Among Four Traveller Types in the Greater Toronto and Hamilton Region,
Who Uses Ride-Hailing?

by

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ABSTRACT

Despite the rising popularity of ride-hailing, planning practitioners are still learning about the use and management of the service. This paper seeks to uncover who the primary users of ride-hailing are through a cluster analysis using traveller behaviour and mobility tool variables, where four traveller types are identified -- Multi-Modal Super-Sharers, Auto + Private Mobility Travellers, Car-Dependent Travellers, and Low Mobility Travellers. This paper finds that current auto-oriented travellers are not using ride-hailing, as demonstrated by Mobility Travellers and Car-Dependent Travellers. Additionally, ride-hailing is primarily used by non-auto-oriented travellers. The largest proportion of regular ride-hailing users, Multi-Modals Super-Sharers, are the youngest, are more educated, have access to the largest variety of mobility tools, and travel the most. For Low Mobility Travellers, the most vulnerable group based on household income, educational attainment, employment status, and car ownership, ride-hailing is filling a transportation gap. Understanding who uses ride-hailing is a key component in understanding the potential changes in travel behaviour.

Table of Contents

LIST OF FIGURES

INTRODUCTION

Ride-hailing has rapidly emerged as a new transportation option, but its implications are still largely uncertain. Ride-hailing is the provision of for-profit rides from a pool of private vehicles organized by a Transportation Network Company (TNC) (Ngo, 2015). The service has been advertised by TNCs as a cheaper, more reliable, and better-quality transportation option while providing an independent, flexible, and well-paid schedule for those working as drivers (Harris, 2017). The introduction of TNCs has also brought unforeseen consequences for cities, including protests from the taxi industry, legal action around employment and labour issues for TNC drivers, as well as concerns surrounding data collection and privacy. For transportation policymakers and planners, understanding these broader implications is vital in assessing whether and how to regulate ride-hailing and TNCs. Nevertheless, planners are still learning about the opportunities and implications of ride-hailing becoming a more prominent and integrated transportation option. This paper aims to gain a better understanding of how residents of the Greater Toronto and Hamilton Area (GTHA) use ride-hailing, specifically two popular TNCs, Uber and Lyft. This study seeks to answer: *Who does and does not uses ride-hailing? And how is the use of different transportation modes and access to mobility tools related to ride-hail use?*

BACKGROUND

Ride-hailing is described as a disruption to the transportation system and commonly mentioned alongside other shared-economy business models. The ideation of ride-hailing can be traced back to reactions to long wait times for taxis and public transportation (Dupre, 2016) and unreliable taxi dispatching. Because the number of taxi plates are determined by government review and policy, the limited number of taxis typically concentrate in the city center, where demand is highest. Furthermore, there is potential for a taxi to not show up at all. In 2006, a report prepared for the San Francisco Taxicab Commission found that 35% of taxis dispatched did not show up (Shafer, 2006). No-show rates ranged largely depending on the time and day as well as regional geography of the request (Shafer, 2006). This undersupply of reliable on-demand mobility and its geographic implications led to a gap in the market for ride-hailing services.

By the late 2000s and early 2010s, many ride-hailing services were being introduced in major American cities, such as RideCharge in 2007, GetTaxi in 2010, Uber in 2009, and Lyft in 2012 (Dupre, 2016; Uber, n.d.). However, according to Dupre (2016), Uber quickly grew as a leader in the industry due to short pick-up times and effective advertising campaigns. In 2012, Uber launched in Toronto (KPMG, 2016). By operating without any regulation and providing vehicle-for-hire services which competed with taxis, Uber received pushback from the taxi industry. By 2014, Uber was operating in 100 cities. In 2015, Toronto City Council voted to make Uber's services illegal (Hui, 2015). It was not until 2016, after comprehensive reviews and research, did Toronto legalize Uber's services with a set of regulations, including requirements on liability insurance, a driver background check, a $3.25 minimum fare price, and a maximum age for the private vehicles being operated (KPMG, 2016). By this time, Uber had grown to operate in 500 cities. At the end of 2017, Lyft also entered Toronto. Aside from Uber and Lyft, there is a number of other TNCs that operate in the area.

As of 2018, Uber has provided 15 million rides each day with operations in over 600 cities worldwide. Uber has far exceed the next competitor, Lyft, providing 1 million rides each day and operating in 300 American Cities (Iqbal, 2019). Uber has decreased average wait times for vehicle-for-hire services in the City of Toronto from 9 minutes for a taxi to 2 to 4 minutes for an Uber (City of Toronto, 2015). In addition to the shorter wait times, real time data on pick-up and drop-off as well as travel time estimates accounting for congestion provides the customer with a better sense of control. TNC mobile applications also allow riders to rate drivers, and vice versa, providing incentive for all parties to conduct the transaction respectfully and professionally (Competition Bureau Canada, 2015). Municipalities, such as New York and Chicago, have experienced a decrease in taxi complaints since the introduction of ride-hailing due to the competition of TNCs (Ngo, 2015).

Without having to consider the high price of taxi plates, with the additional option of ride-sharing, and frequent discount campaigns, ride-hailing is also much more affordable than a traditional taxi ride (Government of Cananda, 2015; Harris, 2017). TNCs have also created a more efficient payment system, relieving users of a reliance on cash or a working card reader, by allowing users to pay directly via the smart phone platform operated by the TNC (Hidalgo, 2018).

Because popular TNCs operate in most major cities around the world, the service is nearly borderless. The mobile app removes the language barrier between the driver and the passenger. The payment process removes the need to exchange currency and understand local tipping customs. The globalization and standardization of the ride-hailing process is as easy abroad as it is at home, reinforcing TNCs to be the default option for vehicle-for-hire services.

The additional vehicles can improve vehicle wait times and travel experiences for those living in more outlying areas of a municipality (Competition Bureau Canada, 2015). Moreover, the use of Uber as transit in Innisfil, Ontario, has demonstrate the potential of ride-hailing to provide cheaper transportation for a larger variety of geographies and demographics. Ride-hailing has been highlighted as a solution to reduce drinking and driving and service lower density transit routes. However, because ride-hailing services are ordered via a mobile application linked to a credit card, the service depends on the individual to have a smart phone, a data plan, and a credit card. A lack of digital literacy, credit card, or financial inability to afford a smart phone and data plan are all barriers to accessing the service.

