University of Calgary

PRISM Repository **https://prism.ucalgary.ca**

The Vault Open Theses and Dissertations

2017

Factors Influencing the Use of Autonomous and Shared Autonomous Vehicles in Alberta

Ghaffari Targhi, Mahsa

Ghaffari Targhi, M. (2017). Factors Influencing the Use of Autonomous and Shared Autonomous Vehicles in Alberta (Master's thesis, University of Calgary, Calgary, Canada). Retrieved from https://prism.ucalgary.ca. doi:10.11575/PRISM/26152

http://hdl.handle.net/11023/3862

Downloaded from PRISM Repository, University of Calgary

UNIVERSITY OF CALGARY

Factors Influencing the Use of Autonomous and Shared Autonomous Vehicles in Alberta

by

Mahsa Ghaffari Targhi

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE

GRADUATE PROGRAM IN CIVIL ENGINEERING

CALGARY, ALBERTA

MAY, 2017

© Mahsa Ghaffari 2017

Abstract

Autonomous vehicles (AV) are expected to have a wide-ranging affect on traffic congestion, safety, comfort, car ownership, land use and the environment. In this thesis, stated preference survey was designed to examine people's willingness to give up driving control to AVs and their willingness to use them as shared autonomous vehicles (SAV). The results indicate that Level 3 automation should be skipped and the market should move directly to full automation. People are willing to pay $3529, $2691 and $4349 per year for the fixed cost of AVs with Level 2, 3, and 4 automation. The early owners of AVs are males over 50 years old and the early adaptors of SAVs are males younger than 35 years old. Also, the willingness to use higher levels of automation is attributed to people's perception towards AVs.

Keywords: autonomous vehicle, shared autonomous vehicle, willingness to pay, demand modelling

Acknowledgements

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Lina Kattan who is a role model for me with her amazing personality. She had a profound impact on my life by trusting me in her research group and teaching me not just the engineering but the life lessons. Fervent thanks to my co-supervisor, Dr. Alex De Barros, for his time and the insightful suggestions and comments.

I would also like to thank my examining committee for their time and for all their comments.

This work was partially funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) and Alberta Motor Association - Alberta Innovates Technology Futures (AMA-AITF) collaborative grant in Smart Multimodal Transportation Systems.

Thanks to the following individuals who supported me during this challenge:

- My parents and my wonderful husband, Vahid, whose existence and love were one of the driving forces.
- Students in the Transportation Lab for generously sharing their professional knowledge; particularly, Mr. Jason Hawkins and Mr. Matiur Rahman for their useful insights during the project and Ms. Jithamala Caldera for her input at early stage of working with Ngene software.
- All my friends who have encouraged and supported me mentally.

Last but not least, this work would not be possible without the cooperation of those who helped in survey circulation and those who completed the survey.

Table of Contents

Abstract ii
Acknowledgements iii
Table of Contents iv
List of Tables vi
List of Symbols, Abbreviations and Nomenclature x
Epigraph xi

CHAPTER ONE: INTRODUCTION 12

CHAPTER TWO: LITERATURE REVIEW 16
2.1 AVs' Introduction 16
2.2 Studies on People's Attitude toward AVs 18
2.3 AVs' Acceptance & Adaption 20
2.4 Studies on Predicting AVs' Market Penetration Rate 24
2.5 AVs' Impact on Urban Sprawl, Safety, Car Ownership and Parking 24
2.6 Barriers and Policies for AVs' Implementation 26
2.7 Literature on Shared Autonomous Vehicles 27

CHAPTER THREE: METHODOLOGY 34
3.1 Survey Design 34
3.1.1 Survey Instrument 35
3.1.2 First SP Part 35
3.1.2.1 Trip Condition Attributes 36
3.1.2.2 Driving Situation Attributes 37
3.1.3 Second SP Part 40
3.1.3.1 Trip Condition Attributes 40
3.1.3.2 Transport Modes' Attributes 41
3.1.4 Sample Size Calculation 48
3.2 Analysis Approach 49
3.2.1 Utility Function 50
3.2.2 Logit Choice Modelling 51
3.2.3 Tree-Structure Adjustment 52
3.2.4 Model's Goodness-of-Fit 53
3.2.4.1 Maximum Likelihood 54
3.2.5 Data Adjustment 55

CHAPTER FOUR: DESCRIPTIVE STATISTICS RESULTS 57
4.1 Study Area 57
4.2 Socio-Economic Attributes Distribution 58
4.3 Age-Gender Distribution 60
4.4 Annual Household Income Distribution 62
4.5 Descriptive Statistics Results 64
4.6 Sample Driving Experience and Behaviour 64
4.7 Attitude and Perception toward AVs 67

CHAPTER FIVE: RESULTS FOR USING AVS AS A PRIVATE TRANSPORT MODE70
5.1 Baseline Function 70
5.2 Level of Automation Sensitivity....76
5.2.1 Commute Trips....78
5.2.2 Non-Commute Trips....85
5.3 WTP for Different Automation Levels....87
5.3.1 Gender Effect....89
5.3.2 Age Effect....89
5.3.2.1 Income Effect....90
5.4 Price Sensitivity Analysis....91

CHAPTER SIX: RESULTS FOR USING AVS AS A SHARED TRANSPORT MODE95
6.1 Baseline Function Analysis....96
6.2 Gender Effect....106
6.3 Age Effect....107
6.4 Income Effect....109
6.5 Carsharing Program Membership Effect....111
6.6 Disability Effect....112
6.7 Demand Estimation....113

CHAPTER SEVEN: CONCLUSION....116
7.1 Results Summary....116
7.2 Contributions....121
7.3 Important Findings and Recommendations....122
7.4 Future Studies....123

APPENDIX A: ETHICS APPROVAL....124

APPENDIX B: NGENE SOFTWARE CODING....125
B.1. 1st SP Part....125
B.2. 2nd SP Part....125
B.2.1. Full factorial....125
B.2.2. Partial Factorial....125

APPENDIX C: SAMPLE ALOGIT INPUT (1ST SP PART)....126
C.1. Commute Trip ALOGIT 4.3 Code:....126
C.2. Non-Commute Trip ALOGIT 4.3 Code: 127

APPENDIX D: SECOND SP PART- BASELINE FUNCTION ANALYSIS FOR RANKING APPROACH....129

APPENDIX E: SECOND SP PART-RANKING APPROACH 130

REFERENCES 131

List of Tables

Table 1. Impacts of Various Factors on AVs' and SAVs' Willingness to Use 17

Table 2. Attributes and Attribute Levels Considered 36

Table 3. Cost Range for different parameters in Autonomous Vehicles 39

Table 4: Trip Condition Attribute and Attribute Levels for Commute trips..... 41

Table 5: Alternatives, Attributes and Attribute Levels for Commute trips 45

Table 6. Percentage Distribution of Occupied Private Dwellings by Structural Type. Source: Statistics Canada, 2016 58

