UNDERSTANDING ADOPTION OF AUTOMATED VEHICLES IN CANADA

UNDERSTANDING BEHAVIORAL INTENTION AND ADOPTION OF AUTOMATED VEHICLES IN CANADIAN CENSUS METROPOLITAN AREAS

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Lay Abstract

This dissertation assesses the conditions under which Canadians are willing to use fully automated vehicles (AVs) and investigates public perceptions and intentions to use “automated ride-hailing services,” which function as a taxi or Uber/Lyft service without a driver, and “pooled automated ride-hailing services,” which are a form of ride-hailing services, where passengers share a ride with someone they do not know to save on the cost of travel. To this end, an online survey (n = 5002) was designed and administered in October and November 2021 across six major Canadian metropolitan areas: Toronto, Vancouver, Ottawa-Gatineau, Montreal, Calgary, and Hamilton. Overall, results suggest that expectations towards AVs suddenly transforming the entire transportation sector, should be moderated and “automated ride-hailing services” and “pooled automated ride-hailing services” (when they are available in the entire Canadian market) are likely to be adopted as a supplementary mobility tool rather than a substitution for current travel modes.

Abstract

Sharing automated vehicles (AVs) is a possible future, where shared automated vehicles (SAVs) and pooled automated vehicles (PooledAVs) are prospective on-demand AV configurations. While SAVs and PooledAVs can contribute to the sustainability of transport systems, the success of on-demand AVs depends on whether and how the public adopts them as regular travel modes. As such, this dissertation investigates five objectives: (1) to scrutinize the essential steps of designing a future mobility survey[1], while the primary focus of the survey is on respondents' intentions to adopt various AV configurations (2) to propose and validate a theoretical model for on-demand AV adoption by extending the Theory of Planned Behavior (TPB), (3) to identify the prospective use cases of SAVs as the potential precursor of on-demand AVs, (4) to identify individual characteristics that may trigger different behavioral intentions [2]among the on-demand AV service types, and finally (5) to investigate Canadians' intentions to adopt on-demand AVs. A nationwide Canadian survey was designed and administered in fall 2021 (n = 5002) among adults (18 to 75 years old) residing in six major Canadian metropolitan areas: Toronto, Vancouver, Ottawa-Gatineau, Montréal, Calgary, and Hamilton. The findings of this dissertation paint a complex picture of on-demand AV adoption in the Canadian context with respect to the application of constructs from common technology adoption models and will help researchers investigating the characteristics of prospective consumers of on-demand AVs to identify the importance of affective motivations regarding adopting such emerging travel modes. The results reveal that many Canadians are yet either uncertain or reluctant to adopt AV technology

[1] The survey was a collaborative effort involving Samira Hamiditehrani, the author of this dissertation, Dr. Darren Scott as the Principal Investigator (PI), and Dr. Matthias Sweet as the project's co-Principal Investigator (co-PI).
[2] Behavioral intention is defined as the immediate antecedents to behavior, which are a function of salient information or beliefs about the likelihood that performing a particular behavior will lead to a specific outcome (Fishbein & Ajzen, 1975).

in shared mobility services. In this light, policymakers and planners should adjust and moderate their expectations regarding the future market for on-demand AVs and be prepared for potential changes in travel behavior by examining incremental changes in existing on-demand ride-hailing services.

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Preface

This thesis consists of an introduction, three original studies conducted by the dissertation author, and a conclusion. The objective of this thesis, as outlined in this document, is to elucidate the significance of public perception towards new and emerging mobility tools. This thesis investigates Canadians' behavioral intention to use on-demand automated vehicles, which are projected to be prominent travel modes in the future. To this end, six major Canadian metropolitan areas are used as case studies: Toronto, Vancouver, Ottawa-Gatineau, Montréal, Calgary, and Hamilton.

The first study presents an overview of a nationwide Canadian survey, called the Future Mobility in Canada Survey (FMCS). Also, this chapter (Chapter 2) emphasizes novel aspects of the survey design and data collection process, while the major focus of the study is scrutinizing the steps taken to obtain respondents' intentions to adopt various configurations of automated vehicles (AVs) including shared AVs, pooled AVs, private AVs, and automated shuttle buses.

The second study in Chapter 3 uses the data collected through FMCS and explores a novel user-centered approach to investigate whether use cases of shared automated vehicles (SAVs) matter in adopting such future travel mode. This chapter's findings call into question what trip purposes or use cases really matter when it comes to SAV adoption. A question concerning whether SAV use is likely to be concentrated in occasional rather than regular trips was pointed out through this study using the user-centered use case approach.

The final study, Chapter 4, also uses data from FMCS to understand the effect of current travel behavior on adopting prospective mobility tools. This chapter identifies the commonalities and differences between the characteristics of shared AVs' and pooled AVs' early adopters and investigates Canadians' intentions to adopt on-demand AVs. The findings of this chapter paint a complex picture with respect to the application of constructs from common technology adoption models to the study of on-demand AVs.

For all three papers, the dissertation author conducted the literature reviews, helped design the nationwide online survey (FMCS), cleaned the data, analyzed the data, estimated models, interpreted the results and wrote the manuscripts. Dr. Darren Scott and Dr. Matthias Sweet co-authored all three papers. Dr. Scott conducted the McMaster University Ethics approval process and supervised the whole process from the beginning through completion and submission by providing valuable feedback, developing research methodologies, and manuscript revising. Dr. Sweet who was a supportive mentor throughout the research, provided professional and valuable contributions in developing all three research papers. The three research papers are:

Chapter 2: Hamiditehrani, S., Scott, D. M., & Sweet, M. (2023). Design of the "Future Mobility in Canada Survey" (FMCS) to assess the evolving mobility landscape in urban Canada with an emphasis on automated vehicles. Revised and Resubmitted to *Transportation*. Revised

Chapter 3: Hamiditehrani, S., Scott, D. M., & Sweet, M. (2022). Do use cases matter when considering whether to use shared automated vehicles? Findings from major Canadian metropolitan areas. Submitted to *International Journal of Human-Computer Interaction* (special issue on Automated Vehicle Acceptance). Submitted

Chapter 4: Hamiditehrani, S., Scott, D. M., & Sweet, M. (2023). Shared versus pooled automated vehicles: Understanding behavioral intentions towards adopting on-demand automated vehicles. Revised and Submitted to *Travel Behaviour and Society*. Submitted.

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List of Abbreviations

AV	Automated Vehicles
CMA	Canadian Metropolitan Area
DIT	Diffusion of Innovation Theory
FMCS	Future Mobility in Canada Survey
PooledAV	Pooled Automated Vehicle
SAV	Shared Automated Vehicle
SCT	Social Cognitive Theory
SP	Stated preference
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
UT	Utility Theory
UTAUT	Unified Theory of Acceptance and Use of Technology
WTP	Willingness to Pay

Chapter 1
Introduction

1.1. Background and research problems

The necessity of adopting eco-friendly travel modes in urban areas has played a significant role in the advent of shared mobility services (Machado et al., 2018; Sopjani et al., 2020), including ride-hailing, car sharing, and bike sharing. The emergence of these alternative transportation options is a precursor to major changes in travel behavior (Chen et al., 2017; Shaheen et al., 2016). Further, these services have had a transformative impact on many global cities by enhancing accessibility (Shaheen & Cohen, 2019).

The integration of shared mobility services and automated vehicle (AV) technology has sparked the novel business models within the on-demand ride-hailing sector, potentially paving the way for the development of on-demand AVs such as shared automated vehicles[3] (SAVs) and pooled automated vehicles[4] (PooledAVs). On-demand AVs could provide alternative shared mobility services that encourage sustainable transport systems, mitigate traffic congestion, and reduce automobile dependency (Fagnant et al., 2015; Fagnant & Kockelman, 2018; Krueger et al., 2016). However, the effectiveness of shared mobility services and AV technology in tackling significant transportation issues depends on public acceptability and adoption (Edison & Geissler, 2003; Heffner et al., 2007; Zhang et al., 2020). As such, it is important to assess people's current

[3] "Shared automated vehicles" (SAVs) refers to automated ride-hailing services without ride sharing.
[4] "Pooled automated vehicles" (PooledAVs) refers to automated ride-hailing services with ride sharing.

use of shared mobility services and their intention to adopt on-demand AVs as prospective alternative mobility modes.

To understand people's behavioral intention towards on-demand AVs and identify conditions under which individuals may adopt such unobserved travel modes, many studies have explored affective motivations which shape on-demand AV adoption. *Affective motivations* refer to feelings such as stress, excitement, pleasure, boredom, and control evoked by traveling, where pleasure and arousal are identified as the sub-dimensions of affective responses upon which all human emotions are based (Anable & Gatersleben, 2005; Russell & Lanius, 1984; Steg, 2005). Affective motivations are frequently considered within the broader framework of technology acceptance and adoption theories applied to AV studies. Examples of such adoption theories include Utility Theory (UT) (Bansal & Kockelman 2017; Fagnant & Kockelman 2015; Hoerl, Becker & Axhausen 2021; Wang et al., 2021), the Technology Acceptance Model (TAM) (Osswald, et al. 2012; Rahman, et al. 2017; Lee, et al. 2019; Panagiotopoulos and Dimitrakopoulos 2018; Xu, et al. 2018; Choi and Ji 2015), the Theory of Planned Behavior (TPB) (Buckley et al., 2018; Dai et al., 2021), the Unified Theory of Acceptance and Use of Technology (UTAUT 1 and 2) (Madigan, et al. 2017; Rahman, et al. 2017; Adell 2010), the Diffusion of Innovation Theory (DIT) (Talebian & Mishra 2018; Lavasani et al., 2017), and the Social Cognitive Theory (SCT) (Ribeiro et al., 2022).

Among the existing theoretical frameworks, the Theory of Planned Behavior (TPB) stands out as a validated and extensively tested model in research related to on-demand AVs (Kaye et al., 2020). Besides components explicitly embedded in adoption theories, the existing literature suggests that other affective motivations such as green lifestyle, ample knowledge of AV technology, driving enthusiasm, sensation seeking, etc., may be robust factors influencing SAV and PooledAV adoptions (Nordhoff et al., 2016b; Xu et al., 2018; Buckley et al., 2018; Choi & Ji, 2015).

While numerous studies have extended models for AV adoption by incorporating additional affective motivations, these constructs have not been applied to the unique use cases of on-demand AVs. Furthermore, research is lacking into whether affective motivations are primarily associated with the specific configurations and use cases of on-demand AVs as opposed to being more broadly tied to the technology and business models of AVs. This dissertation seeks to address this research gap by examining these aspects in greater detail.

A comprehensively designed and inclusive survey evaluating potential changes in travel behavior from the uptake of new or unobserved mobility solutions, such as various AV configurations, can serve as a pivotal resource (Abotalebi et al., 2018). To this end, a nationwide future mobility survey, called Future Mobility in Canada Survey, was designed and administered from October 20th to November 29th, 2021. The acronym "FMCS" (**F**uture **M**obility in **C**anada **S**urvey) is used to avoid repeating the name of the survey instrument throughout this thesis. Through FMCS[5] 5002 observations were collected across six Canadian Census Metropolitan Areas (CMAs), Toronto, Vancouver, Montréal, Ottawa-Gatineau, Calgary, and Hamilton, which together represent approximately half of the Canadian population. The process of survey design and all details associated with it is described in full in chapter 2.

[5] While a wide range of information such as the use of telework, the impact of the COVID-19 pandemic on its demand, and the effect of the pandemic on current ownership and use of mobility tools, is also collected through FMCS the primary focus of this dissertation is on behavioral intention towards AVs.

1.2. Research questions and objectives

The main goal of this dissertation is to assess automated vehicle adoption– particularly on-demand AV adoption among residents of mid-to-large CMAs. The three objectives are carefully crafted with the intention of directing the research towards its main goal. The overall structure of the present dissertation is composed of three objectives as outlined below.

Objective 1 is to review the procedure of a nationwide survey instrument used to collect 5002 observations across CMAs including Toronto, Vancouver, Ottawa-Gatineau, Montréal, Calgary, and Hamilton. The insights of this research chapter are relevant for other survey-based studies and are applicable for researchers who investigate adoption of new mobility tools and consequent travel behavior changes. The groundwork for the current thesis is laid out by objective 1, which involves developing the dataset that has led to the two additional research papers.

Objective 2 is to validate a new approach, called user-centered use case approach, to identify prospective use cases of shared automated vehicles (SAVs) and to distinguish between "*use-case-variant"*[6] and "*use-case-invariant*"[7] individuals. Using ordered probit models, intention to use SAVs for use cases is modelled for each participant group. Additionally, through this objective, a theoretical model by extending the original Theory of Planned Behavior (TPB) is proposed, and Canadians' intentions to adopt SAVs based on the proposed theoretical framework and the user-centered use case approach are investigated. The findings from this research will help researchers investigating the characteristics of prospective consumers of SAVs to identify the importance of affective motivations in deciding to use such emerging travel mode.

[6] Use-case-variant individuals are those who differentiate between use-case scenarios by choosing different outcomes along a five-point Likert scale, for two or more questions related to behavioral intention towards using SAVs.
[7] Use-case-invariant individuals are those who do not differentiate between use cases; that is, they choose the same option along the five-point Likert scale for all questions related to behavioral intention towards using SAVs.

Objective 3 is to investigate behavioral intention to use two distinct yet related configurations of on-demand automated vehicles (AVs): shared automated vehicles (SAVs) and pooled automated vehicles (PooledAVs). This research paper identifies the characteristics of early adopters of SAVs, who prefer to have shorter and private rides that are more expensive, versus prospective users of PooledAVs, who choose more affordable but longer and shared trips, by assessing the current use of ride-hailing services for work/school trips and comparing the use of these existing mobility services to SAV and PooledAV adoptions. The findings of this research paint a complex picture with respect to the application of constructs from common technology adoption models to the study of on-demand AVs.

1.3 Thesis Structure

The remainder of this dissertation is structured as follows.

Chapter 2 reviews the process of designing a nationwide Canadian survey which aimed to capture the complex decision-making processes of travel behavior changes and the adoption of new mobility tools, while the major focus was on AV adoptions by assessing individual preferences, affective motivations, and behavioral intentions. Since fully automated vehicles are not commercialized yet, it was decided, for FMCS, to design a novel and new approach involving user-centered use-case scenarios. This chapter serves as the central point of the thesis and provides the foundation for the other research chapters. The data collection took place between October and November 2021 and 5,002 observations were collected across six Canadian metropolitan areas: Toronto, Vancouver, Ottawa-Gatineau, Montréal, Calgary, and Hamilton.

Chapter 3 proposes and validates a theoretical model by extending the original TPB model using additional affective motivations. Afterward, using a binomial probit model, this chapter distinguishes between the characteristics of “use-case-variant” participants, who responded with different intentions to use SAVs depending on the use-case scenario, versus “use-case-invariant” respondents, who did not differentiate between use cases. Finally, using ordered probit models, intention to use SAVs for use cases is modelled for each participant group. The results of this research chapter will be useful for researchers investigating the characteristics of prospective SAVs’ consumers.

Chapter 4 focuses on understanding the effect of current travel behavior on adopting prospective mobility tools such as SAVs and PooledAVs, and accordingly, proposing a theoretical model for behavioral intention to use on-demand AVs based on a mediation analysis. Furthermore, through a full structure equation model (SEM) this chapter identifies the commonalities and differences between the characteristics of SAVs’ and PooledAVs’ early adopters, and consequently, investigates Canadians’ intentions to adopt each of these on-demand service types. This research chapter will not only be of interest to academics, but also the results could be used by policymakers, planners, and the vehicle and technology industries that are investing in on-demand AVs since identifying prospective users of SAVs and PooledAVs is a necessary precursor for anticipating their future markets and the travel behavior changes that could arise from such technology.

Chapter 5 of the dissertation draws upon the three papers to present concluding remarks that connect them and contextualize their relevance to the adoption of on-demand AVs in Canada. This chapter contains a summary of thoughts on how the results from this research contribute to the larger body of literature on adopting unobserved and emerging mobility tools.

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Chapter 2

Design of the "Future Mobility in Canada Survey" (FMCS) to assess the evolving mobility landscape in urban Canada with an emphasis on automated vehicles

2.1. Introduction

Reducing the use of conventional private vehicles and promoting the use of more sustainable travel modes in cities have helped shape shared-mobility services (Machado et al., 2018; Sopjani et al., 2020), such as ride hailing, car sharing, and bike sharing. The advent of such alternative transportation services is a potential precursor to major changes in travel behavior (Chen et al., 2017; Shaheen et al., 2016). Further, these services have had a transformative impact on many global cities by enhancing accessibility (Shaheen & Cohen, 2019). There are other emerging mobility tools such as automated vehicles (AVs), which are postulated to offer a wide range of opportunities for the transportation sector, such as reductions in traffic congestion and road accidents (Balać et al, 2020; Fagnant & Kockelman, 2015; Piao et al., 2016; Wadud et al., 2016). The benefits of AV technology have triggered the development of various travel modes including privately-owned automated vehicles (PAVs), shared automated vehicles (SAVs), pooled automated vehicles (PooledAVs), and automated shuttle buses. However, the success of shared mobility services and AV technology in addressing major transportation challenges depends on whether the public will adopt and use them as regular travel modes (Balać et al, 2019; Edison & Geissler, 2003; Heffner et al., 2007; Zhang et al., 2020). As such, it is important to assess people's current use of shared mobility services and their intention to adopt AVs as prospective alternative mobility modes.

In addition to the importance of shared mobility services and AV technology, telework has also been considered as another strategy for reducing the use of private vehicles and the associated negative environmental impacts of mobility (Baruch & Nicholson, 1997). Since March 2020, due to the COVID-19 pandemic, telework has been required or recommended by several governments (Belzunegui-Eraso & Erro-Garcés, 2020). The benefits of telework, such as time and cost savings in terms of commuting (Baruch & Nicholson, 1997), have led to an ongoing demand for telework in the post-pandemic era (Elldér, 2020; Heimgartner & Axhausen, 2023; Nguyen & Armoogum, 2021). In this respect, telework could influence travel behavior and the demands for conventional mobility modes, meaning telework should be reconsidered a significant policy instrument and a prospective solution to environmental impacts of daily travel. Alongside the impact of the COVID-19 pandemic on telework, the pandemic has also changed the use of many mobility tools such as public transit and other shared mobility services (Neuburger & Egger, 2021). Hence, it is necessary to assess how the COVID-19 pandemic has affected current ownership and use of mobility tools to estimate future demand for each travel mode. Overall, there is considerable need for appraising (1) the use of telework, (2) the impact of the COVID-19 pandemic on its demand, and (3) the effect of the pandemic on current ownership and use of mobility tools.

A well-designed and inclusive survey assessing travel behavior changes due to the high demand for telework, the emergence of unpredicted challenges such as COVID-19 pandemic, and the adoption of new or currently unavailable mobility tools, plays a critical role in guiding transportation planners and policy makers in responding to current and future travel changes (Abotalebi et al., 2018). To this end, a future mobility survey was designed and administered from October 20th to November 29th, 2021, to address four aims of future mobility research: (1) identify respondents' intentions towards adopting AVs, (2) investigate respondents' use of shared mobility services including bike sharing, car sharing, ride hailing and public transit, (3) examine respondents' recent experience with telework and identify the impact of the COVID-19 pandemic on telework, and (4) reveal the impacts of the COVID-19 pandemic on travel behavior by assessing Canadian travel behavior across the pandemic for modes acutely affected by it – notably, ride hailing and public transit.

The acronym "FMCS" (Future Mobility in Canada Survey) is used to avoid repeating the name of the survey instrument throughout this paper. FMCS is the first nationwide survey in Canada (n = 5002) focusing simultaneously on AV adoption, telework, use of shared mobility services, and the impacts of the COVID-19 pandemic on travel behavior. This survey includes several novel aspects. First, the survey is administered across six Canadian Census Metropolitan Areas (CMAs), Toronto, Vancouver, Montréal, Ottawa-Gatineau, Calgary, and Hamilton, which together represent approximately half of the Canadian population. Second, many questions were customized based on the respondents' existing travel behavior and accessibility to different modes, employment status, telework status, and some background information. Third, since AVs are not yet commercially available in Canada, to better estimate potential future uptake of SAVs and/or PooledAVs , a series of use-case scenarios were presented to the survey respondents. This allows a further understanding of contexts in which people may use on-demand AV services (SAVs and PooledAVs) in the face of uncertainty. Fourth, a series of indirect attitudinal questions based on technology adoption theories are posed to identify the affective motivations in adopting new mobility tools.

While some new technology use cases cannot be independently verified because they cannot be observed (a limitation with respect to external validity), the key affective motivations based on technology adoption theories enable theoretically grounded and internally valid approaches to test those technologies that are not yet commercially available (notably AVs). Studies identifying the affective motivations towards AV adoption have included these motivations within the broader framework of technology acceptance and adoption theories applied to AVs. Examples of these theories applied within AV adoption studies include Utility Theory (UT) (Bansal & Kockelman, 2017; Becker, 2020; Krueger et al., 2016; Sweet, 2021; Yap et al., 2016), the Technology Acceptance Model (TAM) (Choi & Ji, 2015; Panagiotopoulos & Dimitrakopoulos, 2018; Rahman et al., 2017; Xu et al., 2018; Zhang et al., 2019), the Theory of Planned Behavior (TPB) (Buckley et al., 2018; Dai et al., 2021; Rahman et al., 2017), the Unified Theory of Acceptance and Use of Technology (UTAUT I & II) (Madigan et al., 2017; Nordhoff et al., 2021; Topolšek et al., 2020), the Diffusion of Innovation Theory (DIT) (Talebian & Mishra, 2018; Yuen et al., 2020), and the Social Cognitive Theory (SCT) (Du et al., 2021; Ribeiro et al., 2022).

Among the existing theoretical frameworks, TPB is one of the most reliable and validated adoption theories (Kaye et al., 2020; Rahman et al., 2017). TPB is an expanded version of the Theory of Reasoned Action (TRA), which was developed by Fishbein and Ajzen (1975). TPB contends that behavioral intention determines real behavior and acceptability and includes three components of intention to perform a behavior: attitude towards a behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC) (Ajzen, 1991). This theory posits that positive attitude and favorable normative and volition control beliefs will generate a positive intention leading one to be more likely to carry out a behavior (Ajzen, 1991). According to Ajzen (2006), behavioral beliefs result in a favorable or unfavorable attitude towards the behavior, normative beliefs produce perceived social pressure or subjective norms, and control beliefs induce perceived behavioral control or self-efficacy. Using an extended TPB framework, FMCS aimed to propose a survey framework where the additional affective motivations alongside the TPB's components are examined through various indices.

An overview of the survey instrument, characteristics of FMCS, the data collection process for each of the four objectives, and the critical decision-making process with special emphasis on AV adoption, are discussed in this paper. Using FMCS instruments, this paper aims to improve the body of existing survey design literature by providing systematic guidance on efficient survey data collection to identify prospective consumers of AVs, and elucidating approaches to measuring the complex decision-making process of adopting currently unavailable mobility tools by assessing individual preferences, affective motivations, and behavioral intention (BI) . Beyond its contribution to the AV literature, this study documents explicitly the methods and considerations involved during survey design to capture changes in travel behavior particularly for shared mobility services and public transit when confronting new challenges such as the COVID-19 pandemic and assesses the existing use of teleworking and preferences towards it with respect to the pandemic. We also report on the response burden and response behavior.

2.2. Overview and characteristics of FMCS

2.2.1. Survey modules

The survey modules and their salient components are summarized in Table 1. The survey began with an introduction highlighting the survey's objectives, information about the survey modules, risks and benefits of completing the survey, privacy and policies, expected completion time, contact information, and a consent letter. Afterward, screening and sample balancing questions were asked. The second module gathered information concerning AV adoption by assessing respondents' willingness to pay for PAVs, willingness to be early/late adopters of PAVs, and intentions to use automated buses, SAVs, and PooledAVs under different use-case scenarios using a series of five-point Likert-scale questions. Also, respondents were asked about their willingness to pay for PAVs in terms of their additional cost relative to a conventional vehicle's cost[8]. Willingness to pay for hourly fees for the option to enable the self-driving features of privately-owned vehicles, rather than increasing the cost of such vehicles upfront, was asked. Intentions to use automated small shuttles and regular-size buses were also assessed through five-point Likert-scale questions. After showing educational materials on SAVs, PooledAVs, and their applications, behavioral intention (BI) questions towards using SAVs and PooledAVs were measured through a range of user-centered[9,] use-case scenarios (discussed in section 4). These scenario-based questions assessed the intention of using such currently unavailable mobility services from the respondents' points of view.

The third module appraised respondents' access to and use of various travel modes, both shared and private. The former included bike sharing, car sharing, and ride hailing, along with public transit; the latter, private vehicle and bicycle ownership. After clarifying usage, by trip purpose for some modes, respondents were asked about modal substitution for their last trips taken using shared mobility modes and public transit[10]. The fourth module highlighted the impact of the COVID-19 pandemic on telework by gathering information on telework frequency before, during, and after the pandemic. In this module, respondents also answered questions concerning their employment status, occupation type, and workplace location.

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[8] Instead of focusing on willingness to pay, Bösch et al. (2018) developed a comprehensive framework to estimate the impact of autonomous vehicle technology on the cost structures of private cars, taxis, and public transport. For private cars, they assumed vehicle price will increase by 20%; however, this would be offset by decreases in other cost components such as fuel, insurance rates, etc. This approach was adopted by Becker et al. (2020) in their investigation of automated vehicle services worldwide.

[9] To our knowledge, no study has focused on use cases of on-demand AVs (SAVs and PooledAVs) considering the characteristics and purpose of trips. We refer to this novelty using the term *user centered*.

[10] An alternative to asking such survey questions is to use an estimated mode choice model to derive modal substitution rates. Reck et al. (2022) demonstrate this approach.

