.5
	1b	1x	10	0	0	0	3.5
	2a	1x	10	0	0	0	3.5
	2b	1x	10	0	0	0	3.5
	3	1x	10	0	0	0	3.5
	4	1x	10	0	0	0	3.5
	5	1x	10	0	0	0	3.5
	6	1x	10	0	0	0	3.5
Nearest fixed stop, access	1a	1.6x	5	0	1	7.5	3.5
	1b	1.6x	5	0	1	15	3.5
	2a	2.2x	5	0	2	11.25	3.5
	2b	2.2x	5	0	2	11.25	3.5
	4	2.6x	5	0	4	18	3.5
	5	1.3x	5	0	1	7.5	3.5
Nearest fixed, access/egress	1a	1.6x	5	0	1	7.5	3.5
	1b	1.6x	5	0	1	15	3.5
	2a	2.3x	5	0	3	7.5	3.5
	2b	2.3x	5	0	3	7.5	3.5
	4	2.7x	5	0	5	14.4	3.5
	5	1x	5	0	2	3.75	3.5
Many-to-few, 30 min transfer	1a	1	5	4	1	7.5	3.5
	1b	1	5	4	1	15	3.5

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Scenario	Case	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare
	2a	1.3	5	0	1	30	3.5
	2b	1.3	5	0	1	30	3.5
	3	1	5	0	0	0	3.5
	4	1.2	5	0	1	30	3.5
	5	3	5	5	1	7.5	3.5
	6	2.6	5	2	1	7.5	3.5
Zonal service, 5 km zones, door-to-door	1a	1x	5	0	1	2.5	3.5
	1b	1x	5	0	1	2.5	3.5
	2a	1x	5	0	1	2.5	3.5
	2b	1x	5	0	1	2.5	3.5
	3	1x	5	0	5	2.5	3.5
	4	1x	5	0	7	2.5	3.5
	5	1x	5	0	0	2.5	3.5
	6	1x	5	0	0	2.5	3.5
Zonal service and pricing	1a	1x	5	0	1	2.5	2
	1b	1x	5	0	1	2.5	2
	2a	1x	5	0	1	2.5	2
	2b	1x	5	0	1	2.5	2
	3	1x	5	0	5	2.5	6
	4	1x	5	0	7	2.5	8
	5	1x	5	0	0	2.5	1
	6	1x	5	0	0	2.5	1
Sectional	1a	1x	5	5	1	7.5	1.4
	1b	1x	5	5	1	15	1.4
	2a	1.7x	5	15	1	7.5	2
	2b	1.7x	5	15	1	15	2
	3	2.1x	5	0	2	12.5	6
	4	2.4x	5	15	3	21.5	8
	5	1x	5	5	0	0	0.8
	6	1x	5	0	0	0	0.8
Flat upcharge ($5 TIR)	1a	1x	5	5	1	7.5	5
	1b	1x	5	5	1	15	5
	2a	1.7x	5	15	1	7.5	5
	2b	1.7x	5	15	1	15	5
	3	2.1x	5	0	2	12.5	5
	4	2.4x	5	15	3	21.5	5
	5	1x	5	5	0	0	5

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Scenario	Case	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare
	6	1x	5	0	0	0	5
Free transit	1a	1x	5	5	1	7.5	3.5
	1b	1x	5	5	1	15	3.5
	2a	1.7x	5	15	1	7.5	3.5
	2b	1.7x	5	15	1	15	3.5
	3	2.1x	5	0	2	12.5	3.5
	4	2.4x	5	15	3	21.5	3.5
	5	1x	5	5	0	0	3.5
	6	1x	5	0	0	0	3.5
Free TIR	1a	1x	5	5	1	7.5	0
	1b	1x	5	5	1	15	0
	2a	1.7x	5	15	1	7.5	0
	2b	1.7x	5	15	1	15	0
	3	2.1x	5	0	2	12.5	0
	4	2.4x	5	15	3	21.5	0
	5	1x	5	5	0	0	0
	6	1x	5	0	0	0	0
Free transit and TIR	1a	1x	5	5	1	7.5	0
	1b	1x	5	5	1	15	0
	2a	1.7x	5	15	1	7.5	0
	2b	1.7x	5	15	1	15	0
	3	2.1x	5	0	2	12.5	0
	4	2.4x	5	15	3	21.5	0
	5	1x	5	5	0	0	0
	6	1x	5	0	0	0	0
Parking ($1.00, $3.00, $15.00)	1a	1x	5	5	1	7.5	3.5
	1b	1x	5	5	1	15	3.5
	2a	1.7x	5	15	1	7.5	3.5
	2b	1.7x	5	15	1	15	3.5
	3	2.1x	5	0	2	12.5	3.5
	4	2.4x	5	15	3	21.5	3.5
	5	1x	5	5	0	0	3.5
	6	1x	5	0	0	0	3.5
+ free transit and TIR	1a	1x	5	5	1	7.5	0
	1b	1x	5	5	1	15	0
	2a	1.7x	5	15	1	7.5	0
	2b	1.7x	5	15	1	15	0
	3	2.1x	5	0	2	12.5	0