Table 7. Sample Description Statistics 59

Table 8. Number and Percentage of the Sample and Population Age-Gender, Source: Statistics Canada, 2016. 60

Table 9. Number and Percentage of the Sample and Population Annual Household Income for One-Person Household in Alberta, (Statistics Canada, 2016)..... 62

Table 10. Number and Percentage of the Sample and Population Annual Household Income for Multi-Person Household in Canada, (Statistics Canada, 2016) 62

Table 11. Survey Sample Driving Behaviour 67

Table 12. Attributes' Notation and Definition 71

Table 13. Baseline Function Analysis Result for Commute Trips 72

Table 14. Baseline Function Analysis Result for Non-Commute Trips 72

Table 15. Partial Utility of Price Levels ($ per day) Including Standard Error and T-Ratio in Baseline Function for Different Trip Purposes. 74

Table 16. WTP for Different Levels of Automation (Price Coefficient in Table 13 is Used)..... 88

Table 17. WTP ($ per year) for People with Different Genders in Different Levels of Automation in both Trip Purposes 89

Table 18. WTP ($ per year) for People with Different Age Groups in Different Levels of Automation in both Trip Purposes 90

Table 19. WTP ($ per year) for People with Different Income Levels in Different Levels of Automation in both Trip Purposes 91

Table 20. Attributes' Notations and Definitions 95

Table 21. Baseline Function Analysis Results 100

Table 22. Partial Utility of Price Levels Including Standard Error and T-Ratio in Baseline Function 102

Table 23. Analysis Result: Gender Effect on SAV's Attributes 107

Table 24. Analysis Result: Age Effect on SAV's attributes 109

Table 25. Analysis Result: Income Effect on SAV's attributes 110

Table 26. Analysis Result: Carsharing Membership Effect on Car2Go & SAV's Attributes 112

Table 27. Analysis Result: Disability Effect on SAV's Attributes 113

Table 28. Finding Summary-Attribute Sign and Explanation 120

Table 29. Baseline Function Analysis Result for Rank Model 129

Table 30. Nest Coefficients for Plausible Nested Structures 130

List of Figures and Illustrations

Figure 1. 1st SP Part Survey Scenario Sample for Commute Trip Purpose 47

Figure 2. 1st SP Part Survey Scenario Sample for Non-Commute Trip Purpose 48

Figure 3. 2nd SP Part Survey Scenario Sample 48

Figure 4. Adjusted vs. Unadjusted Tree Structure 53

Figure 5. Calgary (left) and Edmonton (right) Population Density, Data Source: City of Calgary & Statistics Canada 58

Figure 6. The Percentage of Male and Female Interviewees in Different Age Ranges 61

Figure 7. The Percentage of Male and Female Residents in Alberta in Different Age Ranges. Source: Statistics Canada, 2016. 61

Figure 8. Respondents' Annual One-Person Household Income Percentage. Source: Statistics Canada, 2016. 63

Figure 9. Respondents' Annual Multi-Person Household Income Percentage. Source: Statistics Canada, 2016. 63

Figure 10. First Three Modes Respondents Use 65

Figure 11. Comparing Mode Share from Calgary Population (2011) and Survey Sample. Source: The City of Calgary, 2016 65

Figure 12. Survey Sample Driving Experience 66

Figure 13. Respondents' Opinions about Benefits Associated with AVs. 68

Figure 14. Driver's Willingness to give up the Control to the Vehicle in Different Tasks 69

Figure 15. What People Do While Riding in AVs? 69

Figure 16. Partial Utility of Price Levels in Baseline Function for Different Trip Purposes. The bars show the variations in the utility of different modes upon change in the attribute. 75

Figure 17. Partial Utility of Levels of Automation in Baseline Function for Commute and Non-Commute Trip Purposes. The bars show the variations in the utility of different modes upon change in the attribute. 75

Figure 18. Most Influential Factors Affecting Drivers' Decision in Driving Situation 76

Figure 19. Coefficients for Different Automation Levels in Short and Long Travel Time in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute. 79

Figure 20. Coefficients for Different Automation Levels for Male and Female Drivers in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute. 80

Figure 21. Coefficients for Different Automation Levels for Drivers in Different Age Groups in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute. 82

Figure 22. Coefficients for Different Automation Levels for Drivers with Different Driving Experiences in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute. 83

Figure 23. Coefficients for Different Automation Levels for Different Kind of Cars Driven in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute. 84

Figure 24. Basic (Unadjusted Tree) Structure for the Second SP Part 97

Figure 25. Partial Utility of SAV Price Levels. The bars show the variations in the utility of different modes upon change in the attribute. 103

Figure 26. Most Influential Factors Affecting Respondents' Mode Choice 104

Figure 27. The Variation of SAV Mode Share Depending on its Fare Based on Different Automobile Parking Costs 114

Figure 28. Demand for Different Modes Based on Different Parking Costs 115

Figure 29. Examples of Plausible Tree-Structures 130

List of Symbols, Abbreviations and Nomenclature

Any symbols, abbreviations, or specific nomenclature in your thesis

Symbol	Definition
AV	Autonomous Vehicle
SAV	Shared Autonomous Vehicle
DRS	Dynamic Ride Sharing
WTP	Willingness to Pay
IIA	Independents of Irrelevant Alternatives
ITS	Intelligent Transportation System
IATS	Integrated Active Transportation System
CAV	Connected and Autonomous Vehicle
VMT	Vehicle Mile Traveled
CV	Connected Vehicle
NHTS	National Household Travel Survey
CBD	Central Business District
SAEV	Shared Autonomous Electric Vehicle
SP	Stated Preference
RP	Revealed Preference
NHS	National Household Survey
LRT	Light Rail Transit

Epigraph

"Seniors can keep their freedom even if they can't keep their car keys. And drunk and distracted driving? History." – Chris Urmson, director of the Self-Driving Car Project

Chapter One: **Introduction**

Emerging vehicular technologies, such as autonomous and connected vehicles, promise to reshape the future of transportation. Autonomous vehicles (AV) are vehicles which can drive themselves without human supervision in driving tasks. They are also known as driver-less vehicles and self-driving vehicles. Connected vehicles (CV) are different from autonomous vehicles. CV technologies allow vehicles to communicate with each other and the world around them. For instance, in available vehicles, dynamic route guidance in the navigation systems (GPS-based) include connected vehicle functionality and it receives information on road congestion and suggests another route based on this information. In addition, the CV can provide the driver with useful information to help him/her to drive safer and make an informed decision. Unlike AV, a CV driver makes all the choices.