Affective motivations refer to feelings such as stress, excitement, pleasure, boredom, and control evoked by traveling, where pleasure and arousal are identified as the sub-dimensions of affective responses upon which all human emotions are based (Anable & Gatersleben, 2005; Russell & Lanius, 1984; Steg, 2005). To examine the role of affective motivations on intention to use AVs, an extended TPB model employing additional affective factors was proposed and implemented through FMCS. A thirty-two Likert-scale matrix was developed to examine the components of the extended TPB model, which contained 13 attitudinal constructs: behavioral intention (BI), perceived behavioral control (PBC), attitude towards behavior (ATB), subjective norms (SN), trust, affinity towards technology, eco-friendliness, knowledge, sensation seeking, driving enthusiasm, multitasking, privacy concerns, and car ownership interest. BI was considered as the main dependent variable for AVs and was measured in the second module as the stated intent to use various types of AVs in the future, while the other attitudinal constructs formed the fifth module of the survey. Whereas the extended TPB model was developed for the emerging modes only – namely AVs – the affective motivations can also be used in understanding usage of current ownership and use of mobility tools and in assessing modal substitution as these questions are of the intent type.

In the last module, additional socio-demographic information was collected. FMCS used only close-ended questions to mitigate response burden.

Table 1. Overview of FMCS modules, submodules, question types, and survey elements

Survey modules	Submodules	Question types	Survey elements
Introduction, consent, and screening	-	Three-page text	Introduction Consent
	-	Single-answer questions	Age, gender, residential location (six-digit postal code), household income[11]
Self-driving vehicles	Private AVs, automated buses	Educational scripts, Likert-scale questions, single-answer questions,	Educational script about AVs Likelihood of being early or late buyers of PAVs Willingness to pay for PAVs compared to conventional cars in terms of additional cost and as an hourly service Intention to use automated small and regular-size shuttle buses
	Shared and pooled AVs	Educational scripts, Likert-scale questions	Educational scripts about SAVs and PooledAVs Intention to use SAVs and PooledAVs for various use-case scenarios: work or school trips, trips other than work or school, trips for special events or performances, and trips to/from airport
Mobility tools and travel behavior	Privately-owned vehicle characteristics	Binary questions, single-answer questions	Driver's license status Number of owned or leased motor vehicles by members of the household and their availability for personal use Type of motor vehicle used most often Whether respondent has driven an electric vehicle
	Private bike, public transit, bike sharing, car sharing, and ride-hailing services	Binary questions, single-answer questions	Bicycle ownership before and after the COVID-19 pandemic Weekly bicycle usage (after the COVID-19 pandemic) and modal substitution (last trip after the COVID-19 pandemic) by trip purpose (non-recreational and recreational trips) Bike-share program membership before and after the COVID-19 pandemic Weekly bike share usage (after the COVID-19 pandemic) by trip purpose (non-recreational and recreational trips) Modal substitution of last non-recreational (after the COVID-19 pandemic) bike share trip Car-sharing service membership after the COVID-19 pandemic Weekly car share usage (after the COVID-19 pandemic) and modal substitution (last trip after the COVID-19 pandemic) Experience using a ride-hailing service Weekly ride-hailing usage before and after the COVID-19 pandemic Modal substitution of last ride-share trip (after the COVID-19 pandemic) Public transit pass ownership before and after the COVID-19 pandemic

[11] Valid responses are: (1) under \$39K, (2) \$40K to \$99K, (3) \$100K to \$124K, (4) \$125K to \$174K, (5) \$175K and above, (6) prefer not to answer, (7) I do not know.

Survey modules	Submodules	Question types	Survey elements
			Weekly public transit usage (before and after the COVID-19 pandemic) and modal substitution (last trip before and after the COVID-19 pandemic) by trip purpose (non-recreational and recreational trips)
Employment and telework	Employment	Single-answer questions, textboxes	Employment status, occupation type, workplace location (six-digit postal code or nearest intersection)
	Telework	Binary questions, single-answer questions	Telework arrangement with employer (required or allowed to telework) Whether respondent teleworked during the COVID-19 pandemic Whether telework was mandatory or optional Frequency of telework during the past month and before the pandemic Ideal number of days respondent would like to telework Change in distance between home and work since March 2020 (beginning of the COVID-19 pandemic) Availability of a dedicated residential space to work from home
Attitudes	-	Single-answer questions, Likert-scale matrix	Thirty-two attitudinal statements: perceived behavioral control, attitude towards a behavior, subjective norms, trust, affinity towards technology, eco-friendliness, knowledge, sensation seeking, driving enthusiasm, multitasking, privacy concerns, car ownership interest
Demographic characteristics	Individual characteristics	Binary questions, single-answer questions, multiple-answer questions	Current student status Highest level of education Immigrant status Ethnic origin[12]
	Household characteristics	Binary questions, textboxes, single-answer questions	Household size Number of people in household who are: licensed drivers, employed full time or part time, retired, children between the ages of 0 and 15 Number of years living at current residence Dwelling type Health problems or disabilities affecting mobility

[12] Valid responses are: (1) North American Indigenous origins, (2) Other North American origins, (3) European origins, (4) Caribbean origins, (5) Latin, Central, and South American origins, (6) African origins, (7) Asian origins, (8) Oceania origins.

2.2.2. Sample strategies

When designing FMCS, four key strategies were considered: (1) design an inclusive and representative survey, rather than focusing on specific population groups or mobility tool owners, (2) propose a novel approach, called user-centered use-case scenario, and substitute it for stated preference (SP), which is dominantly used in AV studies, to capture behavioral intentions towards adopting currently unavailable mobility tools, (3) use unique logical prompts to reduce respondent burden, and (4) design the survey based on a stratified random sampling approach. Inclusiveness of FMCS to capture a wide range of population segments throughout various geographical regions, along with assessing an extensive variety of existing and emerging mobility tools, were the main strategies considered within FMCS. A sample size of 5000 was the target.

Stated preference is a popular approach to elicit people's preferences towards emerging technologies. Respondents choose or rank their preferred travel mode by comparing the service/monetary attributes of each provided alternative (Louviere et al., 2000). Although the SP method attempts to elicit and predict prospective choices through a variety of scenarios, it is uncertain whether the expected alternatives will be chosen when available. The second key FMCS strategy proposed a novel approach substituting use-case scenarios for SP alternatives to elicit the prospective choices and preferences towards on-demand AVs (SAVs and PooledAVs). As such, in this survey, instead of designing choice sets based on alternatives, a series of use-case scenarios using a wide range of trip purposes, were designed to assess what circumstances people are inclined to use shared or pooled AVs. This approach is discussed later in this chapter.

The survey was programmed and administered by Savanta, in both English and French, Canada's official languages, using a unique logical prompt to capture a stratified random sample with a minimum response burden, which is the third key strategy taken throughout the survey design and data collection processes. In this regard, skip logic for specific questions was designed, which is discussed in more detail in section 2.7. Also, since greater confidence can be placed in the representativeness of probability samples, the survey was designed based on stratified random sampling using quotas for CMAs, gender, and age groups. Specifically, respondent quotas for each CMA were derived by the authors – that is, the 5000 sample target was shared proportionally among CMAs according to their 2020 populations. The sample also targeted approximately equal shares of self-identifying males and females as well as approximately equal shares of individuals from the following age groups: 18-35, 36-55, and 56-75.

2.2.3. Respondent eligibility and sampling control

Respondents less than 18 years old or older than 75 were excluded from the survey as were individuals residing outside the six CMAs. Besides the survey logic provided by the research team, technical criteria were applied by the panel operator to disqualify respondents. One such criterion, speeder disqualification, was based on completion time. Specifically, the panel operator of FMCS used a time-period measurement that disqualified questionnaires completed in less than one third of the median Length of Interview (LOI). Respondents suspected of clicking on any response were considered careless respondents and disqualified. The panel operator caught careless responses by checking for logical conflicts, checking for contradictory responses, and seeing whether respondents provided the same rating on many rows in a rating grid .

Based on the survey quota, an over quota disqualification criterion was assigned to a few respondents (127) who were then withdrawn by Savanta from the sample due to avoid oversizing or unbalancing the sample. The shares of other disqualified respondents are shown in Figure 1. In total, 10,279 individuals accessed the survey, where 9708 continued onto the next question meaning 94% consented and 6% declined to participate in the survey after reading the letter of consent. Of those consenting, 1871 respondents completed the survey partially and were removed automatically from the sample; 3279 respondents were disqualified to take part due to their age (under 18 or above 75), residing outside of targeted CMAs, short completion time, careless responses, and other unspecified terminates. Altogether, 3406 respondents were unqualified and were removed from the final sample by Savanta, leaving 5002 (2493 male and 2494 female) respondents. From the disqualified respondents, respondents residing outside the case study area had the largest share (70%), followed by careless respondents at 18%.

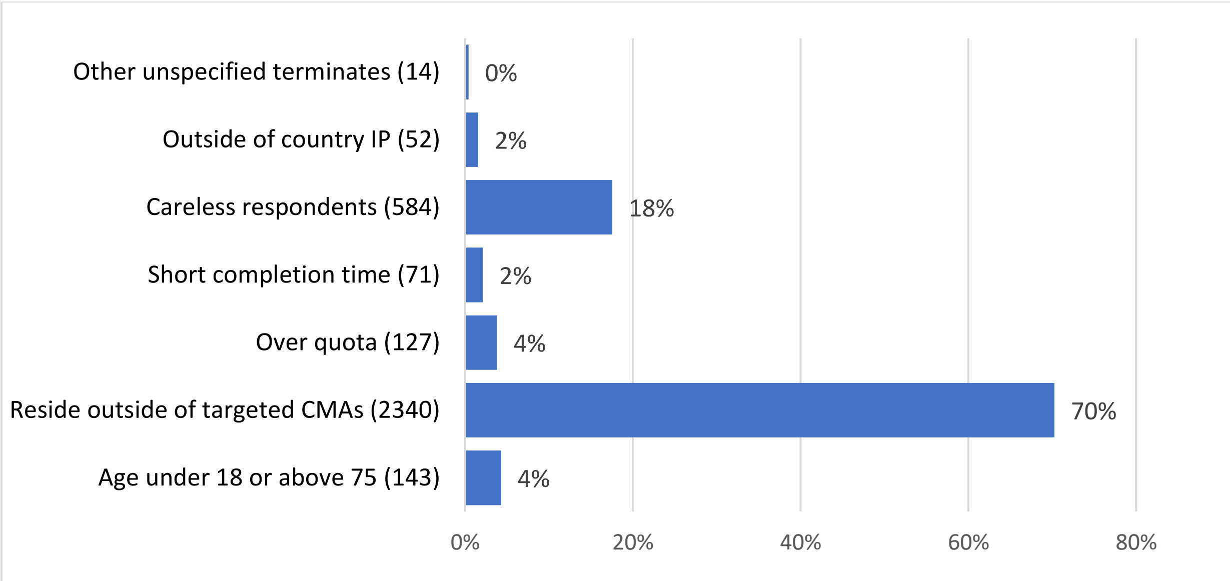


Figure 1. Respondents withdrawn from the survey according to disqualifying criteria. Percentages and counts (in parentheses) are shown.

2.2.4. Recruiting and incentives

Survey panels are a recent approach to collect travel data, providing a comprehensive and representative geographic sample in a short period of time (Abotalebi et al., 2018). Survey panels are facilitated by respondents' access to the internet, where questionnaires are completed by survey panelists for an incentive. Perhaps the most important salient feature of such panels, which are maintained by panel operators, is the specificity of the targeted respondents based on geography and/or socio-demographic features (Cunningham et al., 2019; Hardman et al., 2019; Nielsen & Haustein, 2018; Schweitzer et al., 2019; Sweet & Laidlaw, 2020).

After receiving research ethics approvals for FMCS through McMaster University and Toronto Metropolitan University, respondents were recruited from Savanta's panel list through emails and online channels. Respondents were awarded loyalty points by Savanta, where the number of points received depended on the length of their engagement with the survey. The average incentive was Can$1.10[13], where the incentive magnitude varied across population segments. For instance, since males are typically harder to recruit than females, the incentive for males was increased to achieve the target sample size. Also, older adults (56 years of age and over) prove harder to reach and their incentive was raised up to Can$6. In some CMAs such as Montréal, the recruitment rate was low and to achieve the target size, a higher incentive was considered. According to survey industry standards, respondents who abandoned the survey before completing it were not eligible to receive the incentive since they were aware of the topic, the estimated completion time, and the incentive amount before starting the survey.

[13] Canadian dollar.

2.2.5. Educating respondents

Respondents were educated in terms of AV technology and its service types but were not tested for their understanding of these currently unavailable mobility tools. Definitions of existing shared mobility services such as ride hailing, car sharing, and bike sharing, along with telework, were provided to respondents through mouse-over definitions in related questions. Before piloting the survey, it was tested using a convenience sample of respondents. Based on their feedback, it was decided to use the term "self-driving vehicle" rather than "automated vehicle" (AV) term, which is suggested by the Society of Automotive Engineers' taxonomy (SAE International, 2021), throughout the educational materials and related survey questions as the former term was better understood than the latter term. The definitions and applications of privately-owned AVs, SAVs, and PooledAVs were discussed in the survey before assessing AV adoption. Automated vehicles which were called self-driving vehicles defined as: "self-driving vehicles are equipped with technologies to navigate streets with no need for a human driver. Such vehicles allow drivers to do something else with their time rather than drive."

SAVs were introduced as "self-driving ride-hailing services." This service was defined as a taxi or Uber/Lyft service without a driver, where users would request a vehicle through an app on their smartphone. Also, it was pointed out that through an SAV service, they could use a ride either alone or share with someone they know. PooledAVs were called "pooled self-driving ride-hailing service" and were defined as a form of ride-hailing service, where passengers are willing to possibly share a ride with someone they do not know to save on the cost of travel. Respondents were informed that during their trips via PooledAVs, vehicles would pick up other passengers, which may cause detours and longer trips, yet lower the fare.

2.2.6. Representativeness of FMCS

Table 2 evaluates the representativeness of FMCS by comparing the sample to the distribution of individuals within the six studied CMAs (Toronto, Montréal, Vancouver, Ottawa-Gatineau, Calgary, and Hamilton) across a range of socio-demographic variables based the 2016 Canadian Census. Since FMCS was administered five years after 2016 Census, its representativeness may differ for some of the socio-demographic variables. Highly educated people are over-represented, as are people who rent their dwelling, speak English rather than French, and are in the age groups 25 to 44 and 55 to 64. Higher educated and young people are more likely to participate in survey panels because of their high level of familiarity with such an approach (Abotalebi et al., 2018). Similar insights are likely to apply for respondents not in the labor force and older adults, who are under-represented in FMCS.

Table 2. Select surveyed socio-demographic characteristics compared to 2016 Canadian census characteristics for studied CMAs

Variable	*Value*	*FMCS*		*Studied*
		Frequency	*Percentage*	*CMAs*
Age	18-24	522	10.4%	11.5%
	25-34	1049	21%	17.7%
	35-44	1021	20.4%	17.4%
	45-54	698	14%	18.5%
	55-64	1054	21.1%	16.1%
	65-74	658	13.2%	18.8
Preferred language	English	4376	87.5%	76.3%
	French[14]	626	12.5%	23.7%
Household size	1	1103	22.1%	27.9%
	2	1557	31.1%	30.7%
	3	1062	21.2%	16.2%
	4	788	15.8%	15.5%
	5 or more	317	9.8%	9.7%
Dwelling tenure	Owner	2910	58.2%	63.8%
	Renter	2092	41.8%	36.2%
Level of education	No certificate or diploma	156	3.1%	16.5%
	High school diploma or equivalency certificate	947	19%	26%
	Registered apprenticeship or other trades certificate or diploma	275	5.5%	7.8%
	College, CEGEP or other non-university certificate or diploma	1315	26.3%	18.4%
	Bachelor’s degree	1681	34%	20.5%
	Graduate degree (masters or doctorate)	553	11.5%	10.9%
Household income	Under $39,999	1096	22%	17.2%
	$40,000 to $99,999	2103	42%	40.2%
	$100,000 to $124,999	625	12.5%	12.4%
	$125,000 and above	815	16.3%	30.2%
	Unknown	363	7.2%	-
Employment status	Employed	3403	68%	61.8%
	Unemployed	494	10%	4.9%
	Not in the labor force	1105	22%	33.3%
Respondents in each CMA	Toronto	1928	38.5%	37.2%
	Vancouver	799	15.9%	15.4%
	Montréal	1222	24.4%	25.7%
	Ottawa-Gatineau	395	8%	8.3%
	Calgary	449	9%	8.7%
	Hamilton	209	4.2%	4.7%

Number of respondents in each CMA is sampled effectively, which is a direct outcome of the quotas imposed to achieve a stratified random sample.

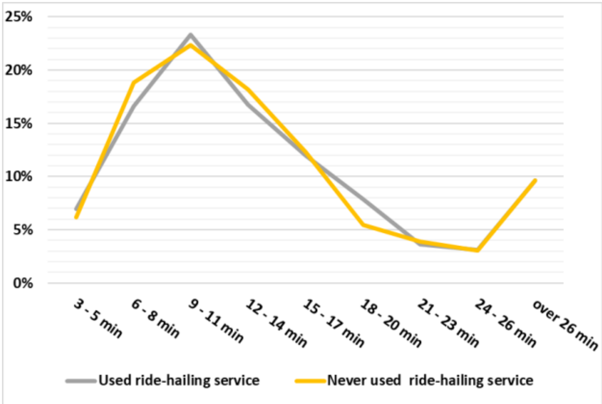
[14] Among respondents who chose French as their preferred language to complete FMCS, 84% (527) were from Montréal (Quebec) and remainder were distributed throughout the other CMAs.

2.2.7. Response burden

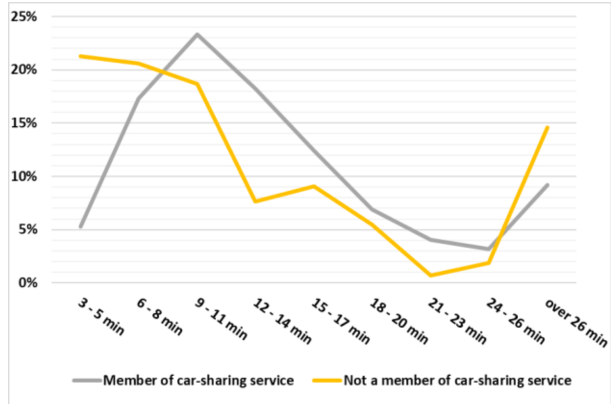
One of the challenges that researchers confront when designing a survey is gathering thorough and high-quality information about respondents while managing response burden (Stopher, 1998). Response burden is one of the main concerns of surveys since responding to some parts could be unfavorable and exhaustive to respondents (Abotalebi et al., 2018; Dubernet, and Axhausen, 2020). Using the methodology proposed by Schmid and Axhausen (2019) to calculate response burden, FMCS ranks in the 10th and 25th percentiles and receives a response burden between 150 and 230 points, where the range fluctuates due to the skip logic for particular questions. Questions concerning demographic and current travel behavior characteristics were added to the end of the survey as they are easier to answer, and therefore, may be less vulnerable to respondent fatigue.

When FMCS was designed, the survey completion time was considered as a rating scheme of response burden, and the normative goal was having the maximum length of the completion time less than 20 minutes, which is suggested for online surveys (Callegaro et al., 2015; Gunn, 2002). The average response time for FMCS was 16 min and 20 s, while the median of completion time was 12 min and 23 s. 77% of respondents completed the survey between 6 and 20 min, while only 16.6% of respondents completed the survey in over 20 min, and 6.6% completed it in under 6 min. The respondents who completed the survey in less than 6 min were mostly unemployed and/or non-members of shared mobility services.

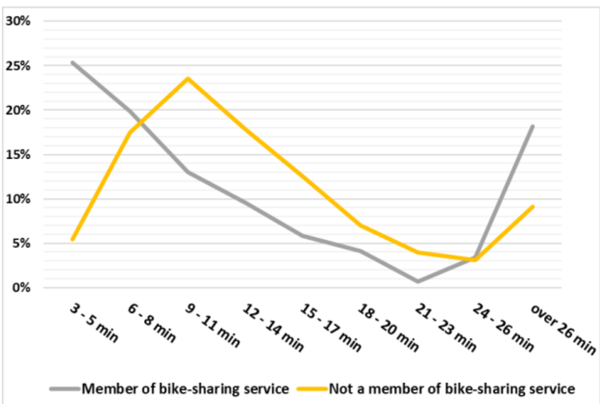
In FMCS, there were many conditional questions, based on the designed skip logic, which were only presented if respondents had a driver’s license, was a member of a car-sharing service, had used ride-hailing services, was a member of a bike-sharing services, was employed, or teleworked during the COVID-19 pandemic. Respondents not qualifying for these questions faced fewer questions to answer and as such completed the survey in less time. This is demonstrated by the completion time graphs shown in Figure 2. For instance, whereas the mean of completion time for those who were members of car-sharing or bike-sharing services was more than that of non-members (Figure 2b, Figure 2c), the mean of completion time for individuals who used ride-hailing services, was less than respondents who have not experienced such services (Figure 2a). Figure 2 indicates that questions concerning current travel behavior have added more response burden than questions associated with socio-demographic profiles such as holding a driver's license (Figure 2e) or employment status (Figure 2d). Regardless of the skip logic questions, Figure 2f proves that younger respondents completed the survey more quickly than older respondents. The mean completion time for respondents aged 56 to 75 was 24 min, while younger respondents (aged 18 to 35) mostly completed the survey in less than 19 min. This issue suggests that although questions associated with travel behavior have imposed a burden on all age groups, this burden is greater among older respondents. Appendix A presents detailed descriptive statistics of completion times based on these characteristics. Specifically, the mean, median, 25% percentile, and 75% percentile of survey completion times are derived according to ride-hailing use, car-sharing use, bike-sharing use, employment status, driver's license status, and age groups.



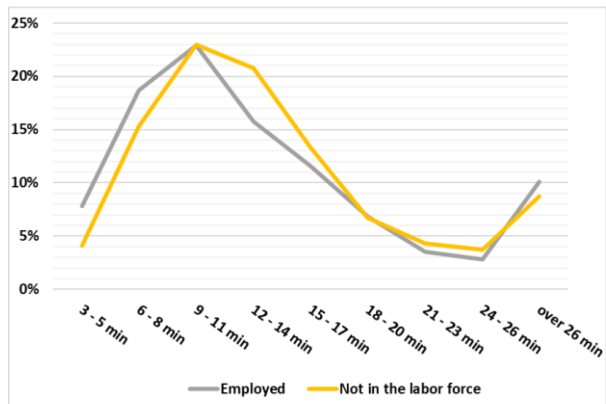
(a) Respondents who have used ride-hailing services vs those who have never used ride-hailing services



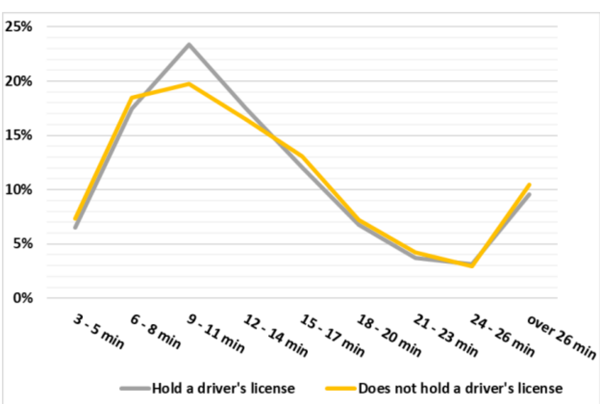
(b) Car-sharing services' members vs non-members



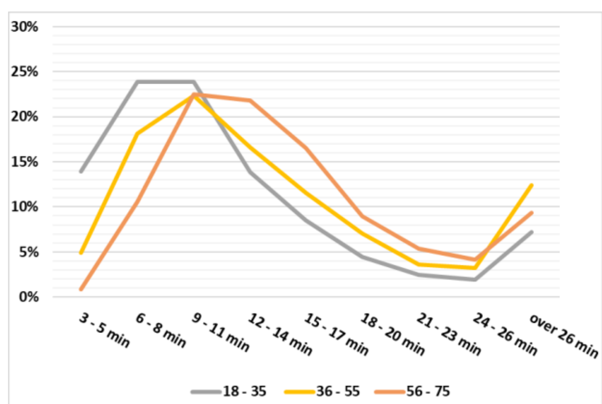
(c) Bike-sharing services' members vs non-members



(d) Employed vs not in the labor force



(e) Hold a driver's license vs does not hold a driver's license



(f) Age groups

Figure 2. Examples of survey completion times by attribute.

2.3. Novel aspects the survey with an emphasis on automated vehicles

2.3.1. Survey alternative, AV types, and use-case scenarios

As FMCS's research mandate was to focus on all types of fully automated vehicles considered in levels 4 and 5 (SAE International, 2021), the AV alternatives comprised: private AVs, shared AVs, pooled AVs, and automated small shuttle buses and regular-size or articulated buses. Aside from the types of alternatives, another important decision was the interpretation of alternatives to assure that respondents understood differences between each AV type and their applications. Previous AV studies have mostly used SP surveys to assess AV adoption (Becker, 2020; Haboucha et al., 2017; Krueger et al., 2016). However, based on insights from the literature (Körber et al., 2018; Nordhoff et al., 2016; Rahman et al., 2017; Xu et al., 2018), it was decided, for FMCS, to design a novel and new approach involving user-centered use-case scenarios. In this approach, the behavioral intention toward using on-demand AVs was not assessed through preferring such modes over other modes, but instead through recognizing situations and trip purposes where respondents might demand SAVs and PooledAVs.

Engaging use-case scenarios defined by trip purposes is an approach to assess behavioral intention to use new travel modes. Although this approach has been applied in a few AV studies (Bjørner, 2019; Cyganski et al., 2015; Wachenfeld et al., 2016; Nielsen & Haustein, 2018; Payre et al., 2014), they were only considered as technical and systematic aspects based on the level of AVs. For instance, Cyganski et al. (2015) investigated use cases of automated vehicles and distinguished four technical scenarios including highway pilot, valet parking, fully automated vehicles, and on-demand vehicles. Likewise, Wachenfeld et al. (2016) used the same technical categories to segment the use cases of AVs. Nevertheless, a few studies have underlined use cases based on trip purposes in examining behavioral intention to use PAVs. For instance, Nielsen &

Haustein, (2018) applied use cases for PAVs as an attribute to segment respondents into homogenous groups. Also, Payre et al., (2014) and Bjørner, (2019) underpinned the use of PAVs in a few conditions like highway driving and parking the car, which could be counted as technical use cases of PAVs. Hence, to the best of our knowledge, no investigation has considered use cases of SAVs or PooledAVs based on trip purposes as a scenario design method.