Ride-hailing can provide on-demand origin to destination rides for those who are unable to drive. For those with physical disabilities and visual impairment, ride-hailing can provide autonomy. According to Shafer (20016), 65% of taxi ramp vehicles dispatched in San Francisco did not show up, a higher proportion than traditional vehicles. Although the fleet of accessible ride-hailing vehicles are also limited and more likely to be geographically located in city centres (Geboers, 2016), they add to the existing fleet of accessible vehicle-for-hire vehicles.

Despite the rising popularity of ride-hailing, planning researchers and practitioners are still learning about how this technology is used and how it should be managed in long-term transportation and planning policymaking. In a Canadian survey by the Angus Reid Institute (2018), 49% of respondents said that they have "heard about it, but don't know much about [ride-hailing]". This general lack of knowledge is also echoed in other studies (Vivoda et al, 2018; Smith, 2016). Similarly, planners and policy makers are also trying to understand the impacts of this new technology. There is a lack of knowledge regarding two key questions: (1) who are the primary users of ride-hailing and (2) what are the broader travel implications of those use patterns. This paper seeks to cover the first question, regarding the primary users, while providing some insight with respect to implications to travel behaviour and planning.

LITERATURE REVIEW

Ride-hailing, e-hailing, ride-sourcing, and on-demand ride services are used interchangeably throughout the existing research. Existing literature on ride-hailing can be sorted into three categories. Firstly, there is discussion on the regulatory frameworks for ride-hailing, including the identification of potential municipal income sources and rivalry with the taxi lobby.

Secondly, precautionary research brings to light the benefits and consequences of ride-hailing with emphasis on congestion-related impacts, including environmental pollution and health impacts. Thirdly, descriptive research documents current ride-hailing users and their impact on vehicle ownership and travel behaviour. This literature review focuses on the third category.

Demographics of Existing Users

There is general consensus that the early ride-hailing users are younger (under 35), more educated, and have higher household incomes (Vivoda et al, 2018; Alemi et al, 2018; Smith, 2016; Rayle et al., 2014; Circella et al., 2017; Clewlow & Mishra, 2017). The characteristics regarding education and socioeconomic status are consistent with those identified by Roger (1995) when describing early adopters in the diffusion of innovation theory. According to Smith (2016), the median age of ride-hailing users is 33. A separate article found that only 4% of those aged 65 and older have used ride-hailing services (Clewlow & Mishra, 2017).

Additional common characteristics include that ride-hailing users are more likely to live in urban areas with greater land use mix (Alemi et al, 2018; Smith, 2016; Rayle et al., 2014; Circella et al., 2017; Circella et al., 2018) and they are frequent users of smartphone applications (Alemi et al, 2018). According to Circella et al. (2018), 47% of respondents that are classified as "higher-educated independent millennials who live in more urban locations" have adopted ride-hailing services. Of those who do not use ride-sharing, they found that only 5% of "rural dwellers and of individuals with low education and/or who live in low-income households" have adopted the technology (Circella et al., 2018).

Aside from this group of early adopters, another subset of frequent users are those making business trips. According to Alemi et al (2018), those frequenting long-distance business trips and trips by plane are more likely to be using TNC services, which is echoed in Circella et al.'s (2018) findings.

Motivations

Ride-hailing users are driven by different motivations aside from the conventional time and cost. Circella et al.'s (2018) article discusses that the rate of adoption is high among those with "stronger technology embracing, pro-environment, and variety-seeking attitudes." Other reasons for ride-hailing use include not having to pay for parking and avoiding drinking and driving (Clewlow & Mishra, 2017). These goals behind ride-hailing use is why De Souza Silva et al. (2018) found that the majority of ride-hailing trips to be for leisure.

Smith (2016) found that ride-hailing provides a cheaper alternative to a traditional taxi while saving time and stress, an option for those who prioritize these qualities more. Furthermore, ride-hailing has shorter wait times than taxis and transit (Rayle et al., 2014). According to Angus Reid Institute's (2018) findings, 46% of respondents between 18-34 found that it was difficult to get a cab when needed. Similarly, this age group also states a preference towards calling an Uber rather than a taxi when needing a ride home (Angus Reid Institute, 2018). Vivoda et al. (2018) found that greater e-hail knowledge is also associated with higher transportation satisfaction and discussion of transportation options with others. A survey of 500 respondents on ride-hailing use in Brazil highlight that almost 60% of women indicated that they were resistant towards using the shared-ride service (De Souza Silva et al., 2018). The authors noted psychological factors, such as a sense of safety and security impact the use of ride-hailing.

Mobility Tools and Travel Behaviour

Smith (2016) found that frequent ride-hailing users are more likely to use a wide range of transportation options. For instance, a study identified a group of people who are "supersharers", those who routinely use several shared modes, including bikesharing, carsharing, and ride-hailing (Clewlow & Mishra, 2016). Ride-hailing users are also more likely to have used taxis and car-sharing services prior to the adoption of ride hailing (Alemi et al, 2018; Circella et al., 2018). In Rayle et al.'s (2014) study, they found that ride-hailing users also travel with companions more frequently.

Another issue is whether TNCs will encourage or discourage private vehicle ownership. Although ride-sourcing provides non-car-owners an additional viable alternative, ride-sourcing also relies on private car owners to drive and provide the passengers with the option. Some researchers have found that ride-hailing users are associated with lower vehicle ownership (Rayle et al., 2014; Smith, 2016) and less car use (Alemi et al, 2018). Circella et al. (2018) also found that those living in "zero-vehicle households are more likely to use Uber/Lyft with higher frequency". However, Clewlow & Mishra (2017)'s study of 4,094 survey respondents in 7 major metropolitan areas, Boston, Chicago, Los Angeles, New York, San Francisco/ Bay Area, Seattle, and Washington D.C., found that ride-hailing and car-centric households have the same vehicle ownership rate, but 9% indicated that they would change their vehicle ownership due to this service. Moreover, they found that ride-hailing users are more likely to own more vehicles than those who only use transit (Clewlow & Mishra, 2017).