However, the number of tasks conceded to the vehicle is based on the level of automation. Different studies have defined different number of automation levels (Khan et al, 2012; Megens, 2015; NHTSA, 2013). The national highway traffic safety administration defined five levels of automation. Levels 0 to 4 which are defined as no automation, function-specific automation, combined-function automation, limited automation, and full automation, respectively (NHTSA, 2013). For this study, four levels of automation have been defined based on Megens (2015). In Level 1 and Level 2, very few (only one) and few (at least two) driving tasks cede to the car, respectively. Therefore, the user is fully responsible for a safe ride in these two levels. In Level 3, many driving tasks cede to the car with the user giving up all driving tasks only under certain driving conditions. In this case, the driver is responsible in the situations where control is needed. In full automation or Level 4, all driving tasks cede to the car under all

driving conditions. The car can perform all driving tasks and the user is not expected to pay any attention to the road during the entire travel journey.

Research on CV has shown that vehicle-to-vehicle communication systems address potentially 81% of all police-reported vehicle target crashes annually (Najm, et la., 2010). Self-driving technology includes elements of connected vehicle technology and is likely to gain similar safety benefits as well. Driver-less vehicles are expected to affect the traffic congestion, safety, comfort, car ownership, land use and the environment in a wide capacity. AVs can use the idle time to park themselves away from city centers; therefore, there might be a reduced need for parking spaces in urban areas. An increase in available space due to a reduction in parking could open opportunities for more densification such as housing or commerce.

Consumer acceptance is the first major requirement need for AVs to become widely adapted (Silberg et al., 2012). Therefore, people's attitudes toward autonomous vehicles are very important and addressing benefits and concerns associated with automated driving can change people's mind on adapting AVs. Driver-less vehicles provide the opportunity for more productive usage of travel time, but people might be concerned with riding in AVs when an unexpected situation appears. In addition, an increase in vehicle usage, security and privacy concerns are some of the disadvantages associated with self-driving vehicles. However, researchers anticipated that young educated people with a propensity for a green-lifestyle, car-sharing users and tech-savvies are the early adaptors/owners of AVs.

One of the big challenges of accepting AVs into society is policy. To prepare the society for autonomous driving, the government should be prepared to adopt policies that ensure safety and other benefits and also provide the required support, including intelligent infrastructure (Khan et al., 2012).

The idea of sharing an AV can start with family members. If there is no trip overlap between drivers within a household, there is a potential for a reduction in average vehicle ownership in a family with a shared family vehicle. Using shared autonomous vehicles (SAV) can increase the total trip travel time because of: 1) the longer route to serve other passengers and 2) the resulting waiting time for other passengers boarding/alighting. However, Burns (2012) estimated that SAVs would result in transportation cost savings and that there will be a crossover between car-sharing programs, such as Car2Go, taxi system and public transportation. While using SAVs would have the convenience of an automobile with door-to-door service, it can also eliminate the parking costs for users, specifically in CBDs. An autonomous taxi network can effectively deal with the congestion problem, make improvements in safety and convenience, be more environmental friendly and economically feasible (Brownell, 2013).

In this thesis, a stated preference survey was designed using Ngene 1.1.2 (ChoiceMetrics, 2012) to examine people's willingness to give up driving control to AVs and willingness to use SAVs. The effect of different socio-economic and demographic differences on people's choices has been investigated. The survey was conducted using an online website: surveygizmo.com. The University of Calgary Conjoint Faculties Research Ethics Board approved this survey to be done online and in-person. Answers were obtained from respondents who are 18 years of age and older and live in the cities of Edmonton or Calgary in Alberta, Canada. Analysis was done by ALOGIT 4.3 (ALOGIT 2016) software with logit choice modelling approach. The contributions of this study are:

- ✓ First study in Canada to include a SP survey on autonomous and shared autonomous vehicles

- ✓ Identifying the factors contributing to willingness to pay for autonomous vehicle purchase
- ✓ Estimating the demand for shared autonomous vehicles
- ✓ Estimating factors that affect AVs' and SAV's adaption by Canadian people
- ✓ Estimating the effect of weather conditions, improved safety and more environmental friendly system in autonomous vehicle technology on people's willingness to use SAVs
- ✓ Recognizing the effect of trip purpose on people's willingness to use different levels of automation

In the following chapters, a literature review on different papers and dissertations is provided and the mythology for the survey design and data analysis is explained. Data analysis results and in depth illustration is provided in the following chapters. The conclusion, recommendations and future study suggestions are listed as well.

Chapter Two: **Literature Review**

This chapter introduces different benefits and concerns associated with autonomous vehicles (AV) and includes a review of the recent works that attempted to recognize different factors that lead to the decisions people make regarding AVs. It then categorizes the factors and the method of study found and used by other studies into a table. This review can help us indicate the most operative method for this study.

2.1 AVs' Introduction

Autonomous vehicles (AV) are vehicles which can drive themselves without human supervision or input. They are also known as driver-less vehicles and self-driving vehicles. They can operate as private or as shared autonomous taxis for passengers who are willing to share their ride and minimize their travel cost. Four levels of automation have been defined for autonomous vehicles. Based on Megens (2015) definition, in Level 1 and Level 2, very few (only one) and few (at least two) driving tasks cede to the car, respectively. Therefore, the user is fully responsible for a safe ride in these two levels. In Level 3, many driving tasks cede to the car with the user giving up all driving tasks only under certain driving conditions. In this case, the driver is responsible in the situations where control is needed. In full automation or Level 4, all driving tasks cede to the car for all driving conditions. The car can perform all driving tasks and the user is not expected to pay any attention to the road during the entire journey. In the following discussion, when the word "autonomous vehicle" (AV) is used, it means full automation.

Full AVs are expected to be beneficial to society by improving safety, increasing mobility, reducing traffic congestion and emissions, and improving access to personal transportation for the mobility impaired (Clark, Parkhurst, & Ricci, 2016). Self-driving

technology includes elements equipped with internet access which allows for the sharing of data with other devices and is likely to increase the safety benefits. This new technology has the power to dramatically change the way in which transportation systems operate (Fagnant and Kockelman, 2014). Table 1. summarizes the literature on the impact of different socio-demographic factors and the benefits/concerns associated with willingness to use and pay for AVs.