The user-centered use cases employed in FMCS disclosed the potential advantages and use of shared and pooled AVs. Five categories of prospective use cases for on-demand AVs came were identified: (1) "first mile/last mile transit," (2) "picking up someone or something," (3) "daily trips," (4) "occasional trips," and (5) "driving milage." However, to manage the burden on respondents, the use cases were encapsulated into two major and inclusive categories: "regular basis trips," and "occasional trips." Regular basis trips category consisted of "trips to/from work/school" and "trips other than work/school" such as trips to/from a store, trips to/from a friend's house, or trips to/from a restaurant or a bar. The occasional trips were considered as special situations where the use cases contained "trips for special events or performances" (e.g., hockey games, concerts, etc.) and "trips to/from an airport."

2.3.2. Selection of affective motivations

The motivations influencing behavioral intention to use currently unavailable mobility tools such as AVs, include two subsets (Anable & Gatersleben, 2005): affective (attitudinal) and instrumental (monetary) factors. Anable & Gatersleben (2005) described affective motivations as the feelings triggered by travelling, such as stress, excitement, pleasure, boredom, and control, whereas instrumental factors are referred as monetary or service-based attributes. Most of the measured attributes in FMCS were affective factors since AVs are yet unprecedented travel modes and factors influencing behavioral intention to use them are still speculative. However, this issue does not lead to overlook the importance of instrumental factors. As such, hourly travel cost and purchase cost were considered as instrumental (monetary) attributes in assessing the adoption of PAVs.

An extended model of TPB was developed and applied when designing the survey, where the components comprise behavioral intention (BI), perceived behavioral control (PBC), attitude towards a behavior (ATB), subjective norms (SN), trust, affinity towards technology, eco-friendliness, knowledge, sensation seeking, driving enthusiasm, multitasking, privacy concerns, and car ownership interest. Unlike previous studies, in FMCS implicit statements embedding the affective motivations to understand respondents' perceptions, inclinations, and preferences towards new/emerging mobility tools like AVs and shared mobility services, were used. For instance, in FMCS statements like "people important to me encourage me to use up-to-date devices" or "seeing people who are important to me using public transit makes me also want to use public transit" were used to assess subjective norms. However, behavioral intentions towards AVs were excluded from this approach since it needed to be asked explicitly and directly. Additionally, ATB needed to be asked directly since it corroborates whether the behavior is favorable to respondents. However, the favourability of using currently unavailable mobility tools like AVs will not be revealed precisely through direct statements, since most respondents have not experienced even a semi-automated vehicle (Kaye et al., 2020). As such, ATB was also treated as a latent affective motivation in FMCS. To measure each affective motivation, at least two statements were considered, while for most of them three or more statements were applied to increase the degree of accuracy in measuring factors (Table 3).

Table 3. Measurement items of attribute constructs

Constructs	Indices	Measuring items	Adapted from
Behavioral intention			
PAVs	BI-P-1	The likelihood of being one of the first people to buy a self-driving vehicle.	Hardman, et al. (2019)
	BI-P-2	The likelihood of eventually buying a self-driving vehicle, but not until they are in common use.	Hardman, et al. (2019)
Automated buses	BI-B-1	The likelihood that you would be willing to ride a small shuttle bus if it was self-driving without a driver.	Olsen, et al. (2018)
	BI-B-2	The likelihood that you would be willing to ride a regular-size or articulated bus if it was self-driving without a driver	Olsen, et al. (2018)
SAVs	BI-S-1	Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for work or school trips.	-
	BI-S-2	Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for trips other than work or school (e.g., trips to/from a store, trips to/from a friend’s house, etc.).	-
	BI-S-3	Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for special events or performances (e.g., hockey games, concerts, etc.).	-
	BI-S-4	Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for trips to/from an airport.	-
Pooled AVs	BI-Pd-1	Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for work or school trips.	-
	BI-Pd-2	Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for trips other than work or school (e.g., trips to/from a store, trips to/from a friend’s house, etc.).	-
	BI-Pd-3	Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for a special events or performances (e.g., hockey games, concerts, etc.).	-
	BI-Pd-4	Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for trips to/from an airport.	-
Affinity towards technology	AFT-1	It is important to keep up with the latest trends in new automation technology.	Chen and Yan (2019)
	AFT-2	I like to have the latest technologies in my car.	Panagiotopoulos and Dimitrakopoulos (2018)
	AFT-3	It is enough for me that a technical system works; I don't care how or why.	-
	AFT-4	When it comes to adopting new technology, are you typically an early adopter, late adopter, or laggard	Kockelman, et al. (2016) Hardman, et al. (2019)
Driving enthusiasm	DE-1	Driving a car is something I enjoy	Kockelman, et al. (2016)
	DE-2	I do not like driving during rush hour.	-
	DE-3	I do not like driving in busy or congested areas.	Asgari & Jin, (2019)

Constructs	Indices	Measuring items	Adapted from
Eco-friendliness	EF-1	Whenever possible, I prefer to walk or bicycle rather than drive.	Clark & Scott, (2013)
	EF-2	Whenever possible, I prefer to take transit rather than drive.	Clark & Scott, (2013)
	EF-3	I try to limit my driving to reduce air pollution.	Clark & Scott, (2013)
Car ownership interest	CO-1	Owing a car is a symbol of success.	Hardman, et al. (2019)
	CO-2	I can complete my daily tasks without a car.	Cyganski,et al. (2015)
Subjective norms	SN-1	People important to me encourage me to use up-to-date devices.	-
	SN-2	Seeing people who are important to me using public transit makes me also want to use public transit.	Chen and Yan (2019)
Perceived behavioral control	PBC-1	I enjoy making my own decisions.	-
	PBC-2	I would rather someone else be the leader on a group project.	-
	PBC-3	Given enough time, I can learn and master high-tech devices.	Klöckner and Friedrichsmeier (2011); Buckley, et al. (2018)
Trust	T-1	I believe online services are committed to protecting my personal information.	-
	T-2	Popular tech companies such as Google, Tesla, and Microsoft are reliable.	-
	T-3	Overall, I trust new emerging technologies.	Choi and Ji (2015)
Knowledge	K-1	I know a lot about self-driving vehicles.	Koppel et al. (2021)
	K-2	Having ample knowledge before purchasing a car is necessary for negotiating a good price.	-
	K-3	It is necessary to learn about new technology before adopting it.	-
Privacy concerns	P-1	I am concerned about privacy when purchasing something online or through an app.	Featherman and Pavlou (2003)
	P-2	Popular tech companies such as Google and Facebook protect my personal data.	-
	P-3	I am concerned that hackers may take control of my phone, tablet, or computer.	Featherman & Pavlou, (2003); Lee et al. (2019)
Multitasking	MT-1	The only good thing about traveling is arriving at the destination.	Hardman, et al. (2019)
	MT-2	Travel time is generally wasted time	Hardman, et al. (2019)
	MT-3	Usually, I use my travel time productively.	Hardman, et al. (2019)
Sensation seeking	SS-1	I like new and exciting experiences even if they are a little frightening or unconventional.	Zuckerman et al. (1978)
	SS-2	I like to explore strange places or parts of town by myself even if it means getting lost.	Zuckerman et al. (1978)
	SS-3	I would like to try parachute jumping.	Zuckerman et al. (1978)

2.3.3. Emphasis on detailed geography and location

Geography played a significant role when conceptualizing FMCS. Six-digit postal codes for residence and workplace were collected for respondents. Such precise geographic information is necessary to identify the spatial context in which respondents would assess shared mobility services, telework, and behavioral intention towards using AVs. With six-digit postal codes, locational considerations are possible such as: (1) identifying whether built-environment factors affect current ownership and use of travel modes or currently unavailable mobility tools, (2) optimizing the suggested locations for shared mobility services in an effort to increase their availability, (2) identifying places with high demand for shared or pooled AVs, (3) assessing the impact of telework on local transportation networks, and (4) evaluating the impacts of adoption of new mobility modes on daily activities and travel behavior in business centers based on the information derived from workplace locations. Such analyses can be conducted for small census geographies, such as dissemination areas, using the detailed location information drawn from FMCS.

2.3.4. Consideration of the COVID19 pandemic on travel behavior and telework

Another novel aspect of FMCS was collecting travel behavior information with respect to the COVID-19 pandemic on modes acutely affected by the pandemic – notably, ride hailing and public transit. For ride hailing, information on usage and travel modes preferred as substitutes was solicited for two periods: pre-pandemic (February 2020) and post-pandemic (October to November 2021, when the survey was completed). For public transit, in addition to the pre- and post-periods, such information was also solicited for the period encompassing the pandemic (March 2020 to July 2021). Bike share membership was also asked pre- and post-pandemic. Further, for bike share and public transit, usage was distinguished by broad purpose (e.g., work/school).

Finally, telework behavior was assessed for three periods: pre-pandemic (February 2020), during-pandemic (March 2020 to July 2021), and post-pandemic (October to November 2021). In addition to telework frequency for each period, questions were asked about the nature of the telework arrangement – namely, whether respondents had a choice in whether they teleworked or not – and respondents' ideal amount of telework. Finally, the effect of telework on changing distances from home to usual workplace was sought through the survey.

2.4. Conclusion

This paper has presented steps for designing a future mobility survey instrument, called FMCS, with an emphasis on automated vehicles. FMCS has followed four main objectives: (1) respondents' behavioral intentions to adopt AVs, (2) respondents' use of shared forms of mobility services, (3) respondents' recent experience with telework and their preferences towards it, and (4) respondents' travel behavior across the COVID-19 pandemic for certain modes. The survey was developed from spring to fall of 2021 and collected 5,002 observations between October and November 2021 for six mid-to-large CMAs: Toronto, Montréal, Vancouver, Ottawa-Gatineau, Calgary, and Hamilton. FMCS also collected sociodemographic characteristics and geographical information of respondents, notably workplace and residential locations by 6-digit postal codes. This information enables future research on detailed spatial variation of preferences towards mobility tools.

There were several novel aspects in FMCS. First, to the best of our knowledge this is the first survey of its kind assessing all types of AVs at a nationwide scale in Canada with a large sample size. Using FMCS, researchers could explore Canadian preferences towards any type of AV. Second, the implementation of questions appraising behavioral intention towards AVs were sensitive to the AV types and prospective consumers' demands. For instance, to assess people's preferences towards using on-demand AVs (SAVs and PooledAVs), a series of user-centered use-case scenarios were designed, whereas for PAVs a few monetary questions were asked to assess willingness to pay. To our knowledge, FMCS is the first survey to use such user-centered scenarios in evaluating respondents' inclinations towards using on-demand AVs. Attitudinal questions exploring the affective motivations, which could influence any travel behavior changes and behavioral intention towards emerging mobility modes – namely, SAVs and PooledAVs – were the other novel facet of FMCS. Fourth, the emphasis on detailed geography using six-digit postal codes of residences and workplaces helps identify the spatial context of potential markets for shared mobility services, telework, and any type of AV. This detailed level of geography could be beneficial in short-term and long-term transportation planning and decision making in (1) identifying the places with high demand for any type of shared or public travel mode, and (2) assessing the impact of new mobility modes on local transportation networks. Finally, exploring the implications of the COVID-19 pandemic on current travel behavior and preferences towards telework at a nationwide scale, was another innovative aspect of FMCS.

Researchers conducting surveys on travel behavior changes can benefit from the novel aspects of FMCS. By acknowledging the impact of new mobility tools, telework, and unforeseen events such as the COVID-19 pandemic, future researchers can build upon the insights gained from this study. Moreover, the use of a similar survey in different places and at different times could provide a means of achieving external validity and comparing results. In this way, FMCS offers valuable potential for advancing the understanding of travel behavior changes and their implications.

Lastly, it is important to note that FMCS's development and design process helped our research team learn the procedure of an inclusive and innovative survey instrument, which is a time-consuming process and demands diligent and several iterations. Obtaining the optimum information in a concise and coherent format, while collecting data from respondents, was one of the other lessons learned during the survey development. Additionally, the positive effect of seeking a range of affective motivations implicitly, was a unique experience for the research team which extended our point of view over the impact of psychological aspects on such transportation surveys.

Pending research ethics approval, an anonymized version of the data collected through the Future Mobility in Canada Survey should be available in January 2027. Inquiries to access the data after this date should be directed to the corresponding author of this study. The FMCS questionnaire, excluding skip logic, is found in Appendix B.

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Chapter 3

Do Use Cases Matter When Considering Whether to Use Shared Automated Vehicles? Findings from Major Canadian Metropolitan Areas

3.1. Introduction

Among the existing theoretical frameworks, TPB has been validated and is among the most tested in SAV research (Kaye et al., 2020). Besides constructs explicitly embedded in adoption theories, the existing literature suggests that other affective motivations such as green lifestyle and eco-friendliness (Menon et al., 2019; Haboucha et al., 2017; Potoglou et al., 2020), and high level of trust (Najm et al. , 2006; Ghazizadeh et al., 2012; Nordhoff et al., 2016b; Xu et al., 2018; Buckley et al., 2018; Choi & Ji, 2015) may be robust factors influencing SAV demand. While many studies have supplemented AV adoption models with additional affective motivations, these constructs have not yet been applied to specific use cases relating to SAVs. In other words, studies have not yet explored whether affective motivations are specific to an AV technology and business model (a technology-centered approach), or whether those motivations relate more closely to how and for what purposes that technology is used (a user-centered approach). This study aims to address this shortcoming.

In past studies, intention to use SAVs is usually measured through online surveys, where direct questions or a stated preferences (SP) approach are applied (Haboucha et al., 2017; Krueger et al., 2016; Rahimi et al., 2020; Zhou et al., 2020). However, using a SP approach to compare SAVs as an unobserved travel mode with conventional existing modes might not reflect the real choices and intentions towards using SAVs (Nordhoff et al., 2017; Rahman et al., 2017; Körber et al., 2018; and Xu et al., 2018) since many people are not yet completely aware of the service attributes and features of this emerging travel mode (Panagiotopoulos & Dimitrakopoulos, 2018). Additionally, since SAVs are not yet available within North America, using observed preference data is not feasible.

Considering user experiences and travel purposes is a critical step towards better understanding how and when SAVs may be adopted. This study uses trip purposes as the prospective SAV user-centered use cases to better understand adoption and attitudes towards SAVs. To the best of the authors' knowledge, this user-centered use case approach, as applied to SAVs, is new (Bjørner, 2019; Cyganski et al., 2015; Maurer et al., 2016; Nielsen & Haustein, 2018; Payre et al., 2014). In this respect, this study has three objectives: (a) to propose and validate a theoretical model by extending the original TPB, alongside exploring the affective motivations influencing intention to use SAVs; (b) to use the user-centered use case approach to distinguish between "*use-case-variant*"[15] and "*use-case-invariant*"[16] individuals; and (c) based on the proposed theoretical framework and user-centered use case approach, to investigate Canadians' intentions to adopt SAVs. Toward this end, this study uses data from an online survey (n = 5,002) of adults (18 to 75 years old) conducted in October and November 2021 for six major Canadian metropolitan areas: Toronto, Vancouver, Ottawa, Montreal, Calgary, and Hamilton.

3.2. Literature Review

While studies of new technology adoption have used various approaches, developing a research design within existing theoretical frameworks is critical to strengthen external validity.

[15] Use-case-variant individuals are those who differentiate between use-case scenarios by choosing different outcomes along a five-point Likert scale, for two or more questions related to behavioral intention towards using SAVs.
[16] Use-case-invariant individuals are those who do not differentiate between use cases; that is, they choose the same option along the five-point Likert scale for all questions related to behavioral intention towards using SAVs.

This study anchors SAV research explicitly within the Theory of Planned Behavior (TPB). This sub-focus is contextualized within a review of previous studies relating AV adoption with affective motivations (including trust and eco-friendliness), as well as socio-demographic and travel behavior characteristics. Notably, studies broadly investigating AV adoption have provided significant insights on SAV adoption (as one type of AV service). Therefore, while findings on SAV adoption are prioritized in the literature review, many reviewed studies reflect broader research on AV adoption. Finally, a concise review on currently available research on use-case scenarios is discussed of which this study makes new contributions.

The emergence of new mobility services, such as on-demand ride hailing, automated vehicles, and the combination of on-demand ride hailing and automated vehicles (SAVs) may alter future travel behavior significantly (Axsen & Sovacool, 2019; Urry, 2004). Previous studies on use of new technologies, such as AVs have employed various theoretical models which include both instrumental and affective motivations. Among these, TPB has been among the most widely applied and most reliably validated (Buckley et al., 2018; Dai et al., 2021; Rahman et al., 2017).

TPB is an expanded version of the *Theory of Reasoned Action* (TRA), which was developed by Fishbein and Ajzen (1975). TPB contends that behavioral intention (BI) determines real behavior and acceptability (Fishbein & Ajzen, 1980). TPB distinguishes between three types of beliefs containing behavioral, normative, and control beliefs, and includes three components of intention to perform a behavior: *attitude towards a behavior*[17] (ATB), *subjective norms*[18] (SN), and *perceived behavioral control*[19] (PBC) (Ajzen, 1991). This theory posits that positive attitude

[17] "The degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" (Ajzen, 1991, p. 188).
[18] "The perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991, p. 188).
[19] "The perceived ease or difficulty of performing the behavior and it is assumed to reflect past experience as well as anticipated impediments and obstacles" (Ajzen, 1991, p. 188).

and favorable normative and volition control beliefs will lead to a positive intention, leading one to be more likely to carry out a behavior (Ajzen, 1991). According to Ajzen (2006), *behavioral beliefs* result in a favorable or unfavorable attitude toward the behavior, *normative beliefs* produce perceived social pressure or subjective norm, and *control beliefs* induce perceived behavioral control or self-efficacy. Within the construct of ATB, there are multiple sub-constructs, including expectations of safety, privacy, and energy saving benefits (Buckley et al., 2018; Woisetschläger, 2016). As such, ATB is a perception based on experiences and emotions resulting through a behavior. Most studies applying TPB to the study of AVs have employed the standard or direct belief assessments evaluated through direct questions to estimate the psychological constructs of TPB - ATB, SN, and PBC (Buckley et al., 2018; Rahman et al., 2017). However, the practice of examining affective factors through indirect beliefs and questions could be a promising research direction in understanding the nuances and key motivations towards using new mobility services (Kaye et al., 2020).

Several studies have examined the intention to use AVs through the theoretical constructs of TPB (Buckley et al., 2018; Dai et al., 2021; Kaye, Lewis, Buckley, et al., 2020; Kaye, Lewis, Forward, et al., 2020; Payre et al., 2014; Rahman et al., 2017; Yuen et al., 2020). For example, Payre et al. (2014) focused on intent to use AVs, where they stated that ATB is a strong positive predictor of BI. Rahman et al. (2017) compared several behavioral models, including TAM, TPB, and UTAUT 1, to assess BI to use *Advanced Driver Assistance Systems* (ADAS). According to findings, TAM and TPB can capture more than 80% of the variation in people's adoption of new travel modes. TAM followed by TPB have the strongest effects on BI through attitudes, while the role of subjective norms is more modest (Rahman et al., 2017). Buckley et al. (2018) confirm the findings of Rahman et al. (2017), leading to further evidence that ATB, SN, and PBC are significant predictors of intention to use AVs. Furthermore, Yuen et al. (2020) investigated the factors influencing adoption of SAV while comparing two theoretical models, TPB and UTAUT 2, concluding that PBC was the single most significant predictor, followed by ATB and SN.

Numerous studies found that alongside the acceptance theories' components, additional affective factors, such as trust, can influence BI to use private and shared AVs (Buckley et al., 2018; Choi & Ji, 2015; Ghazizadeh et al., 2012; Kaye et al., 2020; Najm et al., 2006; Nordhoff et al., 2021; Panagiotopoulos & Dimitrakopoulos, 2018). Although it is acknowledged that trust in automation is a multi-faceted concept, based on Shariff's et al. (2017) definition, trust in AVs is defined as the belief that using AVs may make people vulnerable, leading the level of trust to shape AV adoption. Choi & Ji (2015) examined user's adoption aspects of AVs assessing the effect of trust on this adoption by using an online survey. They found that trust could positively affect BI to use AVs beyond perceived usefulness and perceived risk. Further, Nordhoff et al., (2016b) demonstrated that an elevated level of trust toward automated vehicles is a requirement for acceptance of this technology. Xu et al. (2018) and Panagiotopoulos & Dimitrakopoulos (2018) added trust as a supporting component to TAM, where both studies disclosed that trust is an essential factor for explaining intention to ride in an AV. Buckley et al. (2018) and Kaye et al. (2020) likewise examined trust alongside the TPB components, concluding that trust contributed to explain a large portion of the variance of SAV adoption. Hence, measures of trust significantly predict intention to use AVs above and beyond TPB components. Meanwhile, people having a positive attitude towards new technologies are more likely to adopt them earlier than others. Many studies have reported that affinity for new technology (AFT) is associated robustly with technology adoption and intention to use AVs (Kaur & Rampersad, 2018; Lavieri et al., 2017; Sener et al., 2018; Zmud et al., 2016). As such, early adopters of new technologies in general are expected to be early adopters of AVs. The eco-friendliness feature of SAVs could be considered as one of the most significant benefits of this emerging technology (Howard & Dai, 2014); however, only a few studies have focused on this factor (Gkartzonikas & Gkritza, 2019; Haboucha et al., 2017; Lavieri et al., 2017; Menon et al., 2019; Potoglou et al., 2020; Spurlock et al., 2019). Some studies have demonstrated that green lifestyles and eco-friendliness are robust factors influencing SAV demand. For instance, Menon et al. (2019) reported that environmental awareness is one of the most significant reasons people consider when relinquishing their own vehicles and considering a future switch to SAVs. Haboucha et al., (2017) also found eco-friendliness to be an important latent factor which positively affected choosing AVs as well as other mobility modes. Consistent with the results of these two studies, Lavieri et al. (2017) concluded that a green lifestyle was associated with choosing a sustainable transportation mode, leading to both direct and indirect impacts of green lifestyles on AV adoption. Similarly, Potoglou et al. (2020) found that self-reporting pro-environmental identity was associated with higher willingness to pay for autonomous cars. Only two studies, Spurlock et al. (2019) and Gkartzonikas & Gkritza's (2019), found evidence that green lifestyles and attitudes were not consistent with AV adoption.

Studies on the links between socioeconomic characteristics and AV adoption have generated some consistent findings but significant disagreement in the literature. While males are consistently more likely to adopt AVs (Hulse et al., 2018; Kyriakidis et al., 2015; Nordhoff et al., 2016), there were some differences within the outcomes regarding the impact of age on AV adoption. For instance, Bansal et al. (2016) reported a lower willingness to pay for AVs across senior participants compared to young males. The results of Krueger's et al. (2016) study is also in line with this study, where individuals between 24 and 29 years old were found to be more willing to use SAVs. In contrast, Fagnant & Kockelman (2015) indicated that SAVs may be more appealing among elderly travelers. Numerous studies have concluded that employed people with higher incomes and more education are more likely to use this emerging travel mode (Bansal et al., 2016; Lavieri et al., 2017; Nordhoff et al., 2016; Sweet & Laidlaw, 2020), while there are studies showing that neither employment status nor educational level and household income have significant influences on intention to use AVs in the future (Cyganski et al., 2015). A few studies have found physical disabilities and conditions prohibiting people from driving to be significant factors in intention to use AVs (Sener et al., 2019; Sweet & Laidlaw, 2020; Zmud et al., 2016). Another characteristic that was found to be inconsistent across previous studies is holding a valid driver's license. Bansal & Kockelman, (2018) concluded that licensed drivers associate lower willingness-to-pay (WTP) values and as a result, these people are estimated to use SAVs less frequently than people without a driver's license. In line with their results, Sener et al. (2019) reported an extensive difference in intention to use AVs between people holding a driver's license and those who are without a driver's license, where respondents who do not hold a driver's license are more likely to use AVs in the future. However, findings from existing studies do not always support the importance of sociodemographic effects, and the results of assorted studies are often inconsistent (Schoettle & Sivak, 2014; Sweet & Laidlaw, 2020; Zmud et al., 2016).

Travel characteristics are also identified as predictors of AV adoption. Sener et al. (2018) reported a higher level of intent to use AVs among current users of ride hailing services compared to non-users of such services. Additionally, they found that intention to use was highest among long-term users of ride hailing services. Sener et al. (2019) investigated the impact of travel behavior on intention to use AVs, where they reported a higher intent to use among vehicle passengers and public transit users. In a nutshell, alongside the influence of affective motivations on intention to adopt AVs, sociodemographic and travel characteristics matter in adopting new mobility tools, which are considered within the current study's research framework.

Most of the studies focused on SAV adoption or AV adoption in general have conducted online surveys to assess intention to use such unobserved mobility tools (Buckley et al., 2018; Haboucha et al., 2017; Krueger et al., 2016; Rahimi et al., 2020; Zhou et al., 2020). These studies have mostly measured intention to adopt AVs through either direct questions or through a stated preference (SP) aproach where respondents rank their most preferred options by comparing this unprecedented alternative to existing travel modes (Buckley et al., 2018; Haboucha et al., 2017; Krueger et al., 2016; Rahimi et al., 2020; Zhou et al., 2020). Engaging SAV us-case scenarios defined by trip purposes is a potential approach to assess intention to use new travel modes. However, this method has been applied only in a few studies where use cases were simply considered as technical and systematic aspects based on the level of AVs, or trip purposes were considered for privately-owned AVs (Bjørner, 2019; Cyganski et al., 2015; Wachenfeld et al., 2016; Nielsen & Haustein, 2018; Payre et al., 2014). For instance, Cyganski et al. (2015) investigated use cases of AVs and distinguished four technical scenarios including highway pilot, valet parking, fully automated vehicles, and on-demand vehicles. Likewise, Wachenfeld et al. (2016) used the same technical categories to segment the use cases of AVs. Nevertheless, a few studies have underlined use cases based on trip purposes to measure intention to use privately-owned AVs (PAVs). For instance, Nielsen and Haustein (2018) applied trip purpose use cases for PAVs as an attribute to segment participants into homogenous groups. Also, Payre et al. (2014) and Bjørner (2019) underpinned the usage of PAVs under a few conditions and implied that the preferred use cases of PAVs are highway, driving in congested areas, as well as parking the car, which could be considered as one of the technical aspects of use cases. Hence, to the best of our knowledge, no investigation has been undertaken on use cases of SAV based on trip purposes and travel characteristics as a scenario design method .