Ride-hailing has the potential to either replace or facilitate transit use and active transportation (Hidalgo, 2018; Welle, Petzhold, Pasqual, 2018; Ditta, Crawford Urban, Johal, 2016). Ride-hailing may complement transit by facilitating transit access or by enabling a low-car ownership lifestyle. However, it can also directly take away from transit ridership. Hall, Palsson, and Price (2018) found that TNCs acted as a public transit substitute in larger cities and a complementary service in other cities. Clewlow & Mishra's (2017) paper found that there was a 6% net reduction in transit use -- with a 6% reduction in bus use, 3% reduction in light rail service, and 3% increase in commuter rail as a result of ride-hailing (Clewlow & Mishra, 2017). Hall et al. (2018) hypothesized that Uber may be complementary to rail ridership, but negative on bus ridership. This may be because rail riders are more likely to have higher incomes and more willingness to pay for the service. Furthermore, rail based trips are typically longer, making the same trip using ride-hailing less cost-competitive.

According to Clewlow & Mishra (2017), 49% to 61% of ride-hailing trips would not have been made at all or would have been made via transit or active transportation without ride-hailing. Hidalgo (2018) also found that ride-hailing took demand away from walking and biking as well. This finding is supported by Circella et al. (2017), who found that Uber and Lyft rides substituted walking or biking trips for Millenials, but substituted car trips for the majority of other respondents. However, Rayle et al. (2014) argue that even if most of the ride-hailing trips would have been taken via transit, the ride-hailing trips were significantly shorter than transit.

Regardless of if the technology is complementary to or competitive with transit and active forms of transportation, researchers have speculated that it will likely contribute to an increase in vehicle kilometers travelled (VKT) (Rodier, 2018). Welle et al. (2018) suggest that ride-hailing is resulting in “dropping public transit rates and increased private vehicle travel”. Additional servicing vehicles also mean additional vehicles roaming around the city both with and without passengers. The number of roaming vehicles on the road severely impacts congestion, resulting in additional emissions and pollution, which is a negative externality for the environment (Ditta et al., 2016; Hall et al, 2018).

Figure 1: Variables Related To Ride-Hailing Use

Variable	**Vivoda et al., 2018**	**Alemi et al., 2018**	**Smith, 2016**	**Clewlow & Mishra, 2017**	**Rayle et al, 2014**	**Circella et al, 2018**	**Circella et al, 2017**	**Angus Reid Institute, 2018**	**Shared-Use Mobility Centre, 2016**	**Young & Farber, 2019**
Younger Age	x	x	x	x	x	x	x	x		x
Male	x									
Higher Education	x	x	x		x	x	x			
Higher Household Income			x	x		x				x
Frequent Business Trips		x				x				
Smart Phone User		x				x				
Live in greater land use mix and more urban areas		x	x	x		x		x		
Also use taxi or other shared mobility tools		x							x	
Takes away from public transit use				x	x					
Complement transit									x	
For urban travel					x	x	x		x	
Pro technology view										
Reduces active travel							x			
Reduces car use							x			
Lower household vehicle ownership									x	x
Full-time employed										x
More active transportation use									x	

Research Gap

The existing literature has identified younger, more affluent, high income, urban context, multi-modal user individuals are linked to ride-hailing. However, they discuss the association between singular demographic or travel variables and ride-hailing use, there is a gap in knowledge surrounding user types that incorporate multiple variables. This investigation identifies user types through creating clusters using variables about different transportation mode use and access to mobility tools. Furthermore, there study fills the understanding about the use of ride-hailing in the GTHA, where TNCs are differently regulated within each municipality or regional municipality.

RESEARCH DESIGN

This paper aims to gain a better understanding of the users of ride-hailing are and are not. To do so, this study employs cluster analysis as a bottom-up approach in estimating the final user clusters. The final user clusters were formed using variables relating travel behaviour and access to mobility tools, not including ride-hail use. The process can be broken into four main steps:

1. Data Cleaning
2. Identifying key travel behaviour variables in relation to ride-hailing use
3. Creating the clusters
4. Unpacking the household and individual characteristics of each cluster

Data Cleaning

The data is taken from a 2018 survey focused on public attitudes regarding automated vehicles collected by the TransForm Lab at Ryerson University. The survey gathered responses about the adoption, use, and response to automated vehicles, car-share, bike-share, and Uber. A total of 3,200 responses were collected from adults aged 18 to 75 residing in the GTHA. To better represent the region, each case is weighed based on age, sex, and geography using 2016 census data. Refer to Appendix 1 for a more detailed breakdown of the age, sex, and region of the respondents.

The survey inquired about Uber use and Lyft use separately. As shown in Figure 2, a higher proportion of respondents have used Uber over Lyft, relating to the late introduction of Lyft in Toronto. Of those that have used ride-hailing, most respondents use the service occasionally, either 1 to 3 times in the past month or less. However, the proportion of those never using ride-hailing in the GTHA dropped, from 75.1% having never used Uber in 2016 to 57.7% having never used Uber or Lyft in 2018.

Figure 2: Uber Use and Lyft Use

Original Use Responses		Uber Use	Lyft Use
1	I never do this	59.2%	79.1%
2	I do this, but not in the past 30 days	19.8%	9.1%
3	1-3 times in the last 30 days	12.9%	6.4%
4	1 day per week	4.4%	2.7%
5	2-4 days per week	2.4%	1.8%
6	5 days per week	1.1%	0.6%
7	6-7 days per week	0.3%	0.2%

To more meaningfully discuss the use of Uber and Lyft, the responses were categorized into bigger groupings, explained in Figure 3.

Figure 3: Categorized Use Responses

Original Use Responses		Categorized Use Responses	
1	I never do this	1	Never
2	I do this, but not in the past 30 days	2	Have used before
3	1-3 times in the last 30 days	3	Use on a monthly basis
4	1 day per week	4	Use on a weekly basis
5	2-4 days per week		
6	5 days per week		
7	6-7 days per week		

The responses of Lyft and Uber use were aggregated to gather a better holistic understanding of ride-hailing use. Figure 4 depicts the rules used to differentiate ride-hailing use based on the categorized use responses.