Table 1. Impacts of Various Factors on AVs' and SAVs' Willingness to Use

Socio-Economic Factors		
Factor	Study	Method, Result
Age & Gender	Megens, 2015	SP Survey, males prefer to release control on dense roads, while female prefer this on open roads.
	KPMG, 2015	Questionnaire, young adult (no difference between genders) will be the earliest adaptors of AVs.
	Lavieri et al., 2017	Travel survey, young urban residents in U.S. are more willing to use SAVs and going to be the early adaptors/owners of AVs.
	Abraham et al., 2017	Questionnaire, results show resistance in ceding the control to the vehicle by older drivers in U.S. even though they are familiar with the technology and might need semi/fully automation more than other age groups.
Income	Howard & Dai, 2013	Questionnaire, people with lower income level were found more concerned with giving up the control to the vehicle.
	Bansal et al., 2016	SP survey, people with higher-income are willing to pay more for AVs.
Education Level	Megens, 2015	SP Survey, higher educated people also prefer to cede driving tasks on dense roads, while lower or basic educated people prefer this on open roads.
	Lavieri et al., 2017	Travel survey, urban residents with higher education level in U.S. are more willing to use SAVs and going to be the early adaptors/owners of AVs.
Trip Characteristics		
Waiting Time	Rigole, 2014	Simulation, SAV users might experience a waiting time of 10 minutes at the start of trips in Stockholm. But the empty drive on AVs with no delay on waiting time results increasing in congestion and more pollution.
	Azevedo et al., 2016	Simulation, average waiting time will be 7 to 25 minutes based on the SAV fleet size in Singapore.
	Krueger et al, 2016 Levin et al., 2016	Simulation, SAV system with DRS can reduce waiting time in commute trips with smaller fleet size (2000 SAVs with 62,836 demand)
	Winter et al., 2017	SP survey, waiting time at the bus station has a statistically different effect on people's choice that the waiting time at home for SAVs.
Travel Time	Rigole, 2014	Simulation, SAVs can be beneficial in Stockholm in lowering the congestion and environmentally if passengers share the vehicle and approve the travel time increase on average of 13% and up to 30% but no delay on travel time results increasing in congestion and more pollution.
	Krueger et al, 2016 Levin et al. 2016	Simulation, SAV system with DRS can reduce travel time in commute trips with smaller fleet size (2000 SAVs with 62,836 demand)
	Megens, 2015	SP Survey, the length of the trip does not contribute much to the willingness to release control.

Road Characteristics		
Type	Megens, 2015	SP Survey, Vehicle users want to release control on highways and they prefer to use the systems on local roads.
Congestion		SP survey, the length of the trip and congestion level does not contribute much to the willingness to release control.
Familiarity		SP Survey, Familiarity with the road contribute slightly to the willingness of vehicle users to release control.
Being Productive During the Trip with AVs		
Menon et al, 2016	Questionnaire, more productive usage of travel time is the best benefit of AVs.	
Cost		
Perception	Howard & Dai, 2013	Questionnaire, people have expressed concerns about technology cost.
	Bansal & Kockelman, 2016	The authors predicted that AVs are not going to be in U.S before 2045 and the reason is the high cost for the technology.
	Fagnant & Kockelman, 2014	Authors believe AVs' cost is unaffordable in the beginning.
	Chen et al., 2015	Simulation, implementation of a SAV service in Austin will have a benefit to cost of 4.42 with the fleet of 400.
	Bansal et al., 2016	Survey, Austenites with higher-income, individuals who live in urban areas, ones who have experienced more accidents and people who are more familiar with technology are willing to pay more for the new technologies.
WTP	Bansal & Kockelman, 2016	Survey, Americans are willing to pay $5,551 and $14,589 for Level 3 and Level 4 automations, respectively and $110 to add connectivity.
	Bansal et al., 2016	Survey, Austenites are willing to pay $3,300 and $7,253 for Level 3 and Level 4 of automation, respectively.
	Lavasani et al., 2017	Questionnaire, People in Miami who had crash experience or recently purchased a new car were less willing to pay for AVs and WTP was higher for younger people with more commute travel time.

2.2 Studies on People's Attitude toward AVs

As commuters shape travel demand, people's attitudes toward autonomous vehicles are very important. Schoettle and Sivak (2014) documented a report on public opinion about autonomous vehicles in the U.S., U.K., Australia, China, India and Japan based on two surveys. 3225 responses have been gathered from people 18 years of age and older in these countries. With the exception of Japanese respondents, most respondents had previously heard about AVs and they also had a positive initial perception towards the technology. However, Japanese respondents were neutral toward technology. The majority of respondents were worried about commercial vehicles and public transit, such as buses and taxis, being driver-less and the related safety issues are a high level of concern for them. However, most of the respondents would like

to have this technology in their own vehicles. Compared to responses from the U.K. and Australia, US respondents were more concerned about riding in driver-less vehicles, data privacy and the interaction of driverless cars with manual driven vehicles. While respondents from China and India showed more positive attitude toward self-driving technology by stating their willingness to adopt these technologies and pay the most for it, the Japanese were willing to pay the least. Generally, the responses in these six countries showed that, despite the fact that respondents express a high level of concern for driver-less vehicle technology, they are optimist about the benefits and stated a willingness to own such an automobile.

Howard and Dai (2013) conducted a survey of 107 likely adopters in Berkeley, California who expressed safety benefits and convenience of AVs as an attraction. The amenities that appealed to the respondents were not having to find parking and/or the ability to multitask while en route. However, they did express concerns with liability, technology cost and giving up control to the vehicle. Interestingly, men were found to be more worried about liability but less worried about giving up control to the vehicle. In addition, while people with a lower income level were found to be more concerned with safety and giving up control to the vehicle, people with a higher income level were most concerned with liability. Giving up driving control to the autonomous vehicles in a mixed traffic environment was a serious concern to other road users such as other manual vehicle commuters and cyclists.

Another study conducted in Austin, Texas, showed that respondents who are more technology friendly and ones with physical disabilities that prevent them from driving are more likely to use AVs. Zmud et al. (2016) conducted a survey with 556 complete responses and reported that most of the respondents preferred private ownership over the shared use of AVs and are more focused on personal rather than societal benefits. Individuals who state their

willingness to ride in an AV are not concerned about data privacy in using online technologies. These respondents also have a positive attitude toward the safety benefits and convenience of AVs.

Addressing benefits and concerns associated with automated driving can change people's mind on adapting to AVs. A survey was conducted on 800 students at the University of Florida by Menon et al. (2016) and the results showed that the demographic differences in intended adaption are due to variations in the perceptions of the benefits of and concerns with AVs. Most of the students believe that more productive usage of travel time is the main benefit of AVs and almost half of them stated that they are going to use AVs when they become available. However, most of them are concerned with riding in AVs when an unexpected traffic situation appears.