3.3. Methodology

3.3.1. Research Framework

To examine users' adoption of SAVs, an extended TPB model which considers affective motivations was developed based on previous studies of SAV adoption. In total, six affective motivations are undertaken within this study's research framework: *attitude towards a behavior* (ATB), *perceived behavioral control* (PBC), *subjective norms* (SN), trust, and eco-friendliness, as intervening variables, and intention to adopt SAVs, which is treated as the dependent variable. In addition to the affective motivations and constructs explicitly embedded in TPB, sociodemographic characteristics and current travel behavior variables are included as instrumental model controls (Figure 3).

Each attitudinal component was measured as a latent variable using multiple items and was estimated with a factor analysis where several items were adapted from extant literature to improve the content validity (Table 4). ATB was measured through indirect items where attitude towards new technologies and travel modes was explicitly embedded to identify the favorability of using SAVs. The dependent variable, behavioral intent to use SAVs, was measured through a series of use-case scenarios. All items of constructs were measured on a 5-point Likert scale from 1 (strongly disagree/very unlikely) to 5 (strongly agree/very likely).

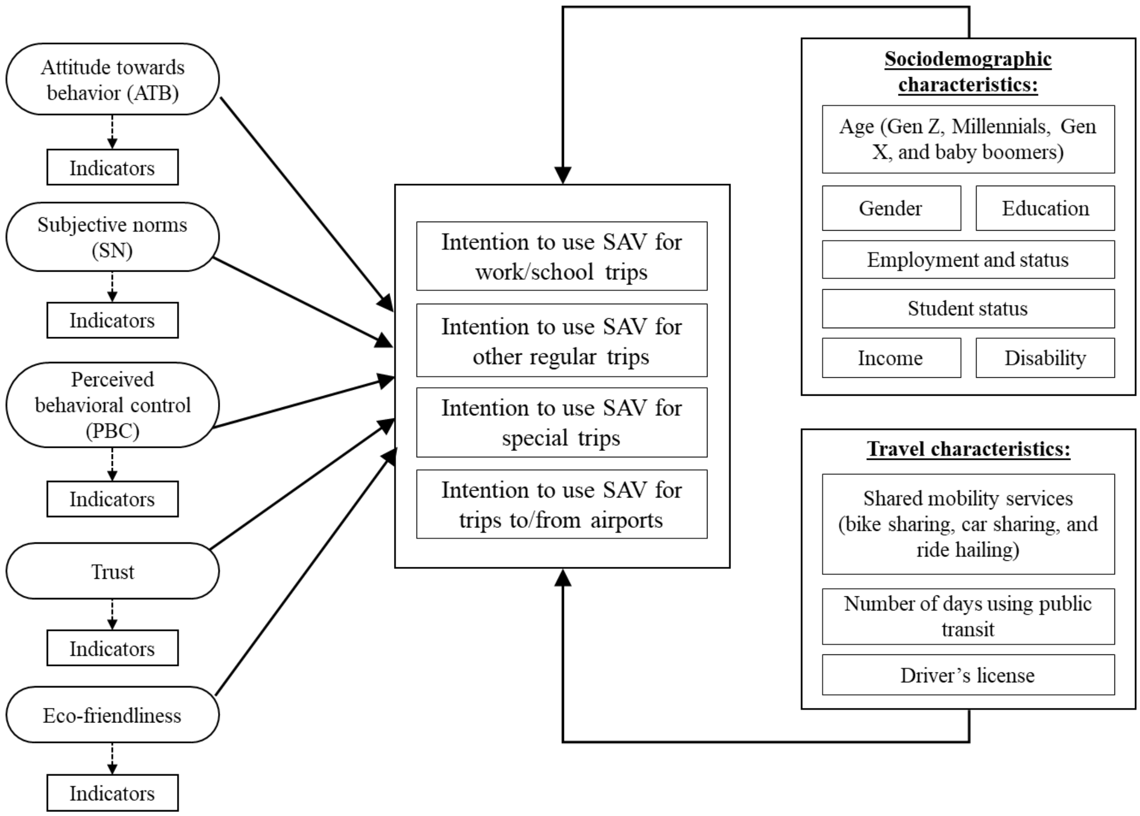

Figure 3. TPB-extended research framework employed within this study.

Table 4. Components and their measurement items used within the proposed research.

Constructs	Indices	Measuring items	Adapted from
Intention to use SAV			
Work/school trips	IU-1	Use a shared self-driving, ride hailing service (where you ride alone or with someone you know) for work or school trips.	-
Other regular trips	IU-2	Use a shared self-driving, ride hailing service (where you ride alone or with someone you know) for trips other than work or school (e.g., trips to/from a store, trips to/from a friend's house, etc.).	-
Special trips	IU-3	Use a shared self-driving, ride hailing service (where you ride alone or with someone you know) for special events or performances (e.g., hockey games, concerts, etc.).	-
Airport trips	IU-4	Use a shared self-driving, ride hailing service (where you ride alone or with someone you know) for trips to/from an airport.	-
Eco-friendliness	EF-1	Whenever possible, I prefer to walk or bicycle rather than drive.	(Clark & Scott, 2013)
	EF-2	Whenever possible, I prefer to take transit rather than drive.	(Clark & Scott, 2013)
	EF-3	I try to limit my driving to reduce air pollution.	(Clark & Scott, 2013)
Trust	T-1	I believe online services are committed to protecting my personal information.	-
	T-2	Popular tech companies such as Google, Tesla, and Microsoft are reliable.	-
	T-3	Overall, I trust new emerging technologies.	Choi and Ji (2015)
Attitude towards a behavior (ATB)	ATB-1	It is important to keep up with the latest trends in new automation technology.	Chen and Yan (2019)
	ATB-2	I like to have the latest technologies in my car.	Panagiotopoulos and Dimitrakopoulos (2018)
	ATB-3	When it comes to adopting new technology, are you typically an early adopter, late adopter, or laggard?	Kockelman, et al. (2016) Hardman, et al. (2019)
Subjective norms	SN-1	People important to me encourage me to use up-to-date devices.	-
	SN-2	Seeing people who are important to me using public transit makes me also want to use public transit.	Chen and Yan (2019)
Perceived behavioral control	PBC-1	I enjoy making my own decisions.	-
	PBC-2	I would rather someone else be the leader on a group project.	-
	PBC-3	Given enough time, I can learn and master high-tech devices.	Klöckner and Friedrichsmeier (2011); Buckley, et al. (2018)

3.3.2. Survey Design

This study uses data collected through an online survey instrument, the Future Mobility in Canada Survey (FMCS). The automated vehicle component of the survey was designed to capture the complex decision-making process of using several potential types of fully automated motor vehicles including private automated vehicles (PAVs), shared automated vehicles (SAVs), pooled automated vehicles (PooledAVs), and automated shuttle buses, though the current study focuses only on SAVs.

The survey content was checked and approved by relevant university ethics boards, leading to 5,002 observations collected in October and November 2021 across six major Canadian Census Metropolitan Areas (CMAs): Toronto (n = 1928), Montreal (n = 1222), Vancouver (n = 799), Calgary (n = 449), Ottawa-Gatineau (n = 395), and Hamilton (n = 209). The sample size was allocated proportionally to each CMA based on its population within the 18-75 age group. The survey also collected key information related to individual preferences, behavioral intention, willingness to share a ride for use-case scenarios, sociodemographic characteristics, residential and work locations, and recent travel behavior.

3.3.3. Participants

Survey respondents were recruited through a private survey company, Savanta, and were reimbursed using proprietary reimbursement methods including redeemable points. Screening questions were administered to test respondent eligibility (whether they were aged 18-75 and resided in one of the six CMAs of interest). In addition to the screening criteria, age, gender, and income quotas, were used to obtain a representative sample. A total of 10,279 panelists accessed the survey, where 5,002 (2,493 male and 2,494 female) observations were collected forming the final dataset. The sample demographics characteristics are shown in Table 5.

Table 5. Descriptive statistics of variables used to understand respondents' intentions to use SAVs

Predictors	Definition	Frequency	Percent
Age			
Gen Z	1 if 18 ≤ age ≤ 25; 0 otherwise	630	13%
Millennial	1 if 26 ≤ age ≤ 41; 0 otherwise	1703	34%
Gen X	1 if 42 ≤ age ≤ 57; 0 otherwise	1269	25%
Baby boomers	1 if 58 ≤ age ≤ 75; 0 otherwise	1400	28%
Female	1 if individual is female; 0 otherwise	2494	50%
Employed	1 if individual is employed part-time or full-time; 0 otherwise	3403	68%
Student	1 if individual is part-time or full-time student; 0 otherwise	786	16%
Post-secondary education	1 if individual has a post-secondary education; 0 otherwise	2309	46%
Bike share	1 if individual is a member of bike sharing services; 0 otherwise	292	6%
Ride hail	1 if individual has ever used ride hailing services; 0 otherwise	2763	55%
Car share	1 if individual is a member of car sharing services; 0 otherwise	418	8%
Public transit usage in the past week			
I never use PT		2308	46%
I did not use PT in the last week		1253	25%
One to two days		586	12%
Three to four days		411	8%
Five to six days		332	7%
Seven days		112	2%
Driver's license	1 if individual holds a valid driver's license; 0 otherwise	4390	88%
Disability	1 if individual has a physical condition prohibiting themself from driving; 0 otherwise	727	15%
Household income			
under 39K	1 if individual's household income is ≤ 39K; 0 otherwise	1096	22%
40K - 99K	1 if individual's household income is 40K ≤ income ≤ 99K; 0 otherwise	2103	42%
100K - 124K	1 if individual's household income is 100K ≤ income ≤ 124K; 0 otherwise	625	13%
125K - 174K	1 if individual's household income is 125K ≤ income ≤ 174K; 0 otherwise	496	10%
above 175K	1 if individual's household income is ≥ 175K; 0 otherwise	319	6%
unknown	1 if individual's household income is not declared; 0 otherwise	363	7%

Note: Values in the last column may not total to 100% due to rounding.

3.3.4. Use-case Scenarios

Five categories of use cases comprising "*first mile/last mile transit*," "*picking up someone or something*," "*daily trips*," "*occasional trips*," and "*driving milage*" were considered in the survey design. However, these options were constrained based on feedback in the process of survey piloting and refinement, leading to two main categories: "*regular trips*" and "*occasional trips*". *Regular trips* include trips to/from work/school, trips other than work/school such as trips to/from a store, trips to/from a friend's house, or trips to/from a restaurant or a bar. *Occasional trips* are special situations where the use cases contained trips for special events or performances (e.g., hockey games, concerts, etc.), and trips to/from an airport. Overall, four use-case scenarios were presented to survey participants: "*work/school trips*," "*other regular trips*," "*special trips*," and "*airport trips*."

3.3.5. Data Analysis

The statistical analyses based on the data derived from FMCS include: 1) descriptive statistics, 2) two-sample difference of means tests, 3) factor analysis to estimate latent constructs, 4) a binomial probit model to distinguish between "use-case-invariant" and "use-case-variant" individuals, and 5) five ordered probit models to estimate intention to use SAVs with respect to use-case scenarios (one model for "use-case-invariant" individuals and four models for the "use-case-variant" group based on each use case). The descriptive statistics consist of intention to use SAVs with respect to use-case scenarios, sociodemographic characteristics, and current travel behavior of respondents. A comparison of mean differences between use-case scenarios using Wilcoxon signed-rank tests is conducted to examine the differences between use cases for all individuals (whether "use-case-variant" or "use-case-invariant" groups). Afterwards, an exploratory factor analysis (EFA) is used to identify affective latent variables through correlations and covariances between measurement items. A binomial probit model is applied to assess whether use cases matter and to determine the characteristics of "use-case-variant" versus "use-case-invariant" respondents.

Intention to use SAVs is measured through ordinal data, where respondents indicated their intention as very unlikely, unlikely, neutral, likely, or very likely. However, in this study a conservative approach was employed, and a sensitivity assessment was considered, where the five-point Likert scale used within the survey was aggregated to a three-point Likert scale synthesizing very unlikely and unlikely options into unlikely, and very likely and likely, to likely. With such ordered data, an ordered probability modeling approach is appropriate (Washington et al., 2020). As such, an ordinal probit model for "*use-case-invariant*" respondents, and four ordinal probit models for "*use-case-variant*" individuals containing "*work/school trips*," "*other regular trips*," "*special trips*," and "*airport trips*," are estimated where intention to use SAVs is the dependent variable in an ordinal scale of unlikely, unsure, and likely. The marginal effects were computed for each respondent and averaged over all respondents to arrive at an average estimated marginal effect for the population.

In a nutshell, the binomial probit model characterizes the "*use-case-variant*" and "*use-case-invariant*" individuals, while the ordered probit models independently identify characteristics of people who are likely to adopt SAVs.

.4. Results

3.4.1. General Trends of Intention to Use

"*Use-case invariant*" individuals and "*use-case-variant*" individuals differ asymmetrically along the continuum of willingness to choose SAVs. While "*use-case-invariant*" respondents are more unlikely to adopt SAVs, they are more assured about their choices (see Table 6). On the other hand, "*use-case-variant*" respondents are more likely to adopt SAVs for travel to/from the airport or for traveling to/from special events but are generally more likely to be unsure. Respondents residing in the three biggest metropolitan areas, Toronto, Montreal, and Vancouver, are more likely to adopt SAVs relative to smaller metropolitan areas (see Figure 4). Except for Toronto, "*use-case-invariant*" respondents are less likely to choose SAVs in the future, while "*use-case-variant*" individuals are more willing to use SAVs as a new travel mode across all CMAs. Ottawa-Gatineau has the lowest level of interest in SAVs among "*use-case-invariant*" people, while Hamilton has the highest level of disinterest in SAVs among "*use-case-variant*" respondents. Wilcoxon signed-rank tests indicate statistically significant ($p<0.01$) mean differences for all individuals in ranking between each pair of use cases except one (the distinctions between "*work/school trips*" and "*other regular trips*").

Table 6. Intention to use SAVs in Canada

Scenarios	Intent to use SAV		
	Likely	Unsure	Unlikely
Use case invariant (N = 2783, 56%)	36.5%	16.5%	47.0%
Use case variant (N = 2219, 44%)			
Work/school trips	33.0%	34.5%	32.5%
Other regular trips	32.1%	37.3%	30.6%
Special trips	45.2%	33.8%	21.0%
Trips to/from an airport	53.5%	28.8%	17.7%
Average of all use cases	41.0%	33.5%	25.5%

Values may not total to 100% due to rounding.

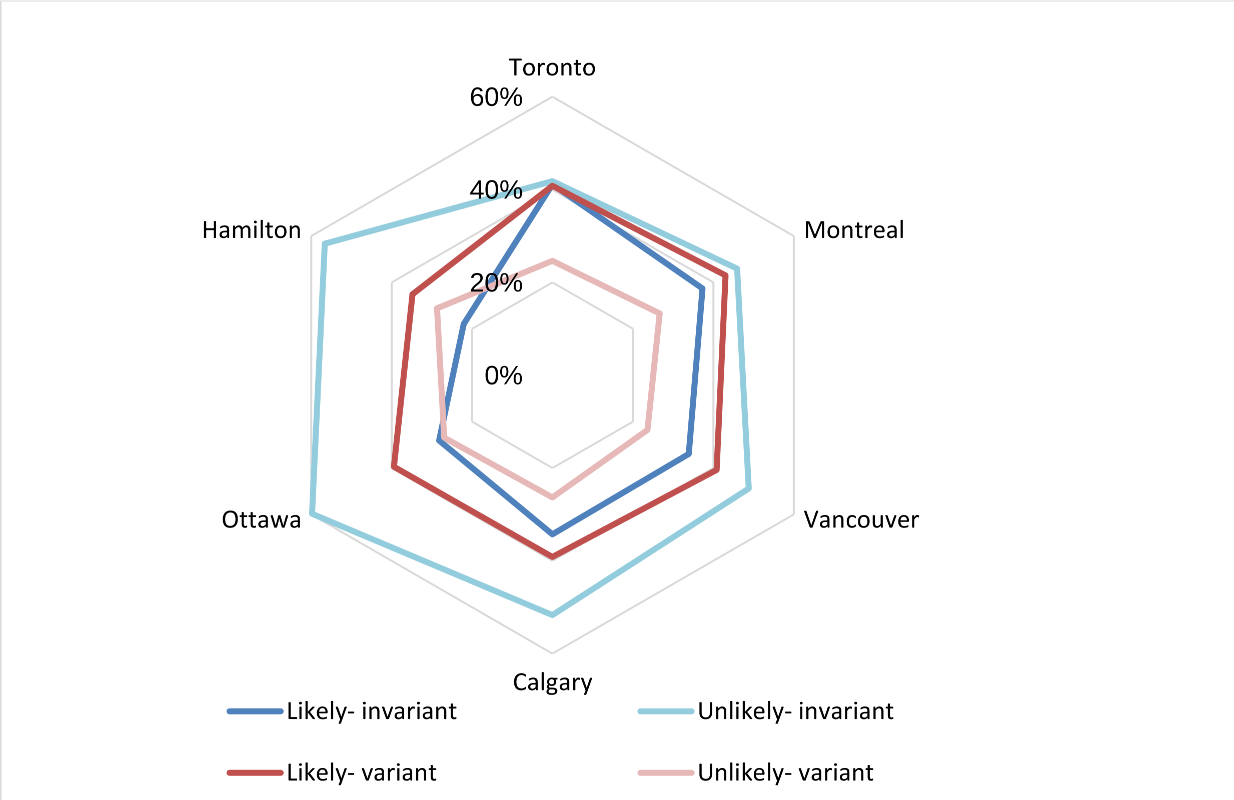

Figure 4. Intention to use SAVs in metropolitan areas (in percent).

3.4.2. Extended TPB Variables

Beyond the descriptive analyses, the next key questions relate to understanding factors influencing use case variance and propensity towards adopting SAVs. Towards that end, an exploratory factor analysis (EFA) was performed to measure and model the roles of affective motivations in this process. An EFA was used to identify the unobserved latent variables from 14 indicator variables (see complete list and abbreviations in Table 4) and yielded 4 factors using an R package called “psych” (Revelle & Revelle, 2022). *Subjective norm* was not identified as a well-defined latent variable, so it was removed from the factor analysis and included as an observed variable with one indicator in the statistical models. Additionally, one of the indicators of ATB did not load properly and was removed. The final EFA was carried out using 11 indicator variables to define four latent factors. The final EFA results are shown in Table 7.

Diagnostic tests indicated (Bartlett, 1950; Cerny & Kaiser, 1977) sampling acceptability and factorability, where Bartlett's test of sphericity (Bartlett, 1950) (Bartlett's K-squared = 3815.2 at p < 0.0001) and the Kaiser-Meyer-Olkin (KMO) test (Cerny & Kaiser, 1977) (Overall MSA = 0.74, which should be above 0.6) supported the model application. A scree plot using eigenvalues indicated that four eigenvalues were preferred. The EFA model used maximum likelihood and varimax orthogonal rotation, leading the four factors to explain 50% of the cumulative sample variance (see Table 7). The model fit is supported by additional diagnostic tests, including the chi-square (which indicates statistically significant differences between the observed and model-implied covariance matrices) (Hu & Bentler, 1999), root mean square error of approximation (RMSEA) (which was 0.069 - slightly higher than the preferred threshold of <0.06) (Everett, 2013), and comparative fit index (CFI) (which was 0.93 - much higher than preferred threshold of >0.90) (Bentler, 1990).

Table 7. Exploratory factor analysis results

Factor Loadings Construct Indices	Factor 1: Trust	Factor 2: ATB	Factor 3: Eco-friendliness	Factor 4: PBC
T_1	0.661			
T_2	0.807			
T_3	0.633			
ATB_1		0.586		
ATB_2		0.368		
ATB_3		-0.566		
EF_1			0.709	
EF_2			0.701	
EF_3			0.615	
PBC_1				0.814
PBC_3				0.452
SS Loading	1.580	1.498	1.416	0.963
Proportion Variance	0.144	0.136	0.129	0.088
Cumulative Variance	0.144	0.280	0.409	0.496
Hypothesis test that 4 factors are sufficient				
Chi-square 107.46 (df = 17)				
P-value < 0.0001				

ATB= Attitude Towards Behavior; PBC= Perceived Behavioral Control; df= degree of freedom

3.4.3. Classifying "Use-case-variant" and "Use-case-invariant" Groups

To begin, a binomial probit model was estimated to predict whether respondents are "*use-case-invariant*" (0) or "*use-case-variant*" (1). Based on the model results (Table 8), younger respondents (Generation Z and Millennials) are more likely to be use-case-variant. Also, employed and student respondents are more likely to distinctly choose their intentions towards SAVs rather than being use-case-invariant. Gender and education levels are statistically insignificant predictors of use case variance. Interestingly, all travel behavior variables are statistically significant, where users of bike share, ride hail, car share, and public transit are more likely to differentiate between use-case scenarios. Additionally, participants holding a valid driver's license have higher probabilities of considering use-case scenarios in their behavioral intent. Participants earning 100K to 174K per year are more likely to be use-case-variant. Among the affective factors of the extended TPB model, only trust is found to significantly affect the use case variance in *behavioral intention* (BI) towards using SAVs.

Table 8. Binomial probit regression results to identify the characteristics of “’*use-case-variant*” respondents versus “*use-case-invariant*” people (0= use-case-invariant, 1= use-case-variant)

Predictors	Estimate	Std. Error	z value	P-value	Marginal effect
(Intercept)	-1.152	0.153	-7.513	0.000***	-0.431
Baby boomer (reference)					
Gen Z	0.278	0.078	3.583	0.000***	0.104
Millennial	0.167	0.053	3.121	0.002**	0.062
Gen X	0.021	0.053	0.395	0.693	0.008
Female	-0.003	0.037	-0.071	0.943	-0.001
Employed	0.138	0.046	2.998	0.003**	0.051
Student	0.192	0.063	3.071	0.002**	0.072
Post-secondary education	0.046	0.039	1.180	0.238	0.017
Bike share	0.415	0.101	4.101	0.000***	0.155
Ride hail	0.139	0.040	3.484	0.000***	0.052
Car share	0.224	0.082	2.729	0.006**	0.084
PT number of days	0.039	0.015	2.522	0.012*	0.015
Driver's license	0.241	0.061	3.976	0.000***	0.090
Disability	0.087	0.055	1.582	0.114	0.033
Income under 39K (reference)					
Income 40K - 99K	-0.022	0.050	-0.437	0.662	-0.008
Income 100K - 124K	0.056	0.069	0.811	0.418	0.021
Income 125K - 174K	0.045	0.074	0.606	0.544	0.017
Income above 175K	0.013	0.087	0.147	0.883	0.005
Income unclear	-0.149	0.079	-1.885	0.059 ·	-0.056
Trust	0.128	0.025	5.190	0.000***	0.048
Eco-friendliness	0.028	0.020	1.433	0.152	0.011
PBC	-0.010	0.027	-0.396	0.692	-0.004
SN	0.015	0.020	0.779	0.436	0.006
ATB	0.026	0.035	0.749	0.454	0.010

Significance levels: *** ≤ 0.001, ** ≤0.01, * ≤ 0.05, · ≤0.1

Table 9. Ordered probit results and marginal effects: invariant use cases.