Figure 4: Aggregate Ride-Hailing Use Rules

Uber Use		Lyft Use		Ride-Hailing Use	
1	Never	1	Never	1	Never
1	Never	2	Have used before	2	Have used before
1	Never	3	Use on a monthly basis	3	Use on a monthly basis
1	Never	4	Use on a weekly basis	4	Use on a weekly basis
2	Have used before	2	Have used before	2	Have used before
2	Have used before	3	Use on a monthly basis	3	Use on a monthly basis
2	Have used before	4	Use on a weekly basis	4	Use on a weekly basis

3	Use on a monthly basis	3	Use on a monthly basis	4	Use on a weekly basis
3	Use on a monthly basis	4	Use on a weekly basis	4	Use on a weekly basis
4	Use on a weekly basis	4	Use on a weekly basis	4	Use on a weekly basis

**Note that the inverse for each case applies as well. For example, Uber Use=2 and Lyft Use=3 was coded the same as Uber Use=3 and Lyft Use=2.*

Identifying Key Variables

The existing literature highlights that younger age, higher levels of education, higher income, more urban context, and multi-modalists are linked to ride-hailing. Cross-tabs were used to see if those variables (and others) are also associated with stated ride-hailing frequency for this sample.

Four main types of variables were considered: demographic variables (Appendix 2), household characteristics (Appendix 3), mobility tools (Appendix 4), and travel behaviour (Appendix 5). Demographic variables are the respondent's individual characteristics, e.g. age and educational attainment as further explained in **Error! Reference source not found.**. Household characteristics (**Error! Reference source not found.**) are traits at the household level, such as household income and household size. Mobility tools are resources that allow respondents to access different types of transportation, such as access to a bike or transit pass ownership (**Error! Reference source not found.**). Lastly, travel behaviour (**Error! Reference source not found.**) includes variables such as commute mode and use of transit the previous day or "yesterday". The descriptive findings reinforce the important variables found in the literature review as well as new variables as identified in Figure 5. Very important variables are those in which there is at least a single 25% difference between the lowest value and the highest value in the same column. Somewhat important variables are those in which there is at least a single 10% difference between the lowest value and the highest value in the same column. The very and somewhat important variables were then carried forward to the cluster creation step, where various combination of these variables were used in the trial-and-error process of cluster creation.

Figure 5: Importance of Variables Related to Ride-Hailing Use

	Variable	Significance	Direction of Relationship with Ride-Hailing Use
Demographic Variables	Age Group	Very Important	Older associated with less use
	Sex	Not Important	-
	Immigration Status	Not Important	-
	Educational Attainment	Very Important	High education associated with more use
	Student Status	Very Important	Student status associated with more use
	Employment Status	Very Important	Employment associated with more use
Household Variables	Household Income	Important	Higher income associated with more use
	Chauffeuring	Important	More frequent chauffeuring associated with more use
	Children Under 15	Important	More children associated with more use
	Household Size	Important	Higher household size associated with more use
Mobility Tools	Smartphone Ownership	Very Important	Smartphone ownership associated with use
	Drivers License	Not Important	-
	Transit Pass Ownership	Very Important	Transit pass ownership associated with more use
	Bike Access	Important	Bike access associated with more use
	Car-share Membership	Very Important	Car-share membership associated with more use
	Vehicle Access	Not Important	-
Travel Behaviour	Car-share Use	Very Important	Car-share membership associated with more use
	Bike-share Use	Very Important	Bike-share membership associated with more use
	Used a vehicle yesterday	Not Important	-
	Used transit yesterday	Very Important	Transit use associated with more use
	Used walked or biked yesterday	Very Important	Active transportation associated with more use
	Commute Mode	Very Important	Use dependent on commute mode

Creating the Clusters

Consumer segmentation has been used in transportation to create traveller types based on motivations, attitudes, and travel behaviour, all of which, contribute to a better understanding of why people travel the way they do. Bosehans and Walker (2018) identified three goal-oriented traveller types ,Convenience Lovers, Time Addicts, and Mode Mixers, among students and staff at the University of Bath. Pronello and Camusso (2011) found four traveller types in Alessandria, Initially, that base their travel behaviour on attitudes. Lastly, Ralph (2016) classified young people based on their travel behaviour. Drawing from Ralph's paper (2016), this study creates traveller types based on travel behaviour and access to mobility tools.

Using a two-step cluster analysis in SPSS, several clusters were explored based on the four themes and combinations thereof: household characteristics, individual demographic variables, mobility tools, travel behaviour, and all variables combined. Ride-hailing use rates were only considered after the creation of the clusters to gain insight on the relationship between cluster membership and ride-hailing use. After reviewing cross-tabulations between cluster membership and ride-hailing use rates, travel behaviour and mobility tool variables were pursued as the best ways to sort respondents into user types. Of these, the majority were variables based on short-term travel behaviour, such as used a bike yesterday or used transit yesterday, and medium-term travel behaviour, such as access to mobility tools. To determine the number of clusters most suitable for the data sample, the two-step cluster analysis in SPSS provides a silhouette measure of cohesion and separation to indicate cluster quality. Further manual trial and error was also used to see if a change in the number of clusters would further tease out the group behaviour.

Household and Individual Characteristics of the Clusters

After identifying the clusters based on mobility tool and travel behaviour variables, cross-tabulations were used to examine the ride-hailing use of each cluster. Furthermore, cross-tabulations were used to understand the individual demographics and household characteristics of the clusters. Lastly, the cases, categorized by cluster and ride-hail use, were mapped using the first three digits of the individual's postal code to understand if there is a geographic pattern related to both cluster membership and ride-hailing use.

RESULTS

Using 11 variables, four clusters of traveller types were identified – Multi-Modal Supersharers, Auto + Private Mobility Travellers, Low Mobility Travellers, and Car-Dependent Travellers.