Other than surveys, social media such as Twitter or Google search engine history has also been a source for understanding people's perception toward AVs (Fraedrich & Lenz, 2014; Horner & Richard, 2016). Fraedrich and Lenz (2014) have used social media to investigate the individual and societal aspects of automated driving in U.S. and Germany. They have analyzed 314 comments and 322 comments on German and U.S. print media website articles respectively, using qualitative document analysis, which is a method to interpret a comment's meaning with the help of systematic verifiable analysis. The analysis showed that U.S. statements focused on the negative societal aspects of AVs while Germans were worried about liability.

2.3 AVs' Acceptance & Adaption

Consumer acceptance is the first major requirement needed for AVs to become widely adapted (Silberg et al., 2012). Some researchers have been exploring how AV implementation and adaption in different countries will take place. Shaheen et al. (2013) designed a survey about

the future of intelligent transportation systems (ITS) and implementing integrated active transportation system (IATS) such as connected and autonomous vehicles in U.S. 106 transportation stakeholders from 102 transportation agencies throughout US have taken the survey. The goal of the survey was to indicate which region is best suited for IATS propagation and what obstacles are associated with it. Also, they wanted to see what elements of IATS can be implemented in upcoming years. The results show that 50% of the East South Central region and 19% of Pacific regions are best suited for the implementation of connected and autonomous vehicles in the near future (Shaheen, Camel, & Ullom, 2014). Senior insurance company executives in U.S think that young adults, with no difference between genders, will be the earliest adaptors of AVs (KPMG, 2015b).

Another study in U.S. conducted by Lavieri et al. (2017) investigated the early candidates for adapting AVs' technology and ridesharing with AVs (SAVs) and the effect of technology savviness and green-lifestyle preference on this adaptation. 1832 respondents were asked for their level of interest and concern in owning an AV or participating in a SAV system in the Puget Sound Travel Survey. The authors concluded that people with a propensity for a green-lifestyle, car-sharing users, individuals who had to forgo a car purchase recently, and tech-savvies are the early adaptors of SAVs. In addition, young urban residents with a higher education level are more willing to use SAVs and thus are likely the early adaptors of AVs.

The development of AVs has opened the door to a wide range of activity and travel decisions permitting productive activities to be potentially performed in- vehicle (Chen & Armington, 2016). The question about who will adapt AVs and how much they are going to pay for it has been investigated in a couple of research projects. Bansal and Kockelman (2016) conducted a survey of 2,167 US respondents to examine how people are going to adapt different

connected and autonomous vehicle (CAV) technologies from year 2015 to 2045. They found that respondents are willing to pay $5,551 for Level 3 and $14,589 for Level 4 automation, respectively. The authors also proposed different simulations with a 5% and 10% annual decrease in technology price and also 0%, 5% and 10% annual increase in Americans' willingness to pay (WTP). They found that respondents are willing to only pay $110 to add connectivity. The authors predicted that AVs are not going to be in U.S before 2045 and the reason is the high cost for the technology. Either people should be willing to pay more or policies should reduce the cost to have the AVs sooner than 2045.

The WTP for AVs have also been investigated in Austin, Texas with a survey from 347 respondents. Bansal et al. (2016) concluded that Austenites are willing to pay $3,300 for Level 3 and $7,253 for Level 4 automation, respectively. They claim that people with a higher-income, individuals who live in urban areas, respondents who have experienced past collisions and people who are more familiar with technology are willing to pay more (Bansal et al., 2016).

421 French drivers have been asked whether or not they will use AVs and 68.1% of the sample responded that they are willing. The conditions in which drivers prefer to use AVs are on highways and during traffic congestion. They also like the automatic parking option in AVs. The drivers who responded that they were not to likely ride in AVs are those who stated their attachment and pleasure towards driving (Payre et al., 2014).

In Eindhoven, Netherland, a combined revealed preference and stated preference survey was conducted in 2014 by Megens (2015) with 673 complete responses from vehicle users. She concluded that on average, vehicle users are only positive about releasing very little or little control of tasks (Level 1 and 2). They do not prefer to release the full control of all tasks (Level 4) and are neutral about releasing many tasks (Level 3). Moreover, vehicle users stated that they

want to release control on highways and they do prefer to use the systems on local roads. The length of the trip and congestion level does not contribute much to the willingness to release control. Familiarity with the road and not performing a secondary task contribute slightly to the willingness of vehicle users to release control. Some striking results can be observed. Firstly, the model with gender and age shows that males prefer to release control on dense roads, while female prefer this on open roads. Moreover, higher educated people also prefer to cede driving tasks on dense roads, while those with a lower or more basic education prefer this on open roads.

Another study in the U.S. investigated people's inclination to use different automation levels by designing an online questionnaire and receiving 2954 responses from drivers. The survey is very limited in terms of the attributes they have considered. The results show resistance in releasing control to the vehicle by older drivers even though they are familiar with the technology and might need semi/fully automation more than other age groups. (Abraham et al., 2017)

Only one study has examined people's WTP for purchasing AVs. Lavasani et al. (2017) have conducted a questionnaire in Miami, Florida and received 146 responses from the university population. They have developed a logit ordered model for WTP based on different attitudes toward AVs and socio-demographic differences. They concluded that these differences in attitudes and socio-economic attributes had a significant effect on WTP. People who had a previous crash experience or recently purchased a new car were less willing to pay for AVs and WTP was higher for younger people with more commute travel time. Also, they have investigated the likelihood of relocation and concluded that male respondents are less concerned with relocation; however, respondents with a lower income and the ones who carpool are more willing to relocate. People between 20 to 34 years of age are the most concerned with relocation

probably due to their housing and childcare needs. Expectedly, the benefits of AVs', such as increased safety, lower congestion and improved environmental friendliness increased the willingness to relocate.

2.4 Studies on Predicting AVs' Market Penetration Rate

One of the important questions about AVs is regarding market penetration. Some researchers have investigated the market penetration rate in different cities or countries and the factors that affect it. Unexpected scenarios such as system failure by hackers or fatal accidents can seriously affect the development path of AVs (Milakis et al., 2016). A survey from experts at an AV symposium in 2014 shows that AVs' market penetration rate is going to be 1% to 11% in 2030 for conditionally automated vehicles in Netherland. For full automated vehicle, the market penetration rate is expected to be 61% by 2050.