Predictors	Estimate	t value	Average Marginal effects		
			Unlikely	Unsure	Likely
Baby boomer (reference)					
Gen Z	0.452	4.222***	-0.179	0.015	0.164
Millennial	0.435	6.308***	-0.172	0.014	0.158
Gen X	0.222	3.328***	-0.088	0.007	0.081
Female	-0.186	-3.827***	-0.007	0.001	0.007
Employed	0.018	0.311	0.074	-0.006	-0.068
Student	0.221	2.522*	-0.050	0.004	0.045
Post secondary education	0.125	2.435*	-0.088	0.007	0.081
Bike share	0.129	0.805	-0.051	0.004	0.047
Ride hail	0.53	10.273***	-0.210	0.017	0.193
Car share	0.058	0.459	-0.023	0.002	0.021
PT number of days	0.087	4.259***	-0.035	0.003	0.032
Driver's license	0.121	1.6	-0.048	0.004	0.044
Disability	-0.048	-0.637	0.019	-0.002	-0.017
Income under 39K (reference)					
Income 40K - 99K	0.011	0.166	-0.004	0.000	0.004
Income 100K - 124K	-0.035	-0.376	0.014	-0.001	-0.013
Income 125K - 174K	0.066	0.664	-0.026	0.002	0.024
Income above 175K	-0.001	-0.076	0.003	0.000	-0.003
Income unclear	-0.153	-1.538	0.061	-0.005	-0.056
Trust	0.232	7.099***	-0.092	0.008	0.084
Eco-friendliness	0.175	6.872***	-0.070	0.006	0.064
PBC	0.036	1.039	-0.014	0.001	0.013
SN	0.162	5.972***	-0.064	0.005	0.059
ATB	0.378	8.132***	-0.150	0.012	0.137
Threshold parameters:					
Unlikely to unsure	3.779	17.630***	-	-	-
Unsure to likely	4.32	19.932***	-	-	-
Log-Likelihood: -2357.505					
McFadden's R2: 0.17					
AIC: 4765.01					

Significance levels: *** ≤ 0.001, **≤ 0.01, *≤ 0.05, . ≤0.1

Table 10. Ordered probit results: variant use cases (four separate ordered probit models)

Predictors	Work/school		Other regular trips		Special trips		Airport trips	
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
Baby boomer (reference)								
Gen Z	0.120	1.239	-0.021	-0.214	0.064	0.654	0.034	0.34
Millennial	0.264	3.550***	0.003	0.041	0.013	0.173	0.028	0.36
Gen X	0.152	2.009*	-0.079	-1.056	0.009	0.124	0.06	0.772
Female	0.185	-2.298*	-0.056	-1.136	0.048	0.967	0.097	1.916 ·
Employed	-0.113	2.887**	-0.01	-0.15	0.005	0.075	0.049	0.751
Student	-0.077	1.167	-0.021	-0.281	-0.013	-0.166	-0.11	-1.432
Post secondary education	0.088	-1.475	-0.006	-0.125	-0.066	-1.255	-0.024	-0.453
Bike share	-0.110	-1.045	-0.141	-1.342	0.014	0.131	-0.142	-1.313
Ride hail	0.172	3.211**	0.193	3.621***	0.191	3.564***	0.093	1.691 ·
Car share	-0.048	-0.533	-0.017	-0.185	0.082	0.892	0.038	0.4
PT number of days	0.049	2.464*	0.038	1.922.	-0.006	-0.296	0.002	0.085
Driver's license	0.022	0.263	-0.189	-2.202*	0.158	1.838 ·	0.304	3.518***
Disability	-0.039	-0.535	-0.023	-0.324	0.012	0.16	0.052	0.697
Income under 39K (reference)								
Income 40K - 99K	-0.132	-1.929 ·	0.021	0.315	0.065	0.947	0.104	1.492
Income 100K - 124K	-0.211	-2.389*	-0.046	-0.532	0.158	1.779 ·	0.090	1.003
Income 125K - 174K	-0.202	-2.1*	-0.047	-0.491	-0.024	-0.252	0.157	1.580
Income above 175K	-0.035	-0.305	0.009	0.076	-0.074	-0.650	0.187	1.588
Income unclear	-0.179	-1.609	-0.095	-0.859	-0.057	-0.514	0.037	0.326
Trust	0.116	3.340***	0.143	4.175***	0.082	2.390*	0.089	2.532*
Eco-friendliness	0.168	6.088***	0.158	5.791***	0.009	0.317	0.017	0.616
PBC	-0.045	-1.24	-0.018	-0.515	0.129	3.570***	0.151	4.114***
SN	0.080	3.059**	0.052	2.024*	-0.03	-1.127	-0.049	-1.821 ·
ATB	0.090	1.927 ·	0.164	3.523***	0.162	3.445***	0.063	1.312
Threshold parameters:								
Unlikely to unsure	1.037	4.751***	0.913	4.169***	0.659	3.003**	0.524	2.351*
Unsure to likely	1.987	9.025***	1.931	8.746***	1.606	7.277***	1.384	6.183***
Log-Likelihood:	-2328.606		-2348.163		-2296.578		-2178.281	
McFadden's R2:	0.045		0.034		0.018		0.018	
AIC:	4707.213		4746.327		4643.156		4406.562	

Significance levels: *** ≤ 0.001, **≤ 0.01, *≤ 0.05, . ≤0.1

Table 11. Average marginal effects for ordered probit models with variant use cases

Predictors	Work/school trips (Other regular trips)			Special trips (Airport trips)		
	Unlikely	Unsure	Likely	Unlikely	Unsure	Likely
Gen Z	-0.043	0.000	0.043	-0.018	-0.007	0.025
	(0.007)	(0.000)	(-0.007)	(-0.009)	(-0.005)	(0.013)
Millennial	-0.094	-0.001	0.094	-0.004	-0.001	0.005
	(-0.001)	(0.000)	(0.001)	(-0.007)	(-0.004)	(0.011)
Gen X	-0.054	0.000	0.054	-0.003	-0.001	0.004
	(0.028)	(0.001)	(-0.028)	(-0.015)	(-0.009)	(0.024)
Female	-0.066	-0.001	0.066	-0.001	-0.001	0.002
	(0.003)	(0.000)	(-0.003)	(-0.013)	(-0.007)	(0.020)
Employed	0.040	0.000	-0.040	-0.014	-0.005	0.019
	(0.019)	(0.000)	(-0.020)	(-0.025)	(-0.014)	(0.039)
Student	0.027	0.000	-0.027	0.019	0.007	-0.026
	(0.002)	(0.000)	(-0.002)	(0.006)	(0.003)	(-0.010)
Post-secondary education	-0.031	0.000	0.032	0.004	0.001	-0.005
	(0.007)	(0.000)	(-0.007)	(0.028)	(0.016)	(-0.044)
Bike share	0.039	0.000	-0.039	-0.004	-0.002	0.006
	(0.049)	(0.001)	(-0.050)	(0.036)	(0.020)	(-0.056)
Ride hail	-0.061	0.000	0.062	-0.054	-0.021	0.076
	(-0.067)	(-0.001)	(0.068)	(-0.024)	(-0.013)	(0.037)
Car share	0.017	0.000	-0.017	-0.023	-0.009	0.033
	(0.006)	(0.000)	(-0.006)	(-0.010)	(-0.005)	(0.015)
PT number of days	-0.018	0.000	0.018	0.002	0.001	-0.002
	(-0.013)	(0.000)	(0.014)	(0.000)	(0.000)	(0.001)
Driver's license	-0.008	0.000	0.008	-0.045	-0.018	0.062
	(0.065)	(0.001)	(-0.067)	(-0.077)	(-0.044)	(0.121)
Disability	0.014	0.000	-0.014	-0.003	-0.001	0.005
	(0.008)	(0.000)	(-0.008)	(-0.013)	(-0.007)	(0.021)
Income 40K - 99K	0.047	0.000	-0.047	-0.018	-0.007	0.026
	(-0.007)	(0.000)	(0.008)	(-0.026)	(-0.015)	(0.041)
Income 100K - 124K	0.075	0.001	-0.076	-0.045	-0.018	0.062
	(0.016)	(0.000)	(-0.016)	(-0.023)	(-0.013)	(0.036)
Income 125K - 174K	0.072	0.001	-0.072	0.007	0.003	-0.010
	(0.016)	(0.000)	(-0.017)	(-0.040)	(-0.022)	(0.062)
Income above 175K	0.012	0.000	-0.012	0.021	0.008	-0.029
	(-0.003)	(0.000)	(0.003)	(-0.048)	(-0.027)	(0.074)
Income unclear	0.063	0.000	-0.064	0.016	0.006	-0.023
	(0.033)	(0.001)	(-0.034)	(-0.009)	(-0.005)	(0.015)
Trust	-0.041	0.000	0.041	-0.023	-0.009	0.033
	(-0.049)	(-0.001)	(0.051)	(-0.023)	(-0.013)	(0.035)
Eco-friendliness	-0.060	0.000	0.060	-0.002	-0.001	0.003
	(-0.055)	(-0.001)	(0.056)	(-0.004)	(-0.002)	(0.007)
PBC	0.016	0.000	-0.016	-0.037	-0.014	0.051
	(0.006)	(0.000)	(-0.007)	(-0.038)	(-0.022)	(0.060)
SN	-0.028	0.000	0.029	0.008	0.003	-0.012
	(-0.018)	(0.000)	(0.019)	(0.012)	(0.007)	(-0.019)
ATB	-0.032	0.000	0.032	-0.046	-0.018	0.064
	(-0.057)	(-0.001)	(0.058)	(-0.016)	(-0.009)	(0.025)

3.4.4. Factors Influencing Intention to Use SAVs (Ordered Probit Models)

Given the results of binomial probit model, the likelihood of intending to use SAVs for both "*use-case-invariant*" (see Table 9) and "*use-case-variant*" (see Table 10) groups of people, was estimated through a series of ordered probit models. In total, five ordered probit models were estimated: one for "*use-case-invariant*" respondents and four for "*use-case-variant*" respondents, where each of the four use-case scenarios was allocated to a separate model. Average marginal effects of the individual variables in the "*use-case-invariant*" model and the four "*use-case-variant*" models are presented (see Table 9 and 11). The average marginal effects show the estimated influence of specific parameters on the probabilities of the three-conservative possible outcomes: unlikely, unsure, and likely.

For "*use-case-invariant*" respondents (see Table 9), age (Gen Z, Millennials, Gen X), gender, education, student status, ride hailing services, number of days commuting by public transit, and affective factors like trust, eco-friendliness, SN, and ATB, were found to be statistically significant predictors of BI. In contrast, for "*use-case-variant*" respondents (see Table 10), parameters vary across SAV use-case scenarios. Findings are introduced in the context of commonalities and differences between use-case-invariant and use-case-variant models, as well as the differences between use-case-variant models.

3.4.4.1. "Use-case-invariant" and "Use-case-variant" Models' commonalities

Although the significant predictors of interest in using SAVs differ between the "*use-case-invariant*" model and the four "*use-case-variant*" models, there are some key commonalities, which are determined based on the signs of the marginal effects in all five models. Estimated marginal effects (see Table 9 and Table 11) indicate that the early adopters of SAVs are likely to be current users of ride hailing services, Millennials, Generation X, individuals with annual household incomes of 40K – 99K, and individuals with affective motivations to be eco-friendly, trusting in new technologies, and positively view new travel modes. Each of these variables is positively associated with being more likely to adopt SAVs in all models. Notably, among the travel behavior factors, ride hailing was found significant (and positive) across all five models (similarly to Sener et al., 2018), while bike sharing use and car sharing use were statistically insignificant in all models (Sener et al., 2018).

Among affective motivations, trust was the only predictor that had a statistically significant estimated effect on BI in all five models, underscoring the impact of affective factors on intention to use AVs (Najm et al., 2006; Ghazizadeh et al., 2012; Nordhoff et al., 2016b; Xu et al., 2018; Buckley et al., 2018; Choi & Ji, 2015). The current study demonstrated that having trust in new technologies and travel modes also induces people to be more positive about SAVs and increases the likelihood of using SAVs in future. Further support was found by Kaye et al. (2020) where lack of trust was identified as the most significant and frequently pointed barrier to use conditional or full AVs. As such, part of the significant level of trust compared to other components might be because trust determines whether people in the first place would like to use SAVs or not.

Other affective motivations also play important roles. Being an eco-friendly person increases the possibility of intending to use SAVs in all models, though this factor has a strong significant influence on intent to use SAVs only in "*use-case-invariant*," "*work/school trips*," and "*other regular trips*" models. This finding is intuitive as individuals may be more concerned about the environment when considering regular basis trips than when taking special and rare trips. The importance of eco-friendliness observed in this study is consistent with the finding of past literature where self-identifying as having a pro-environmental identity and being concerned about the environment were significant predictors of SAV use (Gkartzonikas & Gkritza, 2019; Haboucha et al., 2017; Howard & Dai, 2014; Menon et al., 2019; Potoglou et al., 2020). Having a positive attitude towards new technologies in travel modes is also positively associated with a higher probability of adopting SAVs in all ordered models. This factor was found to be significant in all models (except in the "*airport trips*" model), validating the broader findings on attitudes and intention to adopt AVs (Buckley et al., 2018; Dai et al., 2021; Kaye, Lewis, Buckley, et al., 2020; Rahman et al., 2017).

3.4.4.2. Differences Between "Use-case-invariant" Model and "Use-case-variant" Models

There are important distinctions in predictors of intention to use SAVs between the "use-case-invariant" and "use-case-variant" models. Whereas belonging to Generation Z, being a student, and having a post-secondary education were independent and statistically significant predictors in the "use-case-invariant" model, their estimated effects were indistinguishable from zero in the "use-case-variant" models. Estimated marginal effects similarly illustrate opposite average effects: while being a student increases the likelihood of using SAVs in the "use-case-invariant" model, its average effect is negative in the "use-case-variant" models. In the case of the estimated effect of having a post-secondary degree, the average marginal effect increases the possibility of using SAVs in "use-case-invariant" model, which is consistent with the findings of Lavieri's et al. (2017) and Cyganski's et al. (2015) studies, though its effect is the opposite in the use-case-variant models.

3.4.4.3. Intention to Use SAVs Based on Use Case Differences

Finally, there are several predictors of intention to use SAVs which vary significantly among use cases – thereby illustrating nuanced variations between the "*use-case-invariant*" and "*use-case-variant*" models as well as across the four "*use-case-variant*" models. Notably, predictors used within this study have shown relatively similar effects in "*use-case-invariant,*" "*work/school* *trips,*” and “*other regular trips*” models, indicating that most people with a high BI, regardless of use-case scenarios, have the same characteristics as people who consider SAVs for regular basis trips. One key difference between models relates to gender. Results suggest that women are more likely to use SAVs for “*special trips*” and “*airport trips*” than men (in “*use-case-variant*” models), while for the “*use-case-invariant*” group, women were categorically less likely to use SAVs. These findings might best be considered in light of other literature suggesting that gender differences in AV adoption may stem from different sensitivity to risk (Bansal et al., 2016; Haboucha et al., 2017; Hulse et al., 2018; Krueger et al., 2016; Menon et al., 2019).

Second, membership of shared mobility services such as bike share and car share were associated with a higher probability of intending to use SAVs in the *“use-case-invariant*” model, “*special trips,*” and “*airport trips*” models, but not in other “*use-case-variant*” models. However, car share members were less likely to choose SAVs for regularly occurring trips including “*work/school trips*” and “*other regular trips.*” Findings related to the “*special trips*” and “*airport trips*” models are supported by studies suggesting that users of shared mobility services are potential early adopters of new mobility technologies to facilitate niche travel needs (Axsen & Sovacool, 2019; Derikx & van Lierop, 2021; Guyader et al., 2021).

Third, similar to Acheampong & Cugurullo (2019), this study finds that the number of days using public transit is significantly linked with intention to use SAVs in the “*use-case-invariant*” model and “*work/school trips*” model. Based on estimated marginal effects, whereas more public transit use reduces the likelihood of using SAVs for “*special trips,*” the probability of using SAVs rises for other use cases.

Fourth, the results of marginal effects suggest that licensed drivers are less likely to use SAVs for “*other regular trips,*” while they are more likely to use SAVs for “*work/school trips,*” "*special trips,*" or "*airport trips.*" The findings of the "*other regular trips*" model are in line with results of a few studies concluding that people who hold a valid driver's license are less likely to choose private or shared AVs (Bansal & Kockelman, 2018; Sener et al., 2019)

Fifth, whereas having physical conditions which affect one's mobility was not statistically significant in any models, people with a disability prohibiting them from driving are more likely to use SAVs for "*special trips*" or "*airport trips.*" Despite a few past studies indicating a higher tendency of intention to use SAVs among people with physical conditions prohibiting driving (Sener et al., 2019; Zmud et al., 2016), this study identified that these people are less likely to use SAVs for regular trips ("*work/school trips*" and "*other regular trips*") or when the use cases are invariant.

Sixth, although household income was not found to be a significant variable in most of the models, compared with low-income households (under 39K per year), all other household income groups are more likely to use SAVs for "*airport trips.*" On the contrary, compared to low-income households, all other groups of income are unlikely to use SAVs for "work/school trips." The results of the "work/school trips" model are supported by Pettigrew et al. (2019), where they concluded that households with lower incomes are more likely to adopt AVs. Notably, whereas individuals from middle-class household income (40K to 124K per year) are more likely to choose SAVs for "*special trips*" purposes, people with relatively higher household incomes (125K and above) are reluctant to use SAVs for such trip purposes. Overall, findings of this study demonstrate that income affects people's BI towards SAVs in general, which is in line with previous studies (Bansal et al., 2016; Lavieri et al., 2017; Nordhoff et al., 2016; Sweet & Laidlaw, 2020) . Additionally, the findings of this study indicate that income levels could determine for what trip purposes people are more willing to use such mobility services.

Seventh, perceived behavioral control was a statistically significant predictor in the "*special trips*" and "*airport trips*" models meaning respondents who found using new technologies comfortable and effortless were more likely to adopt SAVs for such trips. However, the estimated effect of PBC was insignificant in the "*use-case-invariant*" model, the "work/school trips" model, and the "*other regular trips*" model. This may suggest that the locus of control matters less in regular trips for which respondents are primarily concerned about travel time and cost (Krueger et al., 2016). Findings on the impact of PBC on AV adoption have been highly variable in different studies. In a few studies, the effect of PBC was a negative and significant predictor of adopting a partial AV (level 3, where a driver's action is needed in some operations) but was an insignificant predictor of intention to use full AVs (Dai et al., 2021; Kaye, Lewis, Buckley, et al., 2020). Since Shared AV is considered as full AVs, it could be stated that the results derived from the "*use-case-invariant*" model, "*work/school trips*" model, and "*other regular trips*" model, are in line with studies that found PBC as an insignificant predictor for BI (Dai et al., 2021; Kaye, Lewis, Buckley, et al., 2020). However, the results of "*special trips*" and "*airport trips*" models might best be considered in the light of studies concluding that PBC is one the most significant factors influencing BI (Buckley et al., 2018; Choi & Ji, 2015; Jing et al., 2019)

Eighth, alongside the "*use-case-invariant*" individuals, subjective norm was also a statistically significant predictor for "*use-case-variant*" respondents. People who perceived social pressure in choosing their travel mode, are less likely to use SAVs for "*special trips*" or "*airport trips,*" whereas these people are willing to adopt SAVs for regular trips such as work/school trips.

Finally, employment status is only statistically significant in the "*work/school trips*" model confirming that full-time and part-time workers are more likely to consider SAVs for their work travel mode. Nair et al. (2018) and Nazari et al. (2018) have touched upon the higher level of adoption towards AVs among employed respondents, which is confirmed by the findings of current study. Although being part-time/full-time employed was not found to be statistically significant for other ordered probit models, based on the marginal effects these people are more likely to adopt SAVs whether the use cases are invariant or variant.

3.5. Conclusion

This study pursued several research aims related to learning about the conditions under which Canadians in large metropolitan areas are likely to adopt shared autonomous vehicles (SAVs). First, this study provided a novel theoretical model for exploring SAV adoption by building upon existing models. It proposed an extended TPB research framework using additional affective motivations where the final proposed framework included five affective motivations: attitude towards a behavior, perceived behavioral control, subjective norms, trust, and eco-friendliness. Results demonstrated that the proposed TPB research framework is valid and affective motivations were found to be the most significant predictors in adopting SAVs, where trust was the most important and attitude towards the behavior was the second strongest predictor.

Second, this study proposed and examined a novel approach, user-centered use-case scenarios, to estimate the likelihood of SAV adoption by employing the four most prospective trip purposes of SAVs: "*work/school trips,*" "*other regular trips,*" "*special trips,*" and "*airport trips*". Using a binomial probit model, this study demonstrated that the use cases of SAVs matter to half of the respondents and distinguished the characteristics of the "*use-case-invariant*" people, who have stated the same behavioral intention towards SAVs regardless of use cases, versus the "*use-case-variant*" individuals, who considered use cases for their behavioral intentions towards adopting SAVs.

Third, using a series of ordered probit models, this study identified the sociodemographic features, travel characteristics, and affective motivations influencing Canadians' likelihood to adopt SAVs. Models show that whereas for each use case, different affective motivations, sociodemographic features, and travel behavior characteristics influence intention to use SAVs, there are some commonalities in characteristics of early adopters. The early adopters of SAVs will be current users of ride hailing services, Millennials, Generation X, individuals with annual household incomes of 40K–99K, and eco-friendly people who trust new technologies easily and have positive attitudes towards new travel modes. Notably, the ordered probit models indicated that trust plays the most significant role throughout affective motivations of interest, begging the question as to whether future prospective users' trust is likely to be addressed or not with respect to commercially designed SAVs. If it is not, findings from this study suggest that forecasts are likely to overestimate future SAV adoption.

This study's findings also call into question what trip purposes or use cases really matter when it comes to SAV adoption. A question concerning whether SAV use is likely to be concentrated in occasional rather than regular trips was pointed out through this study using the user-centered use case approach. Results demonstrated that people are more willing to use SAVs for occasional trips rather than regular basis trips. These findings suggest a need to examine and identify more occasional trips in future research for SAVs as a new mobility option.

Overall, the results of this study suggest that policymakers, planners, the vehicle and technology industries, and the public at large should moderate their expectations that AVs may suddenly transform the entire transportation sector. Instead, this study suggests that SAVs (when they entire the Canadian market) are likely to be adopted as a supplementary mobility tool rather than a substitution for current travel modes. Broadly, this implies that policymakers may be well served to look at incremental changes in similar existing mobility tools, such as on-demand ride hailing, to explore how such new technologies change the transportation sector on the margins. Nevertheless, while evidence of a niche role appears to be strong, it is not clear whether this role may be more normalized in everyday mobility experiences as automated vehicle technologies become more commonplace.

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Chapter 4

Shared Versus Pooled Automated Vehicles: Understanding Behavioral Intentions Towards Adopting On-Demand Automated Vehicles

4.1. Introduction

The convergence of on-demand ride-hailing and automated vehicle (AV) technology has given rise to considering new business models in shared mobility services, which can trigger developing on-demand AVs such as shared automated vehicles (SAVs) and pooled automated vehicles (PooledAVs). Although many countries around the world are showing interest in on-demand AVs (Fagnant & Kockelman, 2018; Nazari et al., 2018; Polydoropoulou et al., 2021) due to their efficiency and environmental friendliness (Wadud et al., 2016), the penetration rate of on-demand AVs in future travel markets remains uncertain. To this end, understanding behavioral intentions towards on-demand AVs and the characteristics of SAVs' and PooledAVs' early adopters is essential for the transportation sector in making public policies that anticipate the future demand of such travel modes (Borowski & Stathopoulos, 2020; Hardman et al., 2019; Milakis et al., 2017).

This study adds to the body of literature related to on-demand AV adoption in several ways. First, except for a few studies (Fagnant & Kockelman, 2018; Krueger et al., 2016; Sweet, 2021), the literature has considered SAVs as the only on-demand AV configuration (Jing et al., 2019; Menon et al., 2019; Yuen et al., 2020; W. Zhang et al., 2020). However, while SAVs can be considered as car sharing or a private ride (without ride sharing) where the vehicle is not owned by the passenger, PooledAVs can embrace the cost, time, and energy efficiency of on-demand services by matching travelers based on their origins and destinations (Fagnant & Kockelman, 2018; Krueger et al., 2016). This study aims to distinguish between these two on-demand AV configurations and investigate both as future on-demand AV services.

Second, many previous studies that investigated on-demand AV adoption concentrated on travel simulations (Fagnant & Kockelman, 2018; Hyland & Mahmassani, 2018; Maciejewski & Nagel, 2012) by assuming such fleets are adopted and exist in the travel market, while the on-demand AV adoption and public acceptability towards these emerging services remain vague and uncertain. This study aims to address this shortcoming by assessing on-demand AV adoption in the Canadian context.

Third, in past studies, on-demand AV adoption is usually measured through online surveys where direct questions or a stated preference (SP) approach is applied (Haboucha et al., 2017; Krueger et al., 2016; Rahimi et al., 2020; Zhou et al., 2020). However, given that current use of existing shared mobility services could influence behavioral intentions towards adopting on-demand AVs (which are unoberved), asking respondents to rank unobserved travel modes among conventional existing modes (which is how the SP approach assesses behavioral intentions) might not reflect their genuine behavioral intentions towards using on-demand AVs (Körber et al., 2018; Nordhoff et al., 2016; Rahman et al., 2017; Xu et al., 2018). To this end, rather than challenging respondents to rank on-demand AVs among present travel modes, this study assesses the indirect effects of current travel behavior towards using ride-hailing services for work/school trips on SAV and PooledAV adoptions for the same trip purposes (work/school trips). In other words, this study appraises whether current use of ride-hailing services frames a pathway towards adopting on-demand AVs.

Fourth, to identify conditions under which individuals may adopt on-demand AVs, previous studies have applied human behavior and technology acceptance theories where Utility Theory (UT) (Bansal & Kockelman, 2017; Fagnant & Kockelman, 2015; Hoerl, Becker, & Axhausen, 2021; Wang, Salehin, & Habib, 2021), the Technology Acceptance Model (TAM) (Osswald, Wurhofer, Trösterer, Beck, & Tscheligi, 2012; Rahman, Lesch, Horrey, & Strawderman, 2017; Lee, Lee, Park, Lee, & Ha, 2019; Panagiotopoulos & Dimitrakopoulos, 2018; Xu, et al., 2018; Choi & Ji, 2015), the Theory of Planned Behavior (TPB) (Buckley, Kaye, & Pradhan, 2018; Dai, Li, & Liu, 2021), the Unified Theory of Acceptance and Use of Technology (UTAUT I & UTAUT II) (Adell, 2009; Madigan et al., 2017; Rahman et al., 2017), the Diffusion of Innovation Theory (DIT) (Talebian & Mishra, 2018; Lavasani, Asgari, Jin, & Pimjari, 2017), and the Social Cognitive Theory (SCT) (Ribeiro et al., 2022) are the most frequently adopted theories. Among the existing theoretical frameworks, TPB has been validated and is among the most tested theoritical framework in on-demand AV research. Besides components explicitly embedded in adoption theories, the existing literature suggests that other affective motivations, which refer to feelings evoked by traveling (Anable & Gatersleben, 2005; Russell & Lanius, 1984; Steg, 2005) such as green lifestyle, ample knowledge of AV technology, driving enthusiasm, sensation seeking, etc., may be robust factors influencing SAV and PooledAV adoptions (Nordhoff et al., 2016b; Xu et al., 2018; Buckley et al., 2018; Choi & Ji, 2015). While many studies have supplemented AV adoption models with additional affective motivations, these components have not yet been applied to differentiate between SAV and PooledAV adoptions. In other words, the existing literature has not yet explored whether affective motivations are specific to on-demand AVs, or whether those motivations relate more closely to the configurations of on-demand AVs people might use for their regular trips. This study aims to address this shortcoming.

Given these shortcomings, this study has three objectives: (a) to propose and validate a theoretical model for behavioral intention to use SAVs and PooledAVs by extending the original TPB model; (b) to identify the characteristics of early adopters of SAVs, who prefer to have shorter and private rides that are more expensive, versus prospective users of PooledAVs, who choose more affordable but longer and shared trips, by assessing the current use of ride-hailing services for work/school trips and comparing these existing mobility services to SAV and PooledAV adoptions; and (c) to jointly investigate Canadians' intentions to adopt on-demand AVs for regular and daily trips. Toward this end, this study uses data from an online survey (n = 3622) of workers and adult students (18 to 75 years old) conducted in October and November 2021 for six major Canadian metropolitan areas: Toronto, Vancouver, Ottawa, Montréal, Calgary, and Hamilton.

4.2. AV Adoption in Previous Studies

Before proceeding, it is necessary to clarify the terminology used in this study for automated ride-hailing services. Whereas Bansal et al. (2016) called any on-demand rental vehicles with full automation capabilities as "shared automated vehicles" (SAVs), automated ride-hailing services were defined as "driverless taxis" by Fagnant & Kockelman (2015). Additionally, in Bansal et al.'s (2016) study, "dynamic ridesharing" (DRS) was used as automated ride-hailing services with ride sharing, where the ride was shared with passengers having similar origin or destination locations. Hyland & Mahmassani (2018) used "shared-use AV mobility service" (SAMS) terminology for automated ride-hailing services without ride sharing. Likewise, Krueger et al. (2016) employed "shared automated vehicles" (SAVs) for both types of automated ride-hailing services (with ride sharing and without ride sharing). In their study, to differentiate between the automated ride-hailing services, "dynamic ride sharing" (DRS) was applied for services that included ride sharing, whilst "SAVs without DRS" was used to refer to automated ride-hailing services without ride sharing. In this study, to distinguish between automated ride-hailing services based on service type, "shared automated vehicles" (SAVs) refers to automated ride-hailing services without ride sharing, and "pooled automated vehicles" (PooledAVs) refers to automated ride-hailing services with ride sharing. Note that whether the automated ride-hailing service is shared (with ride sharing) or private (without ride sharing), the term "on-demand AVs" is employed throughout this study to imply both forms of automated ride-hailing services.