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Scenario	Case	IVTT ratio	Wait (min)	Walk (min)	Transfers	Avg. transfer time (min)	Fare
	4	2.4x	5	15	3	21.5	0
	5	1x	5	5	0	0	0
	6	1x	5	0	0	0	0
+ free transit and TIR, $2.50/min RH	1a	1x	5	5	1	7.5	0
	1b	1x	5	5	1	15	0
	2a	1.7x	5	15	1	7.5	0
	2b	1.7x	5	15	1	15	0
	3	2.1x	5	0	2	12.5	0
	4	2.4x	5	15	3	21.5	0
	5	1x	5	5	0	0	0
	6	1x	5	0	0	0	0
+ free transit and TIR, many (door)	1a	1x	10	0	0	0	0
	1b	1x	10	0	0	0	0
	2a	1x	10	0	0	0	0
	2b	1x	10	0	0	0	0
	3	1x	10	0	0	0	0
	4	1x	10	0	0	0	0
	5	1x	10	0	0	0	0
	6	1x	10	0	0	0	0

Glossary

accessible paratransit

A transit mode where passengers with disabilities may request an accessible vehicle for transportation purposes as a supplement or replacement for conventional fixed-route transit service, often used as the narrow definition of paratransit.

bikesharing

A mode enabling sharing of a bicycle where an agency maintains a fleet of bicycles that may be used for a short period of time, typically on an hourly rate.

carpool

A mode enabling sharing of a passenger ride, where the driver offers a ride to passengers on the driver's terms.

carsharing

A mode enabling sharing of a vehicle where an agency maintains a fleet of cars or a network of individually-owned cars that may be used for a short period of time, which differs from rental cars which operate in the transportation network more like private auto transport.

demand-responsive transport

Also 'demand-responsive transit', which can refer to a) an on-demand transit service that is operated publicly or privately (e.g. taxis), b) an on-demand service that is offered in partnership with the public sector, or c) dial-a-ride service

dial-a-ride

Also 'dial-a-ride transit', a transit mode where agency-owned and operated vehicles are booked hours or days in advance for subsidized shared passenger rides.

flexible transit

A variation of conventional transit routes where routes or stops deviate to accommodate variances in passenger demand.

microtransit

A mode enabling sharing of a passenger ride, typically operated through the private sector, where an employed driver operates a large van that can operate on fixed or flexible routes. A North American evolution of jitneys and vanpools.

ridesourcing

A mode enabling sharing of a passenger ride, where a driver 'sources' a passenger through a matching service, often through transportation network companies (e.g. UberX, Lyft). Typically less regulated and centralized than a taxi.

ridesplitting

A variant of ridesourcing where rides can be shared between strangers (e.g. UberPool, Shared Lyft).

taxi

A mode enabling sharing of a passenger ride, offering licensed and regulated passenger transport.

transit-integrated ridesourcing

A ridesourcing service typically operated as a partnership between a private sector transportation network company and a public sector transit agency that is designed to integrate with fixed-route transit service. Differentiates from traditional demand-responsive transport by having an immediate booking platform through a digital interface.

vanpool

A mode enabling sharing of a passenger ride, similar to carpooling, but with larger vehicles and typically through a more centralized operating mechanism where an agency or employer provides the van.