Many transportation experts expect that the public will tilt towards acceptance and use of self-driving vehicles (Zmud et al, 2016). The market penetration rate of AVs in the U.S. has also been investigated using historical data on previous technology adoption experiences like automobiles, hybrid electric vehicles, the internet and cell phones from 1920 to 2014. Lavasani et al. (2016) has modeled the historical data of the aforementioned parameters with a Generalized Bass diffusion model and concluded that in 2059 the market will be saturated when the AVs market size will be 75% (almost 87 million).

2.5 AVs' Impact on Urban Sprawl, Safety, Car Ownership and Parking

Driver-less vehicles are expected to affect the traffic congestion, safety, comfort, car ownership, land use and the environment in a wide array. AVs can use the idle time or park

themselves away from city centers, therefore, there might be a reduced need for parking spaces in urban areas. Zhang and Guhathakurta (2017) estimated a 4.5% reduction in parking land use in downtown area in Atlanta, U.S. with only 5% market penetration rate of SAVs. An increase in available space due to a reduction in parking could free up space for other purposes like housing or commerce. In this case, AVs would combat urban sprawl and provide more useful land for living spaces (Lari et al, 2014). The only study in Toronto, Canada used EMME 4 for simulation and shows huge travel time savings with different market penetration rates (1% to 7%: 50% market penetration; 12% to 21%: 90% market penetration) so that analyzing 2011 AM peak period shows CAD$400 to CAD$500 million savings in value of time (Kloostra, & Roorda, 2017). Also, driverless vehicles may eliminate jobs, including taxi drivers, parking attendants, valet parkers, car mechanics, meter attendants, traffic officers, and potentially bus and freight drivers.

Connected and autonomous vehicle (CAV) technologies can decrease crash severity and the possibility of a crash. Kockelman and Li (2016) have investigated the safety benefits of CAVs based on analyzing pre-crash scenarios using the U.S General Estimates System crash records. They have shown that these technologies can decrease crash severity and the possibility of a crash. They also concluded that eleven CAV technologies can save 740,000 functional-life-years each year for Americans ($76 billion in economic costs). It is, however, not a foregone conclusion that a self-driving vehicle would ever perform more safely than an experienced, middle-aged driver (Sivak & Schoettle, 2015).

In an analysis in South Korea, the presence of AVs shows more dispersed development of the city and revolutionary changes in transportation and land use (Kim, Yook, Ko & Kim, 2015). The presence of AVs might impact pedestrian and cyclists' choice of facility. As the

research results from students at Ohio State University shows, there is a very strong influence on cyclists' preferences for more separated facilities, as traffic volume and speed are increased (Blau, 2015).

LaMondia et al. (2016) argues the impact of AVs on a long-distance travel mode shift. They used Michigan State's 2009 long-distance travel survey to model long-distance trip generation and mode choice. They have added autonomous vehicles as a new mode and investigated the change in trip volume for other modes (e.g. personal vehicles and airlines). For trips under 500 miles, the change in trip volumes by both personal vehicles and airlines is approximately the same. However, for trips that were more than 500 miles, airlines were preferred. In the model, they assumed that people weight cost and travel time similarly regardless of mode. This unrealistic assumption can be negated using a stated preference survey and by including AVs as a mode.

2.6 Barriers and Policies for AVs' Implementation

According to Nord et al., 2017, autonomous vehicles will be adopted in the mainstream faster than many agencies are anticipating. Planners will need to be prepared to develop flexible regulations that will be essential in allowing the technology to achieve its full potential. Fagnant and Kockelman (2014) looked at the impacts of AVs and implementation barriers. They discussed that AVs will increase vehicle mile traveled (VMT) 10% to 20% when the market penetration rate is 90% to 100%, respectively. AVs can also impact travel behavior, vehicle safety in the form of crash savings, parking, fuel efficiency and decrease congestion which can be valued at $199 billion per year. Yet there are barriers in AVs' implementation: unaffordable AV cost in the beginning, AV licensing, litigation and liability, security, and privacy. Finally,

they have recommended some polices including determining appropriate standards for liability, security, and data privacy and developing federal guidelines for AV certification. In order to prepare society for autonomous driving, the government should be prepared to adopt policies that ensure safety and other benefits and also to provide the required support, including intelligent infrastructure (Khan et al., 2012). Nord et al. (2017) recommends that local governments should develop land use policies and roadway regulations that enforce how and where AVs can be used. Also, a designated lane can be assigned to AVs only for better performance. Making such regulations would be simple for the government as there are policies for designated lanes presently available. In this way, cities and governments can use the integration of AVs as an opportunity for developing cities and for economic growth.

2.7 Literature on Shared Autonomous Vehicles

Brownell (2013) has declared five transit criteria that need to be satisfied by a transportation system in order to depose the conventional manually operated cars. The transportation system should: 1) effectively deal with the congestion problem, 2) have safety improvements, 3) be more environmental friendly, 4) be economically feasible, and 5) have comfort and convenience improvement. He came up with a potential solution according to the recent advancements in the field of vehicle autonomy: an autonomous taxi network.

The idea of sharing an AV can start from family members. As, in a family, there might be more than one person with the ability to drive, physically and legally, some of the family members might need the car at the same time. However, the majority of households do not have trip overlap between drivers within a family based on the data from the latest U.S. National Household Travel Survey (NHTS). Schoettle and Sivak (2015) analysed the data and concluded

that there is a potential for a reduction in average vehicle ownership in U.S. households. Each family can use a driver-less vehicle and share it as a shared family vehicle. This could reduce average ownership rates by 43%, from 2.1 to 1.2 vehicles per household, in the most extreme hypothetical scenario. Conversely, this shift would also result in a 75% increase in individual vehicle usage, from 11,661 to 20,406 annual miles per vehicle. These results may serve only as an upper-bound approximation of the potential for household sharing of autonomous vehicles (Schoettle & Sivak, 2015).

Increasing vehicle usage by introducing AVs to society is one of the issues associated with this technology. Truong et al. (2017) have also studied the effect of AVs on trip generation in Victoria, Australia. Their results show that AVs can increase the daily trips by average of 4.14% and almost 20% of these trips will be made by people who are older than 76 years of age. The trips that are made with cars will increase by 7.31% if the car occupancy remains constant. However, their analysis shows that if the goal is not to have any increase in car trips, the car occupancy should increase by 5.3% to 7.3%.