Among past studies focusing on AVs, there are significant variations in investigated (1) AV configurations, (2) employed theories, motivation types, and significant variables with respect to AV adoption, (3) conducted methodologies, and (4) results and findings. First, previous studies explore a variety of potential AV alternatives, including private AVs (Buckley et al., 2018; Du et al., 2021; Ho et al., 2020; Hohenberger et al., 2017; Kyriakidis et al., 2015; Topolšek et al., 2020), shared AVs (Buckley et al., 2018; Fagnant & Kockelman, 2014; Haboucha et al., 2017; Yuen et al., 2020) where the ride is private from origin to destination, pooled AVs (Acheampong & Cugurullo, 2019; Fagnant & Kockelman, 2018; Kolarova et al., 2018; Krueger et al., 2016; Sweet, 2021) where multiple travelers with similar origins, destinations, and departure times are pooled in the same vehicle, car sharing using AVs (Hao & Yamamoto, 2018), and automated shuttle buses (Battistini et al., 2020; Mouratidis & Cobeña Serrano, 2021; Nordhoff et al., 2021; Soe & Müür, 2020; Sweet et al., 2023).

Second, among the existing human behavioral theories, utility theory has been applied in many past studies (Asgari & Jin, 2020; Ashkrof et al., 2019; Haboucha et al., 2017; Kolarova et al., 2018; Krueger et al., 2016; Saxena et al., 2020; Stoiber et al., 2019) exploring AV adoption motivations. In those studies, travel costs are mostly considered as financial travel costs, travel times, waiting times, walking times, and access or egress times. Pooling a driverless ride

(PooledAVs) is also pointed out as a travel cost motivation in some studies (Kolarova et al., 2018; Krueger et al., 2016; Saxena et al., 2020; Stoiber et al., 2019). On the other hand, regardless of monetary and instrumental motivations, which are the main components of utility theory, many studies have explored affective motivations shaping AV adoption. Affective motivations are frequently considered within the broader framework of technology acceptance and adoption theories applied by AV adoption studies. Examples of such adoption theories include the Technology Acceptance Model (TAM) (Rahman, et al., 2017; Panagiotopoulos & Dimitrakopoulos, 2018; Choi & Ji, 2015), the Theory of Planned Behavior (TPB) (Buckley, et al., 2018; Dai, et al., 2021), the Unified Theory of Acceptance and Use of Technology (UTAUT I and II) (Madigan, et al., 2017; Rahman, et al., 2017; Adell, 2010), the Diffusion of Innovation Theory (DIT) (Talebian & Mishra, 2018; Lavasani, et al., 2017), and the Social Cognitive Theory (SCT) (Ribeiro et al., 2022). Besides constructs explicitly embedded in adoption theories, the existing literature suggests that other affective motivations such as green lifestyle and eco-friendliness (Menon et al., 2019; Haboucha et al., 2017; Potoglou et al., 2020), driving enthusiasm (Haboucha et al., 2017; Kockelman et al., 2016; Kyriakidis et al., 2015), sensation seeking (Payre et al., 2014; Zhang et al., 2020), and ample knowledge (Jing et al., 2019; Sener et al., 2019) may be robust factors influencing demand for SAVs and PooledAVs.

Along with theoritical and motivational variables, current travel behavior such as current use of shared mobility services is also found to be a significant mediator for on-demand AV adoption in past studies (Acheampong & Cugurullo, 2019; Bansal et al., 2016; Haboucha et al., 2017; Kelley Blue Book & Cox Automotive, 2016; Krueger et al., 2016; I. N. Sener et al., 2018; Ipek N. Sener et al., 2019; Ipek N. Sener & Zmud, 2019). For instance, Sener et al. (2018) found that overall AV adoption was higher across users of ride-hailing services than among non-users of such services.

Also, their results suggested that the longer respondents have used ride-hailing services, the more likely they would use AVs in future. In line with Sener et al.'s (2018) findings, Kelley Blue Book & Cox Automotive (2016) found that ride-hailing users are more likely than non-users of ride-hailing services to adopt on-demand AVs. Similarly, Bansal et al. (2016) found that respondents familiar with current shared mobility services would rather use on-demand AVs than buy private AVs. Accordingly, Acheampong & Cugurullo (2019) concluded that current users of shared mobility services are likely to be early AV users as the respondents believe that the utilitarian environmental and commuting benefits provided by shared mobility services will be also met by AVs. In other words, favorable attitudes towards shared mobility services positively correlates with AV adoption (Acheampong & Cugurullo, 2019). Overall, the acceptability/likely usage of on-demand AVs is expected to increase with experience using a ride-hailing service.

Third, AV studies have used various methodologies to estimate behavioral sensitivities to AVs as new mobility tools. The methods include (1) stated preference choice experiments using online surveys, (2) the likelihood of using a particular AV service using online surveys, (3) direct experience with semi-automated vehicles along with surveys, and (4) agent-based simulation, which could be a further development of survey results. Many AV studies have used stated preference choice experiments to assess behavioral intention towards any AV type. For instance, Krueger et al. (2016) investigated the travel behavior impacts of SAVs by eliciting willingness to pay measures for the defined service attributes, Haboucha et al., (2017) investigated individual motivations to own and use private AVs, and Yap et al. (2016) focused on PooledAVs as last-mile solutions for train trips.

Some studies have investigated the likelihood of AV adoption using online surveys. For instance, Menon et al. (2019) assessed SAV adoption through measuring the likelihood of relinquishing current private vehicles. Topolšek et al. (2020) investigated factors affecting the intention to purchase private AVs by assessing their significance in deciding whether to buy a private AV. Dirsehan & Can (2020) examined the likelihood of adopting AVs by appraising trust and sustainability concerns as affective motivations towards AV adoption.

Direct experience using partial AVs is another approach in some studies that explore the behavioral intention towards fully automated vehicles. For instance, Xu et al. (2018) applied a direct experience approach on AV level 3 to estimate behavioral intention towards fully AVs (level 5). Rahman et al. (2017) used direct experience of AV level 2 alongside an online survey to assess intention to use AVs.

Studies focusing on the environmental, travel behavior, land use, and built environments impacts of AVs have mostly applied agent-based simulations (Cyganski et al., 2018; Fagnant & Kockelman, 2014; Zhang et al., 2015). For example, Cyganski et al. (2018) used value of time (VOT) estimates to explore the potential implications of AV services on travel demand using an agent-based simulation. Fagnant & Kockelman (2014) described the design of an agent-based model for SAV operations and the estimated environmental benefits of SAVs versus conventional vehicle ownership and their use. Likewise, Zhang et al. (2015) estimated the potential impact of the SAV system on urban parking demand under different system operation scenarios using an agent-based simulation model.

Lastly, there is significant variation in the findings of AV studies. While some studies suggest that people are sensitive to monetary motivations (Haboucha et al., 2017; Kolarova et al., 2018) and service-oriented attributes of on-demand AVs (Krueger et al., 2016), other studies suggest that willingness to share rides with strangers is more significant than financial cost factors (Stoiber et al., 2019) and the role of affective motivations are more significant in shaping AV adoption (Buckley, et al., 2018; Choi & Ji, 2015; Kaye, et al., 2020; Nazari, et al., 2018; Sweet & Laidlaw, 2020). Additionally, there is uncertainty and inconsistency between the results of AV studies about the role of socio-demographic and current travel behavior characteristics, whereby they may play strong (Bansal et al., 2016; Kockelman et al., 2016; Kyriakidis et al., 2015; Sener et al., 2019) or ineffective (Buckley et al., 2018; Krueger et al., 2016; Madigan et al., 2017) roles. Also, findings differ across various geographical contexts (Haboucha et al., 2017; Kyriakidis et al., 2015). For instance, Haboucha et al. (2017) sought individual motivations for adopting privately-owned AVs and SAVs in Israel and North America and found different preferences and distinct behavioral intentions towards adopting AVs in these contexts.

Overall, this study aims to address the research gaps in existing literature and improve the body of on-demand AV adoption literature through (1) distinguishing behavioral intentions of SAVs from PooledAVs which are different on-demand AV configurations, (2) understanding on-demand AV adoption in the Canadian context, (3) assessing the effect of actual behavior (current use of ride-hailing services) on behavioral intentions towards on-demand AVs, and (4) exploring the role of affective motivations in adopting on-demand AVs. Building upon the limited literature in these areas, the present study makes contributions to the literature in terms of possible travel behavior changes due to emerging mobility services.

4.3. Methodology

4.3.1. Survey design

This study uses data collected through an online survey instrument, the Future Mobility in Canada Survey (FMCS). The automated vehicle component of the survey was designed to capture the complex decision-making process of using several potential types of fully automated motor vehicles including private automated vehicles (PAVs), shared automated vehicles (SAVs), pooled automated vehicles (PooledAVs), and automated shuttle buses, though the current study only focuses on SAVs and PooledAVs, which are configurations of on-demand AVs.

The survey was approved by relevant university research ethics boards, leading to 5002 observations collected in October and November 2021. Given this study's focus on propensity to use on-demand AVs for trips related to work or school, it includes the 3622 respondents who are either part-time/full-time workers or adult students. This study focuses on six major Canadian Census Metropolitan Areas (CMAs): Toronto (n = 1400), Montréal (n = 924), Vancouver (n = 597), Calgary (n = 293), Ottawa-Gatineau (n = 269), and Hamilton (n = 139). The sample size was allocated proportionally to each CMA based on its 2020 population within the 18-75 age group. The survey also collected key information related to individual preferences, behavioral intention, willingness to share a ride for use-case scenarios[20], socio-demographic characteristics, residential and work locations, and recent travel behavior with an emphasis on the use of ride-hailing and public transit.

The median time taken to complete the survey was approximately 16 minutes. Survey respondents were recruited through a private survey company, Savanta, and were reimbursed using proprietary reimbursement methods including redeemable points. Screening questions were administered to test respondent eligibility (aged 18-75, resided in one of the six CMAs of interest). In addition, age, gender, and income quotas were used to obtain a representative sample.

[20] In FMCS based on the trip characteristics and trip purposed, four use-case scenarios were considered: (1) work/school trips, (2) other regular trips such as trips to/from a store, (3) trips to special events or performances such as hockey games, concerts, etc., and (4) trips to/from an airport.

4.3.2. Research framework and modeling approach

Using the FMCS data, the methodology includes: (1) the proposed research framework, (2) descriptive statistics for all variables, (3) a mean differences test using the Wilcoxon signed-rank test to assess whether there is a difference between SAV and PooledAV adoptions, (4) a measurement model using factor analysis to estimate latent constructs, (5) a mediation analysis, and (6) a full structural equation model (SEM). The rest of this section discusses, in more detail, the research framework and modelling approach applied to this study.

This study focuses on the intention to use two configurations of on-demand AVs – namely, shared automated vehicles (SAV Intent) and pooled automated vehicles (PooledAV Intent). Both intentions were asked through a 5-point Likert scale question ranging from 1 (strongly disagree/very unlikely) to 5 (strongly agree/very likely). In addition to estimating intention to use on-demand AVs, usage of existing on-demand ride-hailing is taken as a mediator (intervening) variable to assess the effects of respondents' current behavior towards ride-hailing technology and willingness to use shared mobility services on behavioral intentions towards on-demand AVs. The mediator variable (current use of ride-hailing services) was measured through a 5-point ordinal scale (from 'never use' to '5 – 7 days a week').

To examine respondents' intentions towards on-demand AVs, an extended Theory of Planned Behavior (TPB) model with emphasis on affective motivations was developed. Overall, seven affective motivations (five as latent constructs and two as observed variables) are used in the research framework: attitude towards a behavior (ATB), subjective norms (SN), perceived behavioral control (PBC), driving enthusiasm, sensation seeking, ample knowledge about AVs, and eco-friendliness, as intervening (exogenous) variables. In addition to the affective motivations and constructs explicitly embedded in TPB, socio-demographic characteristics are also included as instrumental model controls (Figure 5).

Regarding the modeling approach, a full SEM system is estimated. The analytic framework focuses on developing a joint model, which includes four parts: (1) exogenous variables, (2) latent constructs, (3) a mediator variable, and (4) endogenous variables, which are the main outcomes. Socio-demographic variables (individual and household characteristics) observed affective motivations (attitude towards a behavior and eco-friendliness), as well as latent affective motivations (subjective norms, perceived behavioral control, driving enthusiasm, ample knowledge, and sensation seeking) are all determinants of the two main outcomes: (1) SAV Intent, and (2) PooledAV Intent (Figure 5).

Through the proposed research framework, this study hypothesizes that some latent affective motivations such as *ample knowledge*, *sensation seeking*, and *driving enthusiasm* will only have direct impacts on unobserved mobility tools such as on-demand AVs since these latent motivations genuinely evoke from attitudes toward unprecedented travel modes rather than existing ones. In other words, these latent affective motivations might not be significant predictors for current use of existing travel modes such as ride-hailing services. As such, this study assumes that *ample knowledge*, *sensation seeking*, and *driving enthusiasm* have only direct effects on behavioral intentions towards SAVs and PooledAVs without any indirect effects of current use of ride-hailing services, meaning these latent affective motivations are not included in the mediation analysis that is part of the research framework. However, *perceived behavioral control* and *subjective norms* are treated as endogenous latent constructs for the dependent variables (SAV Intent and PooledAV Intent) as well as the mediator variable (current use of ride-hailing services) since these motivations can also rise from the experience of using existing travel modes.

Note that *attitude towards a behavior* and *eco-friendliness* were not identified as well-defined latent variables, so they are treated as observed, single-indicator variables in the statistical models. Additionally, in the SEM, the dependent variables are estimated as functions of both latent and observed variables. As all dependent variables are ordered, this study uses diagonally weighted least squares estimators (WLSMV), which employs polychoric correlations based on the concept that a normally distributed latent construct is situated behind the observed ordered responses (Li, 2016; Muthén, 1984). The SEM also includes a measurement model that estimates the latent constructs; covarying error terms (between latent constructs and between dependent variables); and the ordinal models, whereby the latent constructs and the two dependent variables are regressed on observed exogenous independent variables (Figure 5).

To understand the relationships among constructs and to assess the structural path of the proposed research framework, a partial mediation analysis is considered. Bootstrapping and the Sobel test are common mediation analysis approaches by conventions (Örs Özdil & Kutlu, 2019), which are both from a product of coefficient approach. Whereas the Sobel approach (a specific implementation type of the Delta method) assumes that the sampling distribution of estimated indirect effects is normally distributed, the bootstrapping approach, which comes from the resampling method, assumes that the sampling distribution of estimated indirect effects is not normally distributed. Since, by convention, the bootstrapping approach is applied more frequently in AV studies (Zhang et al., 2020; Zhu et al., 2020), in this study a percentile bootstrapping resampling (an implementation of the resampling method) is conducted with 5000 subsamples to estimate the indirect effects of current use of ride-hailing services on SAV and PooledAV adoptions. This study uses the lavaan package from R to analyze the full SEM and mediation analysis (Rosseel, 2012).

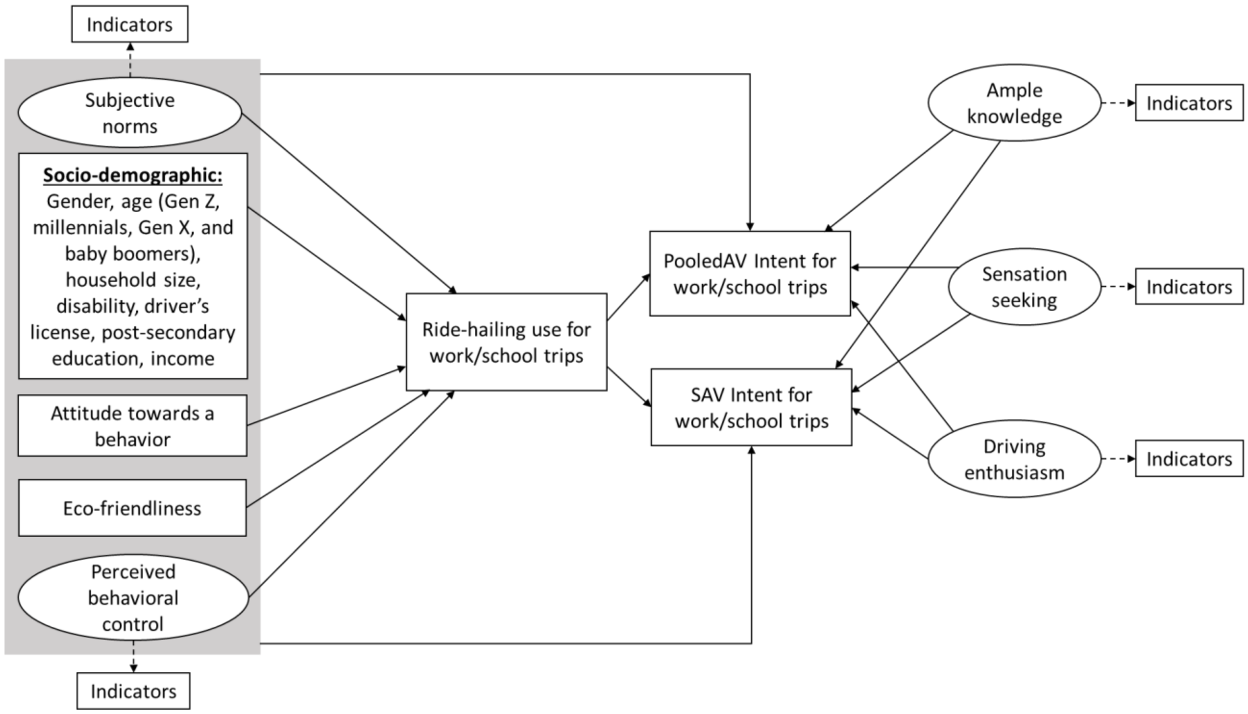


Figure 5. Path diagram for structural equation model.
Solid arrows refer to estimated effects in the SEM while hatched arrows signify a measurement model. Boxed variables represent observed variables, whereas oval variables indicate latent constructs estimated using a measurement model.

Each latent variable was measured through multiple items and was estimated by a factor analysis, where several items were adapted from extant literature to improve the content validity (Table 12). Except for ATB, which was measured on a binary scale, all other items of constructs were measured on a 5-point Likert scale from 1 (strongly disagree/very unlikely) to 5 (strongly agree/very likely). However, in this study a conservative approach was employed for the dependent variables, and a sensitivity assessment was considered, where the 5-point Likert scale used within the survey was aggregated to a 3-point Likert scale synthesizing very unlikely and unlikely options to unlikely, and very likely and likely, to likely.

Note that alongside the current use of ride-hailing, the frequency of using public transit was also examined as a mediator variable in the initial model. However, the effects of this variable on both endogenous variables (SAV Intent and PooledAV Intent) were statistically insignificant using the bootstrapping method, whereas it had significant effects on PooledAV Intent when the Sobel test was used as the mediation analysis method. Since the bootstrapping method is the ultimate chosen approach in this study, the result of that method was used and the frequency of using public transit as a mediator variable was eliminated from the final model.

Overall, using the mediation analysis, this study assesses whether the actual behavior towards ride-hailing services, which has a similar functionality with on-demand AVs in terms of shared mobility, affects the behavioral intentions towards SAVs and PooledAVs, which are unobserved and unprecedented mobility tools.

Table 12. Components and their measurement items used within the study

Constructs	Type of variable	Indices	Measuring items	Adapted from
SAV Intent for work/school trips	Dependent		Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for work or school trips	-
PooledAV Intent for work/school trips	Dependent		Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for work or school trips	-
Attitude towards a behavior (ATB)	Independent, observed		When it comes to adopting new technology, I am typically an early adopter	Kockelman, et al. (2016) Hardman, et al. (2019)
Eco-friendliness	Independent, observed		Whenever possible, I prefer to take transit rather than drive (to reduce air pollution)	Clark & Scott (2013)
Subjective norms	Independent, latent	SN-1	People important to me encourage me to use up-to-date devices.	-
		SN-2	Seeing people who are important to me using public transit makes me also want to use public transit.	Chen and Yan (2019)
Perceived behavioral control		PBC-1	I enjoy making my own decisions.	-
		PBC-3	Given enough time, I can learn and master high-tech devices.	Klöckner and Friedrichsmeier (2011); Buckley, et al. (2018)
Sensation seeking	Independent, latent	SS-1	I like new and exciting experiences even if they are a little frightening or unconventional.	Zuckerman et al. (1978)
		SS-2	I like to explore strange places or parts of town by myself even if it means getting lost.	Zuckerman et al. (1978)
		SS-3	I would like to try parachute jumping.	Zuckerman et al. (1978)
Ample knowledge	Independent, latent	K-2	Having ample knowledge before purchasing a car is necessary for negotiating a good price.	-
		K-3	It is necessary to learn about new technology before adopting it.	-
Driving enthusiasm	Independent, latent	DE-2	I do not like driving during rush hour.	-
		DE-3	I do not like driving in busy or congested areas.	(Asgari & Jin, 2019)

4.4. Results

4.4.1. Descriptive analyses

The sample demographics are shown in Table 13. These variables include individual characteristics (age, gender, employment/student status, education, disability, driver's license) and household characteristics (household income, household size). The descriptive statistics of affective motivations and the endogenous variables are found in Table 14. As indicated, the prospective early adopters of SAVs and PooledAVs differ asymmetrically along the continuum of on-demand AV adoption. A comparison of mean differences between SAV adoption and PooledAV adoption using a Wilcoxon signed-rank test indicates a statistically significant ($p<0.01$) mean difference in ranking between SAV adoption and PooledAV adoption.

Table 13. Descriptive statistics of socio-demographic variables used to understand respondents' intention to use on-demand AVs

Predictors	Definition	Frequency	Percent
Age			
Gen Z	1 if 18 ≤ age ≤ 25; 0 otherwise	591	16.3%
Millennial	1 if 26 ≤ age ≤ 41; 0 otherwise	1491	41.2%
Gen X	1 if 42 ≤ age ≤ 57; 0 otherwise	1002	27.7%
Baby boomers	1 if 58 ≤ age ≤ 75; 0 otherwise	538	14.9%
Female	1 if individual is female; 0 otherwise	1911	52.8%
Employed	1 if individual is employed part-time or full-time; 0 otherwise	3403	94.0%
Student	1 if individual is a part-time or full-time student; 0 otherwise	786	21.7%
Post-secondary education	1 if individual has a post-secondary education; 0 otherwise	2962	81.8%
Disability	1 if individual has a physical condition that prohibits driving; 0 otherwise	346	9.6%
Driver's license	1 if individual holds a valid driver's license; 0 otherwise	3276	90.4%
Household income			
Under 39K	1 if individual's household income is ≤ 39K; 0 otherwise	609	16.8%
40K - 99K	1 if individual's household income is 40K ≤ income ≤ 99K; 0 otherwise	1535	42.4%
100K - 124K	1 if individual's household income is 100K ≤ income ≤ 124K; 0 otherwise	536	14.8%
125K - 174K	1 if individual's household income is 125K ≤ income ≤ 174K; 0 otherwise	426	11.8%
above 175K	1 if individual's household income is ≥ 175K; 0 otherwise	285	7.9%
unknown	1 if individual's household income is not declared; 0 otherwise	231	6.4%
Household size			
1	1 if individual's household size is one; 0 otherwise	726	20.0%
2	1 if individual's household size is two; 0 otherwise	993	27.4%
3+	1 if individual's household size is three and above; 0 otherwise	1903	52.6%

Values in the last column may not total to 100% due to rounding.

Table 14. Dependent variable descriptive statistics

Variables		Scales				
		Unlikely	Unsure	Likely		
SAV Intent for work/school trips		35.4%	25.0%	39.6%		
PooledAV Intent for work/school trips		47.6%	24.5%	27.9%		
		Scales				
		Never use	Didn't use in the past week	1 to 2 days a week	3 to 4 days a week	5 to 7 days a week
Ride-hailing use for work/school trips		37.3%	44.0%	12.5%	4.2%	2.0%
		Scales				
		Very unlikely	unlikely	Unsure	Likely	Very Likely
Eco-friendliness		26.0%	20.5%	21.9%	20.4%	11.2%
Subjective norms	SN-1: In using up-to-date devices	5.0%	16.5%	37.3%	31.3%	9.8%
	SN-2: In using public transit	16.9%	19.5%	19.5%	21.6%	7.1%
Perceived behavioral control	PBC-1: In making decision	1.1%	2.6%	14.6%	35.1%	46.5%
	PBC-3: In learning use of new technologies	1.5%	4.8%	21.4%	44.6%	27.7%
Sensation seeking	SS-1: Enjoying new experiences	4.0%	14.4%	34.3%	34.5%	12.8%
	SS-2: Exploring strange places	8.1%	17.2%	26.9%	33.4%	14.4%
	SS-3: Experiencing risky activities	27.7%	16.8%	20.6%	20.8%	14.1%
Ample knowledge	K-2: The essential of ample knowledge	2.3%	5.0%	21.9%	44.3%	26.6%
	K-3: The essential of learning	1.5%	5.4%	21.5%	48.8%	22.8%
Driving enthusiasm	DE-2: Avoid driving in rush hour	2.9%	6.4%	19.7%	30.3%	40.8%
	DE-3: Avoid driving in congested areas	2.5%	6.7%	19.4%	31.4%	40.0%
		Scales				
		Yes	No			
Attitude towards a behavior (adopting new technologies)		34.9%	65.1%			

Values may not total to 100% due to rounding.

4.4.2. Measurement model (latent TPB variables)

The measurement model is exclusively a component of the full SEM, and it estimates five latent constructs: *subjective norms*, *perceived behavioral control*, *sensation seeking*, *ample knowledge*, and *driving enthusiasm* (Table 15). Factor loadings for the measurement model range between 0.6 and 1, where the only factor loadings that stand out significantly is for PBC-3, implying the importance of learning about new technologies before adopting them.