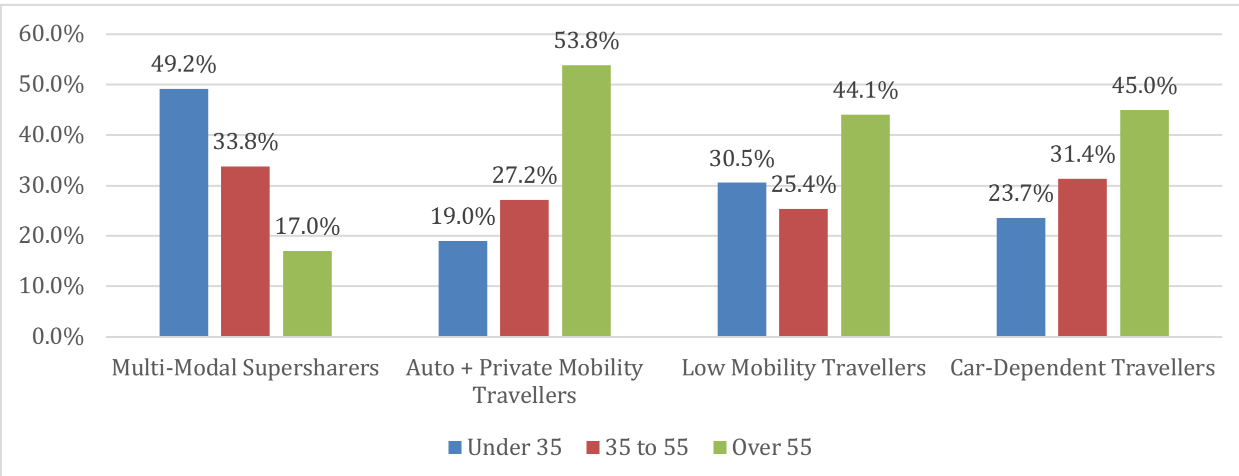
Figure 6: Cluster Analysis Results: Four User Types

	Multi-Modal Supersharers	Auto + Private Mobility Travellers	Low Mobility Travellers	Car-Dependent Travellers
Has a G2 or G drivers license	78.6%	84.1%	53.5%	100%
Owns a smartphone	97.1%	97.1%	19.9%	99.4%
Owns a transit pass	42.6%	0%	17.1	0%
Owns a carshare membership	22.7%	0%	3.3%	0%
Travelled by a vehicle yesterday	95.5%	100%	0%	100%
Travelled by transit yesterday	55.6%	0%	33.1%	0%
Travelled by active transportation yesterday	33.7%	11.6%	21.5%	0%
Has access to a vehicle	99.4%	100%	53.5%	100%
Has access to a bicycle	58.9%	78.2%	32.6%	0%
Made trips by bike-share in the past 30 days	39.0%	0.3%	4.9%	0%
Made trips by car-share in the past 30 days	53.0%	5.0%	11.5%	0.2%

The Multi-Modal Supersharers make up 26.3% of the respondents. As coined by Clewlow and Mishra (2017), these Supersharers have access to the largest variety of traditional mobility tools, including vehicles, bikes, and transit passes, and are the biggest user of shared-mobility tools, including bike-share and car-share. These travellers are the most frequent users of ride-hailing. The Low Mobility Travellers make up 21.7% of the respondents. They have the lowest number of mobility tools at their disposal, but have a relatively high ride-hailing use rate as show in Figure 9. The Auto + Private Mobility Travellers is the largest group, 32.2% of the respondents. They heavily rely on their cars and have a high bicycle ownership rate. 70.5% of this group have never used ride-hailing before. Lastly, Car-Dependent Travellers are generally reliant solely on their personal vehicles. This group has the lowest ride-hailing adoption rate, with only 23.9% of respondents having used ride-hailing before.

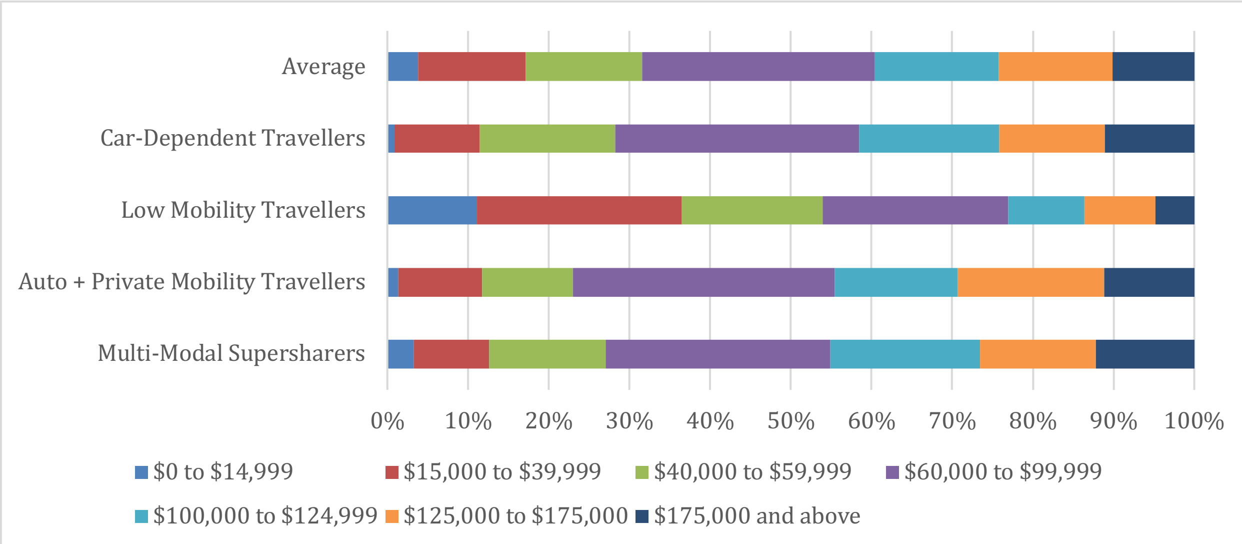
Individual and Household Characteristics of Traveller Types

Figure 7: Traveller Type by Age Group



As displayed in Figure 10, the 35 to 55 age group is almost equally likely to be in any of the four groups. The biggest difference relates to the youngest and oldest age group. The Multi-Modal Supersharers have the highest proportion of respondents in the under 35 age group, 49.2%, with an average age of 38.6 years old. The Low Mobility Travellers group has an average age of 48 years. The average age of the Car-Dependent Travellers is age 49. Over half of the Auto + Private Mobility Travellers are over 55 years old, with an average age of 52.5. While this user group also has the highest proportion of retired individuals at 30.8%, just below half (45.0%) of respondents are full-time employed.