One study in Belgium investigated the effect of SAVs on mobility. For this purpose, Cools et al. (2017) have designed a survey with key variables including: waiting time for SAVs, willingness to share the ride, and willingness to share the ride with agenda. This means the person who is willing to use SAVs and share it with other users, would share his/her agenda in advance so that he/she does not need to wait for the ride. Analysis of 661 responses showed that 47.14% of people are willing to share their ride and they are prepared to wait on average of 12.96 $\pm$ 8.8 minute for a SAVs to pick them up. Surprisingly, only 47.45% of the respondents were willing to share their private daily trip schedule (for zero waiting time). The authors have stated that market segmentation is very challenging because the parameters they considered does not

apprehend a good portion of variability. They suggested that in the future studies life-style and psychological factors should be considered as well.

Using shared autonomous vehicles (SAVs) will involve benefits like solving parking problem, reducing congestion, decreasing air pollution, etc. Some research on different cities has been conducted to study the potential benefits of a fleet of SAVs. In Central Business District (CBD) of Singapore, the impacts of using autonomous vehicles have been explored and results show that Autonomous Mobility on Demand systems led to higher utilization rates, therefore they are more efficient compared to the private vehicles (Marczuk et al. 2015). Also, the Earth Institute at Columbia University admits that after studying Ann Arbor, Babcock Ranch and Manhattan, this system is capable of supplying better mobility with lower cost under a wide range of circumstances and it offers substantial sustainability benefits through improved roadway safety, reduced congestion and emission, increased energy efficiency, improved land use and enhanced equality of access (Burns et al., 2013).

In Stockholm, Rigole (2014) provided an analysis of the potential benefits of SAVs to replace private automobile commuter trips in the metropolitan area. He found that a SAV-based transportation system rather than a personal vehicle is able to provide door-to-door service with a high level of service. However, it uses less than 10% of today's personal vehicles and parking space. This SAV-based transport system can also lower the congestion and be environmentally beneficial if the passengers agree to share the vehicle and approve the travel time increase on average of 13% and up to 30%. The users might experience a wait time of 10 minutes at the start of their trip as well. With this scenario, if the passengers accept these three conditions, the mileage will be reduced to 89% of the baseline case, although only 5% of the today’s vehicles and parking lots would be used. As expected, if users decline the aforementioned conditions that

cause a lower level of service and when the empty drive on AVs with no delay on waiting or travel time is provided for each passenger, increasing in congestion and more pollution caused by vehicles is resulted. The author declared that envisioning a future using a SAV-based system and electrical vehicle technology seem to be a "perfect" match that could definitely contribute to a sustainable mobility system in Stockholm.

Research in Singapore in 2016 shows that using SAVs will cause a 18.2% reduction in trips to CBD, 1.5% reduction in non-commute trips to CBD and 7% reduction in private trips within the CBD. Also, average wait time will be 7 to 25 minutes based on the SAV fleet size and for a 5-minutes wait time, a fleet size of 2400 vehicles is needed (Azevedo, Marczuk, Raveau, Soh, Adnan, Basak, & Ben-Akiva, 2016). Shen et al. (2017) have investigated the effect of using SAVs as a feeder between origin or destination to heavy rail transit stations in Singapore during morning peak hours. Their simulation results show that if the suitable fleet size is provided, less roads will be occupied (compared to buses), and passenger will spend less time out of the vehicle for their commute trips.

SAVs may be a major game changer in the mobility industry (Krueger et al., 2016). Fagnant and Kockelman (2015) analyzed the impact of shared autonomous vehicles (SAVs) in Austin, Texas using MATsim software. They assumed a low market penetration of 1.3% regional trips for SAVs and concluded that each SAV can replace around 9 conventional vehicles with a good level of service in a $24\,\text{mile} \times 12\,\text{mile}$ area and only 8% more travel mile has been observed. The market potential of shared autonomous electric vehicles (SAEVs) was also investigated in Austin. Analysis shows that the mode share of SAEVs is 14% to 39% when only manual automobiles, buses and SAEVs are considered in the network, assuming the fare is between \$0.75 to \$1 per mile (Chen, Donna, & Kockelman 2015). In China, Yang et al. (2017)

believes that long daily travel distances are possible with SAEVs and based on their simulations, the entire demand can be served with 59% of the current fleet size. Implementation of a SAV service in Austin will have a benefit to cost of 4.42 and with a fleet of 400 SAVs, each one can eliminate 14 vehicles on the roadway by serving 11,400 people per day (Levin, Li, Boyles, & Kockelman, 2016).

Dynamic ride-sharing (DRS) pools multiple travelers with similar origins, destinations and departure times in the same vehicle (Fagnant, & Kockelman, 2015). SAVs would be more beneficial than DRS in denser locations during peak hours that have substantial ridesharing potential. They would help alleviate roadway congestion while delivering excellent mobility at reduced energy and environmental costs (Zachariah et al., 2014). SAV system with DRS can reduce travel time, wait time and fare specifically during commute trips (Krueger, et al., 2016; Levin et al. 2016) with smaller fleet size (2000 SAVs with 62,836 demand) (Levin et al., 2016).

Car-sharing involves a fleet of vehicles scattered around a city for use by a group of members (Jorge & Correia, 2013). SAVs merge the concept of conventional car-sharing and taxi services with self-driving vehicles and could provide inexpensive mobility in-demand services (Krueger, Rashidi, & Rose, 2016). Recently, a study of Dutch urban populations by Winter et al. (2017) conducted a SP survey which asked 732 respondents to choose between SAVs, free-floating car-sharing, taxi, public transit (bus) and private vehicle. The authors considered travel time, wait time, parking cost for a private vehicle, trip cost, the time to walk to and from the vehicle or bus stop, and the time to find a parking spot as attributes. However, the trip cost attribute levels for SAVs are limited to only three levels. In addition, the minimum cost level is more than that of car-sharing, bus and private vehicle. The maximum cost level of SAV is equal to the maximum cost level of a taxi but still more than car-sharing, bus and private vehicle. The

literature by Menon, et al., 2016 and Rigole, 2014 are against this assumption. The travel time levels in SAVs are also assumed to have the same level as private vehicles. The authors analysed the data with Biogeme software and concluded that vehicle automation has a strong impact on mode choice. People who do not have access to car-sharing show a higher preference for it compared to those that already are using it. Also, wait time at the bus station has a statistically different effect on people's choice than the wait time at home for SAVs or a taxi. The authors defined early, late, and normal adaptors based on their or one of their family members' usage of Uber or other car-sharing companies. The results show a strange finding in that cost increases the utility for normal and late adaptors but is insignificant for early adaptors and does not affect their decision on mode choice. This might be because the limited cost levels cause a bias in the study. Even though, this is the only study using a SP survey on SAVs and including a wide range of modes, it could have covered additional attributes or attribute levels for more precise results.