Table 15. Measurement model results

Measurement model	Estimate	Standardized coefficient
Latent construct: *Subjective norms*		
SN-1: In using up-to-date devices	1.000	0.671
SN-2: In using public transit	0.678***	0.436
Latent construct: *Perceived behavioral control*		
PBC-1: In making decision	1.000	0.634
PBC-3: In learning use of new technologies	1.046***	0.633
Latent construct: *Sensation seeking*		
SS-1: Enjoying new experiences	1.000	0.809
SS-2: Exploring strange places	0.815***	0.579
SS-3: Experiencing risky activities	0.634***	0.379
Latent construct: *Ample knowledge*		
K-2: The essential to have ample knowledge	1.000	0.677
K-3: The essential to learn before adoption	0.967***	0.699
Latent construct: *Driving enthusiasm*		
DE-2: Avoid driving in rush hour	0.916***	0.775
DE-3: Avoid driving in congested areas	1	0.860

Significance is denoted at 0.10-level (*), 0.05-level (**), and 0.01-level (***)

4.4.3. Mediation analysis and SEM results

In this section, the role of current use of ride-hailing as a mediator variable in predicting significant factors affecting SAV and PooledAV adoptions is discussed. As noted in Section 4.3.2, among the employed affective motivations, driving enthusiasm, sensation seeking, and ample knowledge were only tested for direct effects, and as such, these predictors are ignored for mediation modeling interpretation.

4.4.3.1. Direct and indirect effects of exogenous variables on shared AV adoption

Table 16 presents the direct and indirect effects of the exogenous variables on SAV Intent as the endogenous variable. The results show that some variables have only a direct impact on SAV Intent but are insignificant in terms of indirect effects. In other words, for certain variables, the mediator variable (current use of ride-hailing services) does not trigger any indirect effects on the likelihood of adopting SAVs. These variables include gender, some of the household income ranges (40K – 99K, 100K – 124K, and 125K – 174K), perceived behavioral control, and household size 2. Whereas females, individuals from households with two members, and individuals with household incomes between 40K and 174K are unlikely to use SAVs compared to their reference groups, respondents who believe that using new technologies is not complicated (high level of perceived behavioral control) are more likely to adopt SAVs in the future.

Some predictors – attitude towards a behavior (adopting new technologies), subjective norms, eco-friendliness, age (except for Gen X), disability, household size 1, and driver's license – have both statistically significant direct and indirect (through current use of ride-hailing services as the mediator variable) effects on SAV Intent. Regardless of respondents' current use of ride-hailing services, individuals who take other people's opinions into account when it comes to using a travel mode, have a positive attitude towards new technologies, hold a driver's license, are young

(Gen Z and millennial), and are eco-friendly, are more likely to adopt SAVs, whereas individuals living alone (household size 1) are less likely to use SAVs in the future. Among respondents with physical conditions that prevent driving, individuals who use ride-hailing services currently are more likely to use SAVs, while individuals who have never used ride-hailing services are reluctant to use SAVs in the future.

There are a few predictors that have statistically significant effects on SAV Intent only indirectly, through current use of ride-hailing as the mediator variable. For instance, whereas having post-secondary education has a significant indirect effect on SAV Intent, this predictor has an insignificant direct effect on SAV adoption. Likewise, among respondents who are from Gen X and households with high levels of income (above 175K per year), only individuals who use ride-hailing services, are likely to adopt SAVs, whereas individuals who never used ride-hailing services, are reluctant to use the AV version of such services. This indicates how the current use of shared mobility services – namely, ride-hailing services – plays an important role in adopting SAVs among individuals who are more educated, are in their late adulthood, and have higher incomes.

4.4.3.2. Direct and indirect effects of exogenous variables on pooled AV adoption

Table 17 shows the direct and indirect effects of exogenous variables on PooledAV Intent. Among the predictors, being female, being in a two-person household, and having an annual household income between 40K and 174K, negatively and only directly affects PooledAV adoption. This means that using ride-hailing services currently does not influence behavioral intention towards using PooledAVs among female respondents who live in a two-person household and have 40K to 174K annual household income. Individuals with such socio-demographic characteristics are less likely to adopt PooledAVs regardless of their experiences on ride-hailing services. In contrast, respondents from Gen X, with post-secondary educations, with physical conditions that prevent driving, and have annual household incomes above 174K, are only likely to adopt PooledAVs if they are using ride-hailing services currently. These results imply that wealthy, educated, older individuals with physical disabilities are mostly precautious in adopting new travel modes and prefer to rely on their experience with similar mobility tools.

Among the affective motivations, while subjective norms, attitude towards a behavior, and eco-friendliness have statistically significant positive direct and indirect effects on PooledAV Intent, perceived behavioral control has neither a direct nor an indirect effect Likewise, socio-demographic predictors such as being Gen Z or a millennial, a household size of one, and holding a driver's license have significant direct and indirect effects on PooledAV Intent. This means that most of the affective motivations and some of the socio-demographic predictors explain the variance of PooledAV Intent, whether through current experiences of ride-hailing services or based on expectations towards PooledAVs.

Overall, the mediation analysis confirms that experience with ride-hailing services substantively triggers many people with certain characteristics to be early adopters of SAVs and PooledAVs. The role of experience with ride-hailing services is more pronounced when the predictors are socio-demographic characteristics such as age, household income, physical conditions, and education.

4.4.3.3. Commonalities and differences of early adopters of PooledAVs and SAVs (only direct effects)

In this section, using the direct effects of predictors, the commonalities and differences of early adopters of SAVs and PooledAVs are discussed.

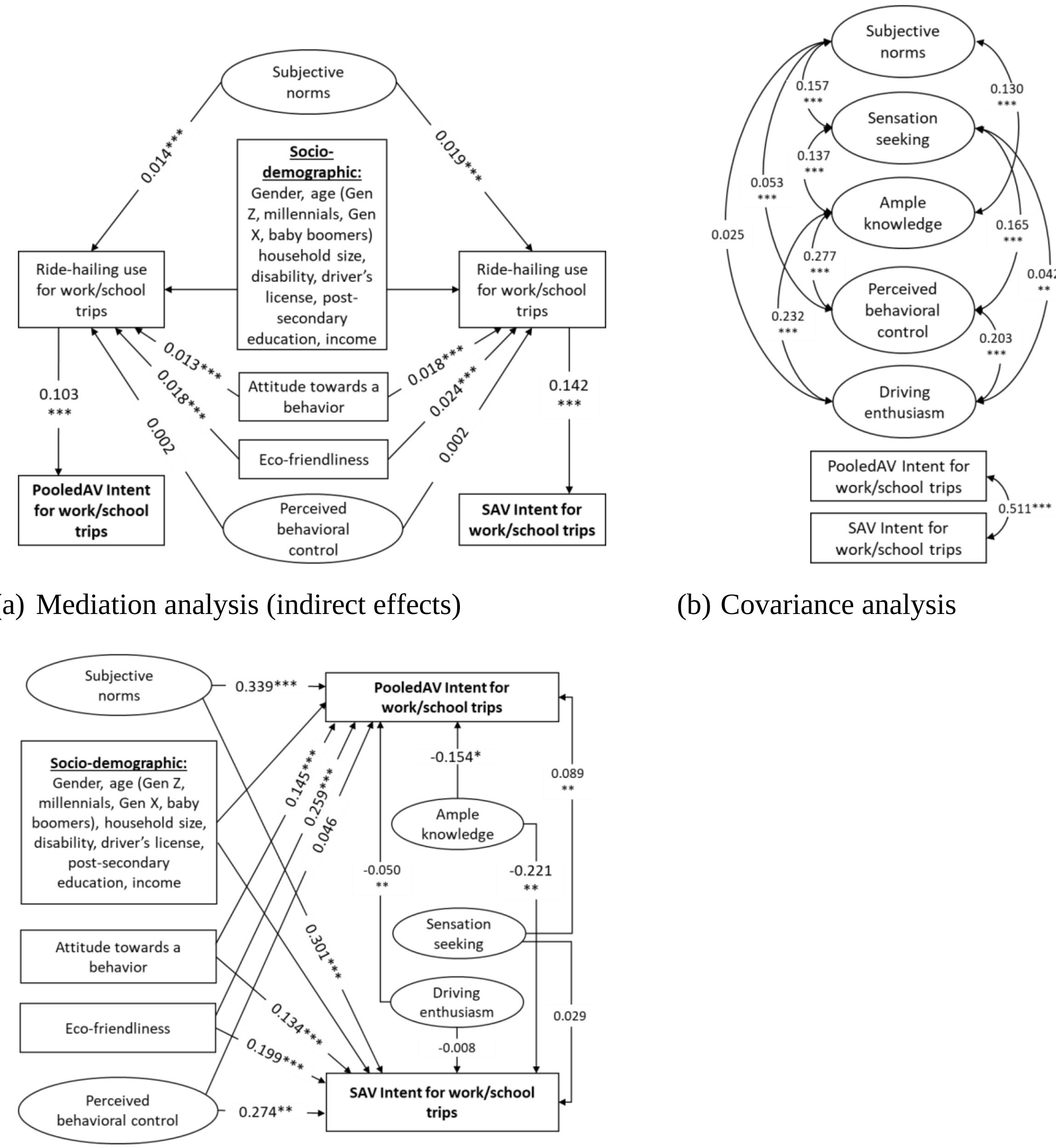
Commonalities:

Among the affective motivations, subjective norms, attitude towards adopting new technologies, and eco-friendliness were strong, positive predictors for both PooledAV adoption and SAV adoption. These findings suggest that respondents who consider other people's opinions and judgments about travel modes, who have positive attitudes towards new technologies and mobility tools (such as AVs), and who value eco-friendliness, are more likely to adopt on-demand AVs. Respondents who believe ample knowledge is essential before adopting new technologies are less likely to be early adopters of on-demand AVs (both SAVs and PooledAVs) perhaps due to their uncertainty about the functionality of these new mobility tools. In other words, these people are uncertain whether they know enough about AV technology and its applications in shared mobility services. Socio-demographic characteristics mostly have a similar effect on PooledAV Intent and SAV Intent. For instance, younger respondents (compared to baby boomers), and individuals who hold a valid driver's license are more likely to adopt both types of on-demand AVs for work/school trips. In contrast, females, individuals residing in single-person and two-person households, and respondents with reported household incomes between 40K and 99K and unknown incomes are reluctant to use SAVs and PooledAVs for their work/school trips. Furthermore, the impact of post-secondary education on the intention to use SAVs and PooledAVs is only significant and positive when the effects are indirect and mediated by ride-hailing experience. In other words, individuals with higher education are more likely to adopt on-demand AVs, but only if they have prior experience with ride-hailing services and are currently using these mobility options. This finding suggests that ride-hailing experience plays a critical role in shaping the intentions of educated individuals towards on-demand AV adoption.

Differences:

The relationship between driving enthusiasm and on-demand AV adoption varies depending on the configuration of on-demand AVs being considered. For PooledAV Intent, driving enthusiasm is a significant negative predictor, whereas it is insignificant for SAV Intent. Moreover, sensation seeking is positively associated with PooledAV Intent but has no significant effect on SAV Intent. On the other hand, perceived behavioral control only has a significant positive association with SAV Intent and is not a significant predictor for PooledAV Intent.

Additionally, socio-demographic variables have different effects on on-demand AV adoption. For example, having a physical condition that prohibits driving is a significant predictor for SAV Intent but not for PooledAV Intent. Household income also plays a role, with those earning between 100K and 174K showing a statistically significant negative relationship with the likelihood of adopting SAVs, but this variable is insignificant for PooledAV Intent.



(a) Mediation analysis (indirect effects)

(b) Covariance analysis

(c) Regression analysis (direct effect)

Figure 6. Results of SEM analysis

Solid arrows refer to estimated effects in the structural equation model while curved arrows represent covarying error terms between latent constructs or between endogenous variables. Boxed variables represent observed variables, whereas oval variables indicate latent constructs estimated using a measurement model. Estimated path coefficients (standardized) are shown for the links between the five latent variables, the intervening variable, and the two dependent (exogenous) variables. Coefficients for estimated effects of individual and household characteristics are not shown, as they are too numerous.

Significance is denoted at 0.10-level (*), 0.05-level (**), and 0.01-level (***).

Table 16. Direct and indirect effects of exogenous variables on SAV Intent using percentile bootstrapping method

Variables	Direct effect		Indirect effect	
	Standardized coefficient	95% percentile bootstrap CI	Standardized coefficient	95% percentile bootstrap CI
Latent constructs:				
Driving enthusiasm	-0.008	[-0.073 0.053]		
Sensation seeking	0.029	[-0.069 0.129]		
Ample knowledge	-0.221**	[-0.816 -0.085]		
Subjective norms	0.301***	[0.340 0.716]	0.019***	[0.019 0.048]
Perceived behavioral control	0.274**	[0.201 1.077]	0.002	[-0.009 0.018]
Observed motivations:				
Attitude towards a behavior	0.134***	[0.219 0.390]	0.018***	[0.027 0.060]
Eco-friendliness	0.199***	[0.129 0.190]	0.024***	[0.013 0.028]
Socio-demographic characteristics:				
Age:				
Gen Z	0.048*	[-0.009 0.285]	0.044***	[0.091 0.176]
Millennial	0.110***	[0.111 0.367]	0.044***	[0.068 0.133]
Gen X	0.045	[-0.021 0.241]	0.013***	[0.014 0.054]
Baby boomers	Reference			
Female	-0.071***	[-0.231 -0.077]	-0.001	[-0.014 0.009]
Education	0.015	[-0.062 0.147]	0.011***	[0.015 0.051]
Disability	-0.055***	[-0.339 -0.075]	0.010***	[0.017 0.059]
Household income (Can$[21]):				
Under 39K	Reference			
40K - 99K	-0.059**	[-0.242 -0.020]	0.001	[-0.063 -0.007]
100K - 124K	-0.059**	[-0.324 -0.039]	0.001	[-0.016 0.019]
125K - 174K	-0.045**	[-0.307 0.004]	-0.001	[-0.019 0.024]
Above 175K	-0.028	[-0.283 0.053]	0.009**	[-0.027 0.018]
Unknown	-0.072***	[-0.491 -0.149]	-0.007**	[0.015 0.068]
Household size				
1	-0.058***	[-0.261 -0.052]	-0.008**	[-0.039 -0.006]
2	-0.048**	[-0.209 -0.026]	0.001	[-0.010 0.015]
3+	Reference			
Driver's license	0.064***	[0.100 0.364]	0.011***	[0.018 0.067]
Mediators:				
Ride-hailing use	0.142***	[0.102 0.183]		
Threshold parameters:				
Unlikely to unsure	0.415***	[0.235 0.665]		
Unsure to likely	1.049***	[0.923 1.359]		

Significance is denoted at 0.10-level (*), 0.05-level (**), and 0.01-level (***)
CI: Confidence interval
CFI: 0.756, RMSEA: 0.061, SRMR: 0.033

[21] Canadian dollar

Table 17. Direct and indirect effects of exogenous variables on PooledAV Intent using percentile bootstrapping method

Variables	Direct effect		Indirect effect	
	Standardized coefficient	95% percentile bootstrap CI	Standardized coefficient	95% percentile bootstrap CI
Latent constructs:				
Driving enthusiasm	-0.050**	[-0.126 -0.001]		
Sensation seeking	0.089**	[0.029 0.219]		
Ample knowledge	-0.154*	[-0.627 0.020]		
Subjective norms	0.339***	[0.408 0.796]	0.014***	[0.013 0.036]
Perceived behavioral control	0.046	[-0.257 0.508]	0.002	[-0.007 0.014]
Observed motivations:				
Attitude towards a behavior	0.145***	[0.256 0.425]	0.013***	[0.017 0.049]
Eco-friendliness	0.259***	[0.182 0.245]	0.018***	[0.008 0.022]
Socio-demographic characteristics:				
Age:				
Gen Z	0.094***	[0.131 0.433]	0.032***	[0.055 0.144]
Millennial	0.146***	[0.199 0.457]	0.032***	[0.041 0.108]
Gen X	0.027	[-0.065 0.203]	0.009***	[0.009 0.043]
Baby boomers	Reference			
Female	-0.108***	[-0.320 -0.163]	-0.001	[-0.010 0.006]
Education	0.029	[-0.025 0.193]	0.008***	[0.010 0.040]
Disability	-0.013	[-0.184 0.083]	0.007***	[0.011 0.047]
Household income (Can$):				
Under 39K	Reference			
40K - 99K	-0.054**	[-0.237 -0.006]	0.000	[-0.012 0.014]
100K - 124K	-0.023	[-0.217 0.072]	0.000	[-0.014 0.018]
125K - 174K	-0.016	[-0.209 0.098]	-0.001	[-0.020 0.014]
Above 175K	-0.034	[-0.320 0.037]	0.007***	[0.010 0.053]
Unknown	-0.052***	[-0.413 -0.060]	-0.005**	[-0.049 -0.005]
Household size				
1	-0.041**	[-0.222 -0.012]	-0.006**	[-0.031 -0.004]
2	-0.043**	[-0.197 -0.015]	0.001	[-0.008 0.011]
3+	Reference			
Driver's license	0.067***	[0.117 0.389]	0.008***	[0.012 0.054]
Mediators:				
Ride-hailing use	0.103***	[0.062 0.151]		
Threshold parameters:				
Unlikely to unsure	0.908***	[0.792 1.232]		
Unsure to likely	1.552***	[1.507 1.954]		

Significance is denoted at 0.10-level (*), 0.05-level (**), and 0.01-level (***)
CI: Confidence interval
CFI: 0.756, RMSEA: 0.061, SRMR: 0.033

Table 18. Standardized covariances of latent constructs and endogenous (dependent) variables

Latent constructs	Driving enthusiasm	Sensation seeking	Ample knowledge	Subjective norms	Perceived behavioral control
Driving enthusiasm	1				
Sensation seeking	0.042**	1			
Ample knowledge	0.232***	0.137***	1		
Subjective norms	0.025	0.157***	0.130***	1	
Perceived behavioral control	0.203***	0.165***	0.277***	0.053***	1
Endogenous variables	SAV Intent	PooledAV Intent			
SAV Intent	1				
PooledAV Intent	0.511***	1			

Significance is denoted at 0.10-level (*), 0.05-level (**), and 0.01-level (***)

4.5. Conclusion

Given the natural synergy between shared mobility services and automation technologies, the present study focused on jointly adopting fully automated on-demand mobility services in the Canadian context with two distinct yet related configurations: (1) shared automated vehicles (SAVs) and (2) pooled automated vehicles (PooledAVs). This study pursued several research objectives related to learning about on-demand AV (pooled AVs and shared AVs) adoption. First, this study provided a novel theoretical model for exploring on-demand AV adoption by building upon existing models. Specifically, it proposed an extended Theory of Planned Behavior (TPB) research framework using additional affective motivations where the final proposed framework included seven affective motivations: attitude towards a behavior, perceived behavioral control, subjective norms, sensation seeking, driving enthusiasm, ample knowledge, and eco-friendliness. Results demonstrated that the proposed TPB research framework is valid and affective motivations were found to be the most important predictors in using on-demand AVs, where subjective norms was the most significant latent construct, meaning individuals are most concerned about others' opinions in adopting on-demand AVs. Also, results show that attitude towards the behavior and eco-friendliness were the strongest observed affective predictors. In other words, eco-friendly individuals who have positive attitudes towards adopting new technologies are more likely to be early adopters of SAVs and PooledAVs.

Second, this study aimed to understand the relationship between the current use of ride-hailing services and the adoption of on-demand AVs using structural equation modeling (SEM) and mediation analysis. In other words, this paper explores the direct impact of each predictor on PooledAV Intent and SAV Intent, as well as their indirect effects through ride-hailing usage as a mediator variable. Through this research, a better understanding of the factors that influence on-demand AV adoption and the role that ride-hailing services play in this process was gained. Based on the findings of this study, it can be inferred that the current use of ride-hailing services can elucidate the variances in behavioral intention towards on-demand AVs, particularly through indirect effects of socio-demographic factors.

Finally, this study identified the commonalities and differences of characteristics of SAVs' and PooledAVs' early adopters. Respondents who consider other people's opinions and judgments about the travel mode, who have a positive attitude towards new technologies and new mobility tools (such as AVs), and who are considered eco-friendly, are more likely to be the early adopters of on-demand AVs (both SAV and PooledAV services). Individuals who are sensation seekers and are not driving enthusiasts are more likely to be early adopters of PooledAVs, whereas respondents who believe using new technologies and new mobility tools is not difficult and/or have physical conditions prohibiting them from driving are more likely to be early adopters of SAVs. In other words, individuals with physical disabilities who possess a strong sense of perceived behavioral control may be hesitant to share a driverless ride with strangers, whereas those who frequently seek out thrilling or intense experiences and are comfortable taking risks may be more inclined to share a driverless ride with strangers.

Overall, this study found that the socio-demographic characteristics of early adopters of SAVs and PooledAVs are not significantly different from one another, and those who embrace one of these potential services are also inclined to use the other on-demand AV service (Table 18).

As in many other studies, the findings of this study should be interpreted as bookends of possibilities. Due to the significant uncertainty in the future market for on-demand AVs, this study's main objective centered on (1) understanding whether on-demand AVs will be adopted for work/school trips in the Canadian context and if so, (2) who and under what conditions may adopt different on-demand AV service types (SAVs and PooledAVs), and (3) what individual characteristics may trigger different behavioral intentions among the on-demand AV service types. This study concluded that although current users of existing ride-hailing services are likely to be early adopters and prospective consumers of on-demand AVs, many Canadians are yet either uncertain or reluctant to adopt AV technology in shared mobility services for daily trips. In this light, policymakers and planners should adjust and moderate their expectations regarding the future market for on-demand AVs and be prepared for potential changes in travel behavior by examining incremental changes in existing on-demand ride-hailing services.

Notes:

1. Other indicators asked in the survey for each of the latent variables were found to be insignificant in the full SEM. Also, besides the affective motivations used in this study, additional indicators were employed: multitasking, privacy concerns, and car ownership interest. However, none were statistically significant.
2. The frequency of using public transit was another mediator variable, designed to mediate the effects of exogenous variables on PooledAV Intent. Its effect on PooledAV Intent was statistically insignificant using the bootstrapping method, whereas both mediator variables (use of ride-hailing services, and use of public transit) were statistically significant when the Sobel test was used for the mediation analysis. Since the bootstrapping method is a more valid approach, the results of that method are shown in this paper, meaning that use of public transit is eliminated as a mediator variable.

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Chapter 5

Conclusions and Future Research

This dissertation investigated Canadians' intentions to use and adopt on-demand AVs – namely, shared automated vehicles (SAVs) and pooled automated vehicles (PooledAVs). The aim was to develop a future mobility framework by assessing the intention to adopt new mobility tools through a theoretical framework based on TPB and additional affective motivations suggested by past AV studies. To this end, a nationwide Canadian survey, called the Future Mobility in Canada Survey (FMCS), was designed to capture the complex decision-making processes of travel behavior changes and the adoption of automated vehicles by assessing individual preferences, affective motivations, and behavioral intentions. Overall, the results of this dissertation will not only be of interest to academics, but also the findings could be used by policymakers, planners, and the vehicle and technology industries that are investing in on-demand AVs since identifying prospective users of SAVs and PooledAVs and the potential use of such services are necessary precursors for anticipating the future market for on-demand AV and the travel behavior changes that could arise from such technology.

In a nutshell, the results of this dissertation suggest that policymakers, planners, the vehicle and technology industries, and the public at large should moderate their expectations that AVs may suddenly transform the entire transportation sector. Instead, this dissertation suggests that on-demand AVs are likely to be adopted as a supplementary mobility tool rather than a substitution for current travel modes since trust in AV technology is still developing. By introducing on-demand AVs as supplementary mobility tools, people can gradually experience the benefits and gain trust in these mobility tools. Broadly, this implies that policymakers may be well served to look at incremental changes in similar existing mobility tools, such as on-demand ride hailing, to explore how such new technologies change the transportation sector on the margins. Nevertheless, while evidence of a niche role appears to be strong, it is not clear whether this role may be more normalized in everyday mobility experiences as automated vehicle technologies become more commonplace.

5.1. Contributions and novel aspects

There are several main contributions and novel aspects associated with this dissertation as follows.

1) Overview and characteristics of FMCS

Chapter 2 provided an in-depth discussion of a future mobility survey design while the survey focus was mostly on automated vehicle adoption. The use of survey panel, screening criteria, emphasis on various AV configurations, the selection of alternatives, affective motivations, and the use-case scenarios, and the approach to reduce response burden were all significant decisions in the survey design process while were not expansively reviewed in the past AV studies. Chapter 2 aimed to improve the body of existing survey design literature by providing systematic guidance on efficient survey data collection to identify prospective consumers of AVs, and elucidating approaches to measuring the complex decision-making process of adopting unobserved mobility tools. Beyond its contribution to the AV literature, chapter 2 documented explicitly the methods and considerations involved during survey design to capture changes in travel behavior particularly for shared mobility services and public transit when confronting new challenges such as the COVID-19 pandemic and assessed the existing use of teleworking and preferences towards it with respect to the pandemic.

2) AV types and use-case scenarios

To the best of our knowledge FMCS is the first survey of its kind assessing all types of AVs at a nationwide scale in Canada with a large sample size. Aside from the types of alternatives, another important novelty of FMCS was the interpretation of alternatives to assure that respondents understood differences between each AV type and their applications. In FMCS, a novel and new approach involving user-centered use-case scenarios was designed and conducted. In this approach, the intention toward using on-demand AVs was not assessed through preferring such modes over other modes, but instead through recognizing situations and trip purposes where respondents might demand SAVs and PooledAVs. Although this approach has been applied in a few AV studies, they were only considered as technical and systematic aspects based on the level of AVs. Hence, to the best of our knowledge, no investigation has considered use cases of SAVs or PooledAVs based on trip purposes as a scenario design method.

3) Selection of affective motivations

Most of the measured attributes in FMCS were affective factors since AVs are yet unprecedented travel modes and factors influencing intention to use them are still speculative. To this end, an extended and comprehensive model of TPB was developed and applied in the survey design, where the components comprise behavioral intention, perceived behavioral control, attitude towards a behavior, subjective norms, trust, affinity towards technology, eco-friendliness, knowledge, sensation seeking, driving enthusiasm, multitasking, privacy concerns, and car ownership interest. Unlike previous studies, in FMCS, implicit statements embedding the affective motivations to understand respondents' perceptions, inclinations, and preferences towards new/emerging mobility tools like AVs and shared mobility services, were used.