Figure 8: Traveller Type by Household Income



Other than the Low Mobility Travellers, household incomes align rather similarly between for all the clusters. Low Mobility Travellers have the highest proportion of lower income households amongst the four groups, with 9.4% of households earning under $14,999 as well as 21.5% earning between $15,000 and $39,999. This group has the highest proportion of unemployed respondents at 14.8%, and those not in the workforce at 5.6%. 10.1% of the group are full time students. These travellers have the least number of children under 15, average 0.15 children per household.

Multi-Modal Supersharers have a relatively higher rate of higher education than the other traveller types, including degrees in medicine, dentistry, veterinary medicine or optometry as well as graduate degrees (e.g. Master's or doctoral degree). 38.7% are not Canadian citizens. This group also has the highest proportion of full-time employed individuals at 65.5%, as well as the highest proportion of students, with 9.8% being part-time students and 14.5% being full-time students. This traveller type also has the highest average household size (3) amongst the traveller types.

72.8% of Auto + Private Mobility Travellers are citizens of Canada, the highest proportion among the four groups. The average household size is 2.7 people. Of the commuters, the average typical commute time is 30.1 mins with 88% of commutes driving, alone or with others, to work.

For Car-Dependent Travellers, just over 57.1% of respondents are employed full time. The average household size is 2.5 persons with an average of 1.7 vehicles per household. This group has the largest proportion of non-citizens respondents at 36.1%. Even more than the Auto + Private Mobility Travellers, 91.0% of respondents drive, either alone or with others, to work. The average typical commute time is 30.8 minutes.

Traveller Types and Ride-Hailing Use

Figure 9: Traveller Type Ride-Hailing Use

	Never	Have used before	Use on a monthly basis	Use on a weekly basis
Multi-Modal Supersharers	33.9%	23.5%	15.7%	26.9%
Auto + Private Mobility Travellers	70.5%	19.8%	5.8%	3.9%
Low Mobility Travellers	66.1%	13.5%	10.5%	9.8%
Car-Dependent Travellers	76.2%	15.1%	5.8%	2.8%
Average	61.1%	18.5%	9.4%	11.0%

Figure 10: Likelihood of Traveller Type Based on Ride-Hailing Use

	Never	Have used before	Use on a monthly basis	Use on a weekly basis
Multi-Modal Supersharers	14.6%	33.3%	43.7%	64.2%
Auto + Private Mobility Travellers	37.2%	34.5%	19.9%	11.4%
Low Mobility Travellers	23.5%	15.9%	24.2%	19.3%
Car-Dependent Travellers	24.7%	16.2%	12.3%	5.1%

As described in Figure 6, Multi-Modal Supersharers have the largest range of mobility tools, including bikeshare, carshare, and transit passes. On average, there are 1.6 vehicles per household. This group also reveals that ride-hailing users are likely to also use other forms of shared mobility. Despite their wide range of mobility tools, 47.9% still drive to work, either alone or with others, while only 5% use active transportation and 35.5% use GO transit or another form of public transit to get to work or school. So even though they make up the largest proportion of ride-hailing on a weekly basis, these trips are more likely to be discretionary. The travel behaviour highlights that although these travellers are frequent users of ride-hailing, the majority of the trips are still non-commute trips. In other words, there is little disruption to their typical commute. Furthermore, the individual demographic variables, including age, education, and income, matter in relation to ride-hailing. The large quantity of mobility tools is probably related to the distance travelled by these users, as they have the longest average typical commute time of 43.1 minutes for student and employed commuters, and/or geography, as shared-mobility tools are more likely to be concentrated in urban centres.

The Low Mobility Travellers have the least number of vehicles at 0.8 vehicles per household on average. Among the student and employed commuters, 61.3% rely on GO transit or another form of public transit for their typical commute, while 16.1% are walking. The average typical commute time is 36.8 minutes. This group has the second largest proportion of ride-hailing adopters, 33.9%, with 10.5% using ride-hailing monthly and 9.8% using ride-hailing weekly. As shown in the individual demographics and household characteristics, such as lower household income and slightly lower education attainment, this group is the most vulnerable group among the four traveller types. Ride-hailing is filling a transportation gap for this carless group. This gap could have been previously attained through a taxi service, but now replaced by ride-hailing due to a lower price.

These Car-Dependent Travellers are also the most likely to have never used ride-hailing, 76.2%. Given the respondent has never used ride-hailing, they are most likely to fall into the Auto + Private Mobility Traveller cluster. Both the Auto + Private Mobility Travellers and Car-Dependent Travellers are least likely to have adopted ride-hailing, suggesting that for those users adopting private automobility for their daily travel behaviour are least likely to adopt ride-hailing. If users have adopted the technology, they are probably very infrequent users, have used it before but not in the past 30 days. These results suggest that the likelihood of ride-hailing reducing VKT among these travelers is very poor and suggest that it may be important to understand the conditions under which individuals may forego auto ownership due to the advantages of on-demand ride hailing.

CONCLUSION

There are three main findings in this paper related to identifying the sub-market of ride-hailing users in the GTHA. Firstly, car dependent lifestyles, such as in the case of Auto + Private Mobility Travellers and Car-Dependent Travellers, are least likely to have adopted and be used ride-hailing. If they have adopted the technology, they are very infrequent users (have used it before but not in the past 30 days). In other words, current auto-oriented travellers are not using ride-hailing. Secondly, as highlighted in the Multi-Modals Super-Sharer cluster, ride-hailing users are likely also using other forms of shared-mobility. Furthermore, they are most likely to be younger in age. Thirdly, the ride-hailing is filling a transportation gap for the Low Mobility Travellers. There is one a small age difference between this group and the other two car-dependent traveller types, but this group is more vulnerable than the other groups, with a lower household income and slightly lower education attainment. The latter two findings highlight that ride-hailing is primarily used by non-auto-oriented travellers.