4) Classification of respondents to "use-case-variant" and "use-case-invariant" groups

Using a binomial probit model, this thesis distinguished the characteristics of the "*use-case-invariant*" people, who have stated the same behavioral intention towards SAVs regardless of use cases, versus the "*use-case-variant*" individuals, who considered use cases for their behavioral intentions towards adopting SAVs. This thesis demonstrated that the use cases of SAVs matter to half of the respondents, and "*use-case-variant*" respondents are more likely to adopt SAVs for occasional trips.

Additionally, the commonality and differences of characteristics of "*use-case-variant*" and "*use-case-invariant*" respondents were determined using five ordered probit models; one for "*use-case-invariant*" respondents and four for "*use-case-variant*" respondents, where each of the four use-case scenarios was allocated to a separate model. This classification showed that whereas for each use case, different affective motivations, sociodemographic features, and travel behavior characteristics influence intention to use SAVs, there are some commonalities in characteristics of early adopters. This novel approach also called into question what trip purposes or use cases really matter when it comes to SAV adoption. A question concerning whether SAV use is likely to be concentrated in occasional rather than regular trips was pointed out through this classification of respondents. Results demonstrated that people are more willing to use SAVs for occasional trips rather than regular basis trips.

5) Use of mediation analysis alongside a SEM in assessing on-demand AV adoptions

To understand the relationship between the current use of ride-hailing services and the adoption of on-demand AVs, a SEM and mediation analysis were developed and proposed. This thesis appraises whether current use of ride-hailing services frames a pathway towards adopting on-demand AVs. In other words, this thesis explored the direct impact of each predictor on PooledAV adoption and SAV adoption, as well as their indirect effects through ride-hailing usage as a mediator variable. Through this thesis, a better understanding of the factors influencing on-demand AV adoption and the role that ride-hailing services play in this process was gained. Based on the findings of this thesis, it can be inferred that the current use of ride-hailing services can elucidate the variances in behavioral intention towards on-demand AVs.

6) Emphasis on characteristics of SAVs' and PooledAVs' early adopters

Using a full SEM based on an extended TPB model, this thesis differentiated between early adopters of SAVs and early adopters of PooledAVs. The commonality and differences of characteristics of early adopters were identified and well described. The results of this analysis could be employed by policymakers, planners, and the vehicle and technology industries that are investing in on-demand AVs since identifying characteristics of prospective users of SAVs and PooledAVs is a necessary precursor for anticipating its future market and the travel behavior changes that could arise from such technology.

5.2. Future research

While this research has made various contributions, a few suggestions for future research are advocated in the following. By dedicating attention to these research suggestions, we can enhance our comprehension of AV adoption, while AVs are still unobserved travel modes in many parts of the world. Gaining a thorough understanding of the public's behavioral intentions towards different

AV configurations can greatly assist policymakers and transportation planners, enabling them to make more informed decisions and effectively prepare for potential changes in travel behavior.

1) Although thorough and meticulous information regarding changes in Canadian travel behavior due to the existence new mobility tools and emerging travel modes are collected through FMCS, the effect of passing of time as a newfound predictor, can be considered by collecting data using further waves of FMCS.
2) Some instrumental (monetary) motivations can be added to the future waves of FMCS to compare the effect of affective and instrumental motivations on on-demand AV adoption. This type of motivations may explain the part of behavioral variances towards AV adoption that could not be addressed through affective motivations.
3) A comparison of the use-centered use-case scenario approach employed in FMCS with similar surveys in the context of on-demand AV adoption using SP approach can be used to provide further knowledge about techniques and strategies that are most suitable to be adopted by researchers. Additionally, these strategies can help uncover effective techniques for minimizing response burden.
4) Despite the suggestion of past studies, this thesis could not find some of the affective motivations such as “multitasking” and “privacy concerns” significant in assessing behavioral intentions towards on-demand AVs. An investigation of the extended TPB model, which is proposed in this thesis in chapter 2, on privately-owned AVs can reveal the role of these variables in explaining behavioral variances towards AVs.
5) Identifying the residential and workplace six-digit postal codes is a critical part of FMCS as it paves the way for future research to explore a targeted geographical analysis of prospective on-demand adopters. One possible research objective using postal codes could be to identify

areas characterized by high demand for on-demand AV hubs and assess their impact on the distribution networks of SAVs and PooledAVs.

6) Incorporating qualitative research methods, such as focus groups or face-to-face interviews, can provide valuable insights into comprehending the factors influencing adoption of each AV configuration.

Appendix

Appendix A: Completion times based on mobility tools and socio-demographic characteristics

Variables	Mean completion time (min:sec)	Median completion time (min:sec)	25% percentile (min:sec)	75% percentile (min:sec)
Ride hailing				
Used ride-hailing service	18:11	12:26	09:07	17:48
Never used ride-hailing service	20:20	12:22	08:59	17:11
Car sharing				
Member of car-sharing service	22:46	10:05	06:36	15:33
Not a member of car-sharing service	18:49	12:33	09:15	17:35
Bike sharing				
Member of bike-sharing service	24:20	10:02	05:55	19:43
Not a member of bike-sharing service	18:50	12:30	09:12	17:25
Employment				
Employed	19:04	12:05	08:48	17:25
Not in labour force	19:21	12:55	09:40	17:34
Driver's license				
Hold a driver's license	19:08	12:22	09:05	17:25
Does not hold a driver's license	21:24	12:57	08:55	17:56
Age groups				
18 – 35	16:26	10:21	07:33	14:49
36 – 55	20:01	12:38	09:12	18:24
56 – 75	20:32	13:25	10:46	18:41
All respondents	16:20	12:33	09:04	17:27

Appendix B: Future Mobility in Canada Survey Questionnaire

Screening Questions

1. What is your age (in years)? _______________

2. What is your gender?
[1] Male/man
[2] Female/woman
[3] Prefer to self-identify as: _______________

3A. What are the six digits of your residential postal code (e.g., A1A 1A1)?

If you do not know your postal code, you can look it up in Google Maps (a new window will open)

3B. Is this correct?
[1] Yes
[2] No
[If the answer to Q3B is "No" [2], return to Q3A and ask for the postal code again. If someone is returned to Q3A a second time, then terminate with the statement: "Thank you for considering this survey. Unfortunately, you do not meet the geographic requirements for participating in it."]

4. What category best describes your total household income in 2020?
[1] Under $ 39,999
[2] $40,000 to $99,999
[3] $100,000 to $124,999
[4] $125,000 to $174,999
[5] $175,000 and above
[6]Prefer not to answer
[7] I do not know

A. Self-Driving Vehicles

In this section of the survey, we are interested in your preferences and opinions related to private self-driving vehicles, self-driving transit vehicles, and shared self-driving vehicles, which operate as a ride-hailing service (like Uber and Lyft).

What is a self-driving vehicle?
Self-driving vehicles are equipped with technologies to navigate streets with no need for a human driver. Such vehicles allow drivers to do something else with their time rather than drive.

5. Imagine that self-driving vehicles are available to buy. Please indicate your likelihood to do the following.

	Very Unlikely	Unlikely	Neutral	Likely	Very Likely
Be one of the first people to buy a self-driving vehicle.	[1]	[2]	[3]	[4]	[5]
Eventually buy a self-driving vehicle, but not until they are in common use.	[1]	[2]	[3]	[4]	[5]

6. If you are purchasing a new vehicle, how much **more** would you be willing to pay for it to be available as a fully driverless vehicle as opposed to a conventional vehicle?
[1] I would not purchase a self-driving vehicle
[2] Less than $1000
[3] $1000 to $4,999
[4] $5,000 to $9,999
[5] $10,000 to $14,999
[6] More than $15,000

7. Some automakers are considering charging an hourly fee for the option to enable the self-driving features of privately-owned vehicles **rather than increasing the cost of such vehicles upfront**. What is the **most** that you would be willing to pay per hour if you choose to use this self-driving service in your vehicle?
[1] I would not use such a service
[2] Less than $3 per hour
[3] $3 to $5.99 per hour
[4] $6 to $8.99 per hour
[5] $9 to $11.99 per hour
[6] $12 per hour or more

8. What is the likelihood that you would be willing to ride a **small shuttle bus** if it was self-driving without a driver (driverless)?
[1] Very unlikely
[2] Unlikely
[3] Neutral
[4] Likely
[5] Very likely

9. What is the likelihood that you would be willing to ride a **regular-size or articulated bus** if it was self-driving without a driver (driverless)?
[1] Very unlikely
[2] Unlikely
[3] Neutral
[4] Likely
[5] Very likely

What is a self-driving, ride-hailing service?

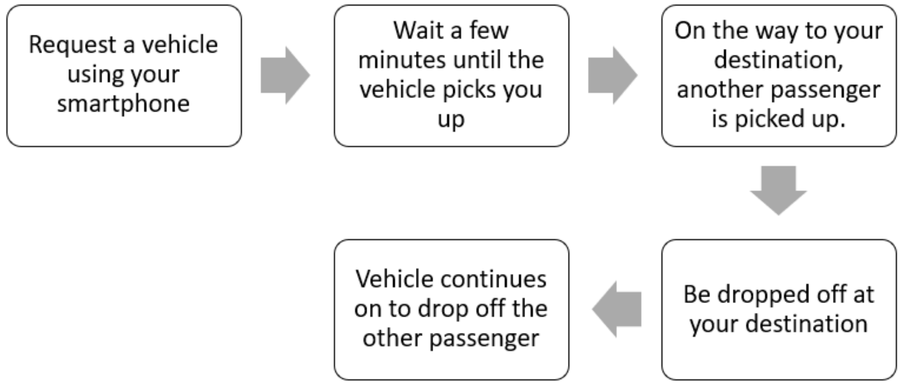
A self-driving, ride-hailing service is a taxi or Uber/Lyft service without a driver. You would request a vehicle through an app on your smartphone.

What is a shared self-driving, ride-hailing service?
This form of self-driving, ride-hailing service is used if you want to travel alone or share a ride with someone you know, such as a family member or friend. You would **not** share your ride with someone you do not know. For this service, you would:

10. Please indicate your likelihood to do the following.

Scenarios	Very Unlikely	Unlikely	Neutral	Likely	Very Likely
Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for work or school trips.	[1]	[2]	[3]	[4]	[5]
Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for trips other than work or school (e.g., trips to/from a store, trips to/from a friend's house, etc.).	[1]	[2]	[3]	[4]	[5]
Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for special events or performances (e.g., hockey games, concerts, etc.).	[1]	[2]	[3]	[4]	[5]
Use a shared self-driving, ride-hailing service (where you ride alone or with someone you know) for trips to/from an airport.	[1]	[2]	[3]	[4]	[5]

What is a pooled self-driving, ride-hailing service?
This form of self-driving, ride-hailing service is used if you want to share a ride with someone you **do not know** to save on the cost of travel. During the trip, pooled self-driving vehicles pick up other passengers who you do not know. Pooling with other passengers lowers the cost, yet may cause detours, making your trip longer. If you want to use a pooled self-driving service (where you ride with people you **do not know**), you would:



11. Please indicate your likelihood to do the following.

Scenarios	Very Unlikely	Unlikely	Neutral	Likely	Very Likely
Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for work or school trips.	[1]	[2]	[3]	[4]	[5]
Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for trips other than work or school (e.g., trips to/from a store, trips to/from a friend's house, etc.).	[1]	[2]	[3]	[4]	[5]
Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for a special events or performances (e.g., hockey games, concerts, etc.).	[1]	[2]	[3]	[4]	[5]
Use a pooled self-driving, ride-hailing service (where you ride with someone you do not know) for trips to/from an airport.	[1]	[2]	[3]	[4]	[5]

B. Mobility Tools and Travel Behavior

12. Do you have a valid driver's license for driving on your own?
[1] Yes
[2] No

13. Do you own a bicycle?
[1] Yes
[2] No

14. Did you own a bicycle prior to the COVID-19 pandemic in Canada (February 2020)?
[1] Yes
[2] No

15. How many days over the past week did you use your bicycle for **non-recreational trips** (e.g., biking to work, to school, to a store, to a friend's house, etc.)?
[1] I never use my bicycle for such trips
[2] I use my bicycle for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days
[6] 7 days

16. Consider your **last non-recreational bicycle trip**. If you would have taken that trip by another travel mode, what mode would you have <u>most likely</u> used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Public transit (e.g., bus, subway, streetcar)
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Bike share
[10] Other
[11] I would not have taken the trip

17. How many days over the past week did you use your bicycle for **recreational trips**?
[1] I never use my bicycle for such trips
[2] I use my bicycle for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days
[6] 7 days

18. Are you a member of a bike-sharing program?
[1] Yes
[2] No

19. Were you a member of a bike-sharing program prior to the COVID-19 pandemic in Canada (February 2020)?
[1] Yes
[2] No

20. How many days over the past week did you use bike share for **non-recreational trips** (e.g., biking to work, to school, to a store, to a friend's house, etc.)?
[1] I never use bike share for such trips
[2] I use bike share for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days

[6] 7 days

21. Consider your **last non-recreational bike share trip**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Public transit (e.g., bus, subway, streetcar)
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Own bicycle
[10] Other
[11] I would not have taken the trip

22. How many days over the past week did you use bike share for **recreational trips**?
[1] I never use bike share for such trips
[2] I use bike share for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days
[6] 7 days

23. Are you a member of a car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)?
[1] Yes
[2] No

24. How many days over the past week did you use a car-sharing service?
[1] I use a car-share service, but have not done so in the past week
[2] 1-2 days
[3] 3-4 days
[4] 5-6 days
[5] 7 days

25. Consider your **last car-sharing trip**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Public transit (e.g., bus, subway, streetcar)
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Bike share
[8] Taxi
[9] Own bicycle
[10] Other
[11] I would not have taken the trip

26. Have you ever used a ride-hailing service (e.g., Uber, Lyft)?
[1] Yes
[2] No

27. How many days over the past week did you use a ride-hailing service?
[1] I use a ride-hailing service, but have not done so in the past week
[2] 1-2 days
[3] 3-4 days
[4] 5-6 days
[5] 7 days

28. Consider your **last trip with a ride-hailing service**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Public transit (e.g., bus, subway, streetcar)
[4] Walk
[5] Own bicycle
[6] Bike share
[7] Car-sharing service (e.g., Zip Car, CarGo)
[8] Taxi
[9] Other
[10] I would not have taken the trip

29. Prior to the COVID-19 pandemic in Canada (February 2020), how many days in a typical week did you use a ride-hailing service?
[1] I did not use a ride-hailing service prior to the COVID-19 pandemic
[2] I used a ride-hailing service prior to the COVID-19 pandemic, but it was less than one day per week
[3] 1-2 days per week
[4] 3-4 days per week
[5] 5-6 days per week
[6] 7 days

30. Do you have a public transit pass or public transit fare card?
[1] Yes
[2] No

31. Prior to the COVID-19 pandemic in Canada (February 2020), did you have a public transit pass or public transit fare card?
[1] Yes
[2] No

32. How many days over the past week did you use public transit to travel to **work or school**?
[1] I never use public transit for such trips
[2] I use public transit for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days
[6] 7 days

33. Consider your **last public transit trip to work or school**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Own bicycle
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Bike share
[10] Other
[11] I would not have taken the trip

34. Prior to the COVID-19 pandemic in Canada (February 2020), how many days in a typical week did you use public transit to travel to **work or school**?
[1] I did not use public transit for such trips prior to the COVID-19 pandemic
[2] I used public transit for such trips prior to the COVID-19 pandemic, but it was less than one day per week
[3] 1-2 days per week
[4] 3-4 days per week
[5] 5-6 days per week
[6] 7 days per week

35. Consider your **last public transit trip to work or school prior to the COVID-19 pandemic in Canada (February 2020)**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Own bicycle
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Bike share
[10] Other
[11] I would not have taken the trip

36. How many days over the past week did you use public transit to travel for a **purpose other than work or school** (e.g., trip to a store, trip to a friend’s house)?
[1] I never use public transit for such trips
[2] I use public transit for such trips, but have not done so in the past week
[3] 1-2 days
[4] 3-4 days
[5] 5-6 days
[6] 7 days

37. Consider your **last public transit trip for a purpose other than work or school**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver

[2] Car, truck, SUV or van as a passenger
[3] Own bicycle
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Bike share
[10] Other
[11] I would not have taken the trip

38. Prior to the COVID-19 pandemic in Canada (February 2020), how many days in a typical week did you use public transit to travel for a **purpose other than work or school**?
[1] I did not use public transit for such trips prior to the COVID-19 pandemic
[2] I used public transit for such trips prior to the COVID-19 pandemic, but it was less than one day per week
[3] 1-2 days per week
[4] 3-4 days per week
[5] 5-6 days per week
[6] 7 days per week

39. Consider your **last public transit trip for a purpose other than work or school prior to the COVID-19 pandemic in Canada (February 2020)**. If you would have taken that trip by another travel mode, what mode would you have most likely used?
[1] Car, truck, SUV or van as a driver
[2] Car, truck, SUV or van as a passenger
[3] Own bicycle
[4] Walk
[5] Ride-hailing service alone (e.g., Uber, Lyft)
[6] Ride-hailing service with other passengers (e.g., Uberpool)
[7] Car-sharing service (e.g., Zip Car, CarGo, Enterprise CarShare)
[8] Taxi
[9] Bike share
[10] Other
[11] I would not have taken the trip

40. How many motor vehicles (cars, trucks, SUVs, vans, etc.) are owned or leased by members of your household including yourself?
[1] 0
[2] 1
[3] 2
[4] 3
[5] 4
[6] 5 or more

41. Which of the following best describes the availability of a motor vehicle in your household for your personal use?
[1] I never have access to a household vehicle
[2] I rarely have access to a household vehicle
[3] I sometimes have access to a household vehicle
[4] I have access to a household vehicle most of the time

[5] I have access to a household vehicle all of the time

42. Which of the following statements best describes the type of motor vehicle that you use most often?
[1] Conventional vehicle (internal combustion engine using gas or diesel)
[2] Battery electric vehicle (e.g., Nissan Leaf or Tesla)
[3] Plug-in hybrid-electric vehicle (e.g., Chevy Volt)
[4] Hybrid electric vehicle (e.g., Toyota Prius)
[5] Other (please specify): _______________

43. Have you ever driven an electric vehicle?
[1] Yes
[2] No
[3] I do not know

C. Employment and Telework

44. What is your current work status?
[1] Employed full time (work 30 hours or more per week)
[2] Employed part time (work less than 30 hours per week)
[3] Unemployed (no job, but looking for a job)
[4] Not in the labor force (no job and not looking for a job)
[5] Retired

45. Which of the following best describes your occupation?
[1] Professional, management or technical
[2] General office or clerical
[3] Sales and services
[4] Manufacturing, construction or trades
[5] Other (please specify): _______________

46. Prior to the COVID-19 pandemic in Canada (February 2020), did you work at a location outside your home, such as an office?
[1] Yes
[2] No, I worked only from home
[3] No, I was not employed

47. During the COVID-19 pandemic in Canada, were you **required** to telework by your employer?
[1] Yes
[2] No, I was not required to telework by my employer
[3] No, I was not employed

48. In the past month, did you telework?
[1] Yes
[2] No

49. Which of the following statements best describes the teleworking arrangement with your employer?
[1] My employer **requires** me to telework.

[2] My employer **allows** me to telework (that is, I can decide whether I want to telework or not).

50. How many days over the past month did you telework?
[1] A few days a month
[2] 1-2 days per week
[3] 3-4 days per week
[4] 5 days or more per week

51. Ideally, how many days would you like to telework in a month?
[1] 0 days
[2] A few days a month
[3] 1-2 days per week
[4] 3-4 days per week
[5] 5 days or more per week

52. Prior to the COVID-19 pandemic in Canada (February 2020), how many days did you typically telework in a month?
[1] My occupation did not allow for telework
[2] 0 days
[3] A few days a month
[4] 1-2 days per week
[5] 3-4 days per week
[6] 5 days or more per week

53. During the COVID-19 pandemic in Canada, how many days did you typically telework in a month?
[1] My occupation did not allow for telework
[2] 0 days
[3] A few days a month
[4] 1-2 days per week
[5] 3-4 days per week
[6] 5 days or more per week

54A. What is the six-digit postal code (e.g., A1A 1A1) of your usual workplace?_______________

☐ I do not know

☐ I work outside Canada

If you do not know your postal code, you can look it up in Google Maps (a new window will open)

54B. Based on your response, your usual workplace is located in [Town/City].

Is this correct?
[1] Yes
[2] No

[If the answer to 54A is "I do not know" or the answer to 55B is "No" [2], then ask 54C.

54C. What is the closest major street intersection to your usual workplace, along with the municipality and province it is located in?

Town/City: _______________
Province: _______________
Street Intersection: Street 1_______________ and Street 2_______________

55. Has the distance from your home to your usual place of work changed since the beginning of the COVID-19 pandemic in Canada (since March 2020 to now)?
[1] Yes
[2] No

56. Which of the following statements best describes the change in commuting distance?
[1] The distance from my home to my usual place of work has increased.
[2] The distance from my home to my usual place of work has decreased.

57. Do you have space in your residence from which you can work from home?
[1] Yes, an entire room
[2] Yes, part of a room
[3] No

D. Attitudinal Statements

58. When it comes to adopting new technology, are you typically an early adopter, late adopter, or laggard?
[1] Early adopter—I am among the first of my friends to adopt new technology
[2] Late adopter—I wait a while before adopting new technology
[3] Laggard—I am among the last of my friends to adopt new technology, if I adopt at all

59. Please indicate the extent to which you agree or disagree with the following statements.

Statements	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
Whenever possible, I prefer to walk or bicycle rather than drive.	[1]	[2]	[3]	[4]	[5]
Whenever possible, I prefer to take transit rather than drive.	[1]	[2]	[3]	[4]	[5]
I try to limit my driving to reduce air pollution.	[1]	[2]	[3]	[4]	[5]
It is important to keep up with the latest trends in technology.	[1]	[2]	[3]	[4]	[5]
I like to have the latest technologies in my car.	[1]	[2]	[3]	[4]	[5]
It is enough for me that a technical system works; I don’t care how or why.	[1]	[2]	[3]	[4]	[5]
Driving a car is something I enjoy.	[1]	[2]	[3]	[4]	[5]

Owing a car is a symbol of success.	[1]	[2]	[3]	[4]	[5]
I can complete my daily tasks without a car.	[1]	[2]	[3]	[4]	[5]
I do not like driving during rush hour.	[1]	[2]	[3]	[4]	[5]
I do not like driving in busy or congested areas.	[1]	[2]	[3]	[4]	[5]
I like new and exciting experiences even if they are a little frightening or unconventional.	[1]	[2]	[3]	[4]	[5]
I like to explore strange places or parts of town by myself even if it means getting lost.	[1]	[2]	[3]	[4]	[5]
I would like to try parachute jumping.	[1]	[2]	[3]	[4]	[5]
The only good thing about traveling is arriving at the destination.	[1]	[2]	[3]	[4]	[5]
Travel time is generally wasted time.	[1]	[2]	[3]	[4]	[5]
Usually, I use my travel time productively.	[1]	[2]	[3]	[4]	[5]
I am concerned about privacy when purchasing something online or through an app.	[1]	[2]	[3]	[4]	[5]
Popular tech companies such as Google and Facebook protect my personal data.	[1]	[2]	[3]	[4]	[5]
I am concerned that hackers may take control of my phone, tablet or computer.	[1]	[2]	[3]	[4]	[5]
I know a lot about self-driving vehicles.	[1]	[2]	[3]	[4]	[5]
Having ample knowledge before purchasing a car is necessary for negotiating a good price.	[1]	[2]	[3]	[4]	[5]
It is necessary to learn about new technology before adopting it.	[1]	[2]	[3]	[4]	[5]
People important to me encourage me to use up-to-date devices.	[1]	[2]	[3]	[4]	[5]
Seeing people who are important to me using public transit makes me also want to use public transit.	[1]	[2]	[3]	[4]	[5]
I enjoy making my own decisions.	[1]	[2]	[3]	[4]	[5]
I would rather someone else be the leader on a group project.	[1]	[2]	[3]	[4]	[5]

Given enough time, I can learn and master high-tech devices.	[1]	[2]	[3]	[4]	[5]
I believe online services are committed to protecting my personal information.	[1]	[2]	[3]	[4]	[5]
Popular tech companies such as Google, Tesla, and Microsoft, are reliable.	[1]	[2]	[3]	[4]	[5]
Overall, I trust new emerging technologies.	[1]	[2]	[3]	[4]	[5]

E. Demographics

60. What is your current student status?
[1] Full-time student
[2] Part-time student
[3] Not a student

61. What is the highest level of education you have obtained?
[1] Did not complete high school
[2] High school diploma or equivalency certificate
[3] Registered apprenticeship or other trades certificate or diploma
[4] College, CEGEP or other non-university certificate or diploma
[5] Bachelor's degree
[6] Degree in medicine, dentistry, veterinary medicine or optometry
[7] Graduate degree (masters or doctorate)

62. What is your immigrant status?
[1] Non-immigrant and/or Canadian citizen by birth
[2] Immigrant
[3] Non-permanent resident

63. How many years has it been since you first obtained landed immigrant or permanent resident status?
[1] Less than 2 years
[2] 2-5 years
[3] 6-10 years
[4] 11-15 years
[5] More than 15 years

64. According to Statistics Canada, **ethnic origin** refers to the "ethnic or cultural origins of a person's ancestors. An ancestor is usually more distant than a grandparent." Based on this definition, what is your ethnic origin(s)? **Select all that apply.**
[1] North American Indigenous origins
[2] Other North American origins
[3] European origins
[4] Caribbean origins
[5] Latin, Central and South American origins
[6] African origins

[7] Asian origins
[8] Oceania origins

65. Including yourself, how many people live in your household? _______________

66. Including yourself, how many people in your household hold a valid driver's license for personal use? _______________

67. Including yourself, how many people in your household are employed full-time or part-time? _______________

68. Including yourself, how many people in your household are retired? _______________

69. How many people in your household are children between the ages of 0 and 15? _______________

70. How long have you lived at your current address (to the nearest year)? _______________ years

71. Do you own or rent your home?
[1] Own
[2] Rent

72. Do you have any health problems or disabilities that affect your mobility?
[1] Yes
[2] No

Survey Completed – Thank You

Thank you for taking our survey. Your efforts are greatly appreciated!