This study provides a cautionary narrative to ride-hailing. The technology is here and the public sector has the authority to dictate the use and popularity of ride-hailing, as demonstrated in the case of Vancouver, BC, where ride-hailing is illegal, and Alberta, where ride-hailing is less popular due to high ride prices. This study provides insight on who the users of ride-hailing are and who is benefitting.

In response to the discussion surrounding the potential for ride-hailing to reduce congestion and auto-dependency, these findings highlight that ride-hailing use is not taking away trips from current auto-oriented travellers. As a result, there is no evidence that there is a decrease in VKT. Furthermore, the majority of trips made using ride-hailing is non-commuting trips. This study finds that ride-hailing is likely not a viable alternative for those who are driving regularly.

Even though the proportion of weekly ride-hailing trips are significant for the Multi-Modal Supersharer group and the Low Mobility Travellers, it is worth noting that ride-hailing trips are still a small proportion of the total trips taken. A limitation of the study is that because it uses crosstabulations to discuss the relationship between ride-hailing use and the various variables, the relationship cannot be described as causal. Future studies should inquire about the motivation of the ride-hailing users as well as the pairing of ride-hailing with other forms of transportation, such as transit as a first-mile last-mile solution.

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APPENDIX

Appendix 1: Age, Sex, and Region

Age Group	Male	Female
Under 35	11.3%	19.0%
35 to 55	15.5%	13.8%
Over 55	25.2%	15.1%
Total	52.0%	48.0%

Region	No. of Respondents	% of Respondents	% of Census Population (2016)
Durham Region	400	12.5%	9.1%
Halton Region	301	9.4%	7.5%
Hamilton	300	9.4%	7.6%
Peel Region	499	15.6%	20.0%
Toronto	1200	37.5%	40.2%
York Region	500	15.6%	15.6%
Total	3200	100.0%	100.0%

Appendix 2: Ride-Hailing Use by Demographic Variables

		Never	Yes, but not in the past 30 days	1-3 times per month	Once or more per week
Age Group	Under 35	36.5%	22.4%	15.9%	25.2%
	35 to 55	60.5%	20.1%	8.8%	10.6%
	Over 55	78.5%	14.6%	4.7%	2.1%
Sex	Female	57.2%	19.9%	10.1%	12.8%
	Not Female	58.3%	18.6%	9.9%	13.2%
Immigration Status	Non-Immigrant and/or Canadian Citizen by birth	58.4%	18.3%	11.0%	12.2%
	Immigrant or non-permanent resident	56.5%	21.2%	7.9%	14.5%
Educational Attainment	Did not complete High school	82.5%	12.9%	1.6%	3.0%
	High school diploma or Equivalent	65.3%	14.7%	9.9%	10.1%
	Registered Apprenticeship or other trades certificate or diploma	59.0%	17.3%	5.1%	18.7%
	College, CEGEP or other non-university certificate or diploma	62.3%	19.2%	9.9%	8.6%
	Bachelor’s Degree	54.0%	21.3%	10.6%	14.2%
	Degree in medicine, dentistry, veterinary medicine or optometry	47.0%	21.2%	10.3%	21.4%
	Graduate Degree (e.g. Master’s or Doctoral Degree)	47.5%	21.1%	10.6%	20.7%
Student Status	Full-time Student	33.1%	23.0%	18.1%	25.8%
	Part-Time Student	33.4%	21.9%	13.4%	31.3%
	Not a Student	61.5%	18.8%	9.0%	10.8%
Employment Status	Employed full-time	51.8%	21.9%	10.1%	16.2%
	Employed part-time	46.6%	19.6%	17.3%	16.6%
	Work at home full-time	47.2%	23.7%	14.9%	14.2%
	Work at home part-time	53.3%	22.4%	7.6%	16.7%
	Unemployed	60.4%	16.2%	11.5%	11.9%
	Not in the labour force	65.1%	18.6%	8.7%	7.6%
	Other	86.3%	10.0%	3.2%	0.6%

Appendix 3: Ride-Hailing Use by Household Characteristics

		Never	Yes, but not in the past 30 days	1-3 times per month	Once or more per week
Household Income	$0 to $14,999	64.0%	11.9%	10.2%	13.9%
	$15,000 to $39,999	67.2%	12.2%	7.1%	13.6%
	$40,000 to $59,999	56.4%	22.1%	8.8%	12.6%
	$60,000 to $99,999	60.8%	19.5%	6.8%	12.9%
	$100,000 to $124,999	51.9%	20.8%	12.2%	15.1%
	$125,000 to $175,000	49.7%	24.6%	13.8%	11.9%
	$175,000 and above	45.9%	19.5%	16.7%	17.8%
	Prefer not to answer	68.7%	16.3%	8.6%	6.4%
	I don't know	53.6%	21.2%	11.3%	13.8%
Chauffeuring	Never	65.5%	15.7%	8.9%	9.9%
	1-2 times per week	51.5%	23.2%	9.9%	15.3%
	3-6 times per week	51.6%	20.4%	13.6%	14.4%
	7 or more times per week	52.5%	21.5%	7.1%	18.9%
Children Under 15	0	58.9%	18.5%	9.8%	12.8%
	1	54.6%	20.2%	9.5%	15.8%
	2	54.5%	23.2%	10.8%	11.5%
	3 or more	48.7%	26.8%	14.4%	10.2%
Household Size	1	66.4%	13.6%	8.2%	11.8%
	2	59.2%	18.9%	9.8%	12.1%
	3	56.1%	19.1%	9.9%	15.0%
	4	51.3%	23.7%	12.4%	12.7%
	5 or more	50.9%	24.2%	9.8%	15.1%

Appendix 4: Ride-Hailing Use by Mobility Tools

		Never	Yes, but not in the past 30 days	1-3 times per month	Once or more per week
Smartphone Ownership	Yes	54.5%	20.5%	10.8%	14.1%
	Unsure	53.9%	18.0%	8.6%	19.5%
	No	92.0%	6.0%	1.3%	0.7%
Driver's Licence	Do not have a driver's licence or only have a G1	53.5%	15.1%	12.7%	18.7%
	G2 or full G	58.9%	20.4%	9.2%	11.4%
Transit Pass Ownership	Yes	31.1%	16.7%	14.6%	37.6%
	No	63.3%	19.8%	9.0%	7.8%
Bike Access	Yes	49.8%	22.8%	10.8%	16.6%
	No	64.9%	16.1%	9.2%	9.8%
Car-share Membershi	Yes	17.5%	14.0%	12.9%	55.6%
	No	61.2%	19.7%	9.7%	9.4%
Vehicle Access	Yes	58.3%	19.6%	9.9%	12.2%
	No	52.8%	17.1%	10.5%	19.6%

Appendix 5: Ride-Hailing Use by Travel Behaviour

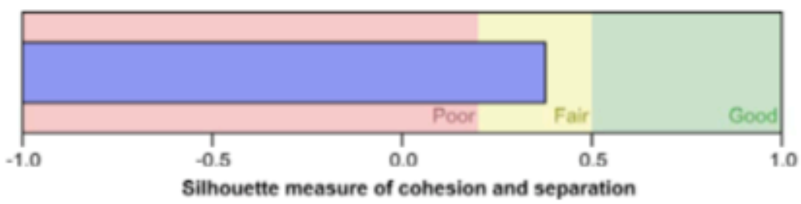
		Never	Yes, but not in the past 30 days	1-3 times per month	Once or more per week
Car-share Use	Never	68.9%	16.6%	7.9%	6.6%
	Yes, but not in the past 30 days	13.6%	57.7%	11.6%	17.1%
	1-3 times per month	7.6%	9.7%	40.4%	42.3%
	Once or more per week	21.3%	6.1%	9.4%	63.2%
Bike-share Use	Never	64.3%	18.8%	9.2%	7.7%
	Yes, but not in the past 30 days	18.7%	36.2%	15.0%	30.0%
	1-3 times per month	9.2%	12.7%	18.2%	59.8%
	Once or more per week	12.5%	3.0%	12.0%	72.5%
Used a vehicle yesterday	Yes	57.1%	20.3%	9.5%	13.1%
	No	59.8%	15.8%	11.6%	12.8%
Used transit yesterday	Yes	37.7%	19.2%	13.9%	29.2%
	No	64.4%	19.3%	8.6%	7.7%
Walked or biked yesterday	Yes	38.2%	18.9%	14.3%	28.6%
	No	62.1%	19.4%	9.0%	9.5%
Commute Mode	Auto driver (alone)	55.5%	23.4%	9.5%	11.6%
	Auto driver (with others)	46.5%	21.5%	10.5%	21.6%
	Auto passenger	57.1%	14.9%	11.4%	16.5%
	Taxi	36.7%	6.1%	3.2%	54.0%
	Uber or Lyft	3.3%	3.0%	16.1%	77.6%
	Motorcycle	100.0%	0.0%	0.0%	0.0%
	Walk	39.1%	23.7%	19.3%	17.9%
	Bicycle	49.8%	27.2%	9.4%	13.6%
	GO Transit	45.9%	22.3%	12.3%	19.4%
	Public Transit (excluding GO Transit)	46.4%	21.0%	15.2%	17.5%
	Other	41.4%	18.6%	26.6%	13.5%
	Non-commuters or non-workers	76.5%	13.2%	5.9%	4.4%

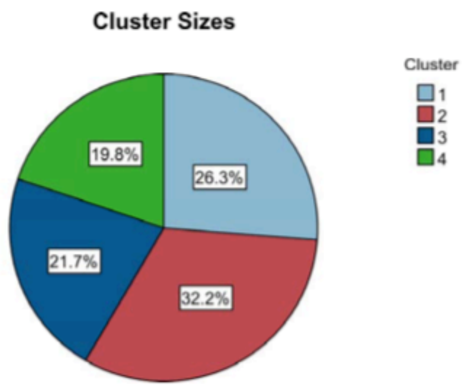
Appendix 6: Model Summary and Size

Model Summary

Algorithm	TwoStep
Inputs	11
Clusters	4

Cluster Quality





Size of Smallest Cluster	634 (19.8%)
Size of Largest Cluster	1031 (32.2%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	1.63

Appendix 7: Original Cluster Output

Clusters

Input (Predictor) Importance

1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1	3	4
Label				
Description				
Size	32.2% (1031)	26.3% (840)	21.7% (694)	19.8% (634)
Inputs	yes.vehicle.yesterday 1 (100.0%)	yes.vehicle.yesterday 1 (95.5%)	yes.vehicle.yesterday 0 (100.0%)	yes.vehicle.yesterday 1 (100.0%)
	vehicle.yes 1 (100.0%)	vehicle.yes 1 (99.4%)	vehicle.yes 1 (53.5%)	vehicle.yes 1 (100.0%)
	yes.transit.yesterday 0 (100.0%)	yes.transit.yesterday 1 (55.6%)	yes.transit.yesterday 0 (66.9%)	yes.transit.yesterday 0 (100.0%)
	bike.yes 1 (78.2%)	bike.yes 1 (58.9%)	bike.yes 0 (67.4%)	bike.yes 0 (100.0%)
	trips.car.share 1 (95.0%)	trips.car.share 1 (47.0%)	trips.car.share 1 (88.5%)	trips.car.share 1 (99.8%)
	trips.bike.share 1 (99.7%)	trips.bike.share 1 (61.0%)	trips.bike.share 1 (95.1%)	trips.bike.share 1 (100.0%)
	transitpass.yes 0 (100.0%)	transitpass.yes 0 (57.4%)	transitpass.yes 0 (82.9%)	transitpass.yes 0 (100.0%)
	carshare.yes 0 (100.0%)	carshare.yes 0 (77.3%)	carshare.yes 0 (96.7%)	carshare.yes 0 (100.0%)
	drivealone.yes 1 (84.1%)	drivealone.yes 1 (78.6%)	drivealone.yes 1 (53.5%)	drivealone.yes 1 (100.0%)
	yes.active.yesterday 0 (88.4%)	yes.active.yesterday 0 (66.3%)	yes.active.yesterday 0 (78.5%)	yes.active.yesterday 0 (100.0%)
	smart.phone 1 (80.8%)	smart.phone 1 (97.1%)	smart.phone 1 (80.1%)	smart.phone 1 (99.4%)