Peoples' attitudes toward car-sharing may help to understand how things will change with SAVs. Car-sharing caused its members in North America to use public transit more and active transportation modes less. Also, half of the members either sold a vehicle or forgo purchasing a new vehicle; and their driving distance decreased by 27% (Brook, 2004).

People in their mid-thirties with median incomes, whom use public transit and were usually, educated, typically use car-sharing services (Brook, 2004). Convenient locations and street parking are very important to these members and they prefer having easy access to several vehicles so that if one of them is reserved, they can use another one (Brook, 2004). Two-thirds of car-sharing members come from carless households (Cervero, 2003). Also, people who are environmentally conscious are more willing to use car-sharing. Costain et al. (2012) believe that if car-sharing wants to compete with personal vehicles, rates must be low enough or even

provide more savings for the user. It is not clear how many of these effects would apply to SAVs, which may be more convenient and potentially more used than human-driven shared vehicles (Richardson, Ampt, & Meyburg, 1995).

For the first time in Alberta, Canada, this thesis will investigate people's perception towards automated vehicles while also considering the different factors that might affect their decision. The demand for SAVs will also be estimated using a stated preference (SP) survey.

Chapter Three: **Methodology**

In this chapter the methodologies used for survey design and modeling framework is explained as well as a detailed discussion regarding different parameters considered in the survey. The survey is conducted using an online website called Surveygizmo (surveygizmo.com). The University of Calgary Conjoint Faculties Research Ethics Board has approved this survey to be done online and in-person (Appendix A:). The link to the survey is being circulated through social media and email. Survey results are being used to estimate the parameters affecting people's choice with ALOGIT 4.3 software (ALOGIT 2016).

3.1 Survey Design

Hensher et al. (2005) states that the source of choice responses comes in two forms: revealed preference (RP) and stated preference (SP). An SP survey provides hypothetical scenarios with respondents responding through questionnaires or simulators to indicate which option they would choose or rank if a similar situation is presented in real life. An RP survey is based on respondents' actual (not hypothetical) responses, and is usually obtained from diaries and real field experiments or pilot studies. RP surveys help us to understand the underlying trade-offs that influence individuals' decisions when we have enough information about the different alternative modes of transport (De Blaeij, 2000). The SP-methods are low-cost, flexible and efficient. One of the advantages of the SP-approach is that the survey is not limited to real-world contexts so they are very useful when considering the choices among existing and future alternatives since the latter cannot be observed in RP data (Hensher et al., 2005). Since autonomous vehicles are not yet available, SP surveys are the best method to determine people's

willingness to give up driving control to AVs, their willingness to use SAVs, to examine the potential demand for SAVs, and people's willingness to pay for owning an AV.

3.1.1 Survey Instrument

In this research, an online SP survey was conducted using the Survey Gizmo website. The focus was on the two major cities in Alberta: Edmonton and Calgary.

In order to gather information on people's perception and attitudes towards this system, different questions were presented about the potential benefits and concerns people might have regarding AVs. Our method may not be completely categorized as a true revealed preference method because the results are not used to develop choice observations. However, the results of the descriptive statistics part will provide us with a good representation of what people's attitudes toward AVs are and give us the opportunity to compare them with SP data analysis results to check if the respondent's answers to the survey are consistent.

3.1.2 First SP Part

Part I of the SP survey investigated people's willingness to own an AV. Respondents were shown two "driving situation" to choose between. The option to choose 'neither' of the scenarios was also available.

In order to design a SP survey, different steps should be taken. The first step is to define the problem and list alternative attributes and attribute levels. The attributes and attribute levels considered in the "driving situation" are shown in Table 2 and are divided into two parts based on two trip purposes: commute and non-commute. Commute trips include trips to place of work

or full-time study; while shopping and recreational trips are good examples of non-commute trips.

Table 2. Attributes and Attribute Levels Considered

Commute Trip Purpose		**Non-Commute Trip Purpose**	
Attribute	**Attribute Levels**	**Attribute**	**Attribute Levels**
Travel Time	Less than 15 min 15 to 40 min	**Travel Destination**	Inside the City Outside the City
Secondary Task	Yes No	**Secondary Task**	Yes No
Level of Automation	Level 1 Level 2 Level 3 Level 4	**Level of Automation**	Level 1 Level 2 Level 3 Level 4
Road Type	Highway Arterial	**Road Type**	Highway Arterial
Road Condition	Normal Icy	**Road Condition**	Normal Icy
Level of Congestion	Congested Not Congested	**Familiarity with the Road**	Familiar Not Familiar
Price (fixed cost per day + variable cost per 30 min)	$18 + $3.5 $20 + $3.5 $22 + $3.5 $24 + $3.5 $26 + $3.5 $28 + $3.5 $30 + $3.5 $32 + $3.5	**Price** (fixed cost per day + variable cost per 30 min)	$18 + $3.5 $20 + $3.5 $22 + $3.5 $24 + $3.5 $26 + $3.5 $28 + $3.5 $30 + $3.5 $32 + $3.5

3.1.2.1 Trip Condition Attributes

The trip purpose, travel time/destination and secondary task attributes are shown as the "trip condition" and the respondents have to choose a "driving situation" scenario preference based on that "trip condition". The trip purpose might affect people's decision on choosing the driving scenario option because in commute trips, the commuter needs to travel every day unlike non-commute trips, which do not necessarily occur on regular basis.

For commute trips, trip time is a more important factor compared to that of non-commute trips. Therefore, in commute trip scenarios, travel time and secondary task attributes have been considered. According to the 2011 National Household Survey (NHS) in Canada, the levels have been assigned based on the average (25.4 minute) and maximum (32.8 minute) travel time of commuters (Government of Canada, 2013). The margins (15 and 40 minute) have been chosen based on the survey size. To reduce the number of SP scenarios, only two levels have been assigned to the travel time: less than 15 minute and 15 to 40 minute.

In addition, vehicle passengers and/or the driver who becomes a passenger in a driverless vehicle with different levels of automation might be involved in other tasks during driving (Megens, 2015). For instance, talking over the phone or with other passengers, studying, etc. can be considered as a secondary task. It is included in the trip condition because it might affect people's decision when choosing between different driving situations (and levels of automation) if they want or have to conduct a productive activity during their trip. The trip duration is also important for the vehicle users. Long trips are more tiring for drivers who need to concentrate more.

The attribute levels for travel time mentioned above might not cover the wide range of time people spend on their non-commute trips. For instance, if a person goes outside of Calgary for a recreational trip, it would take around one hour to get to their destination. Therefore, instead of travel time, travel destination was chosen as an attribute for non-commute trips and its levels are: inside the city and outside the city.

3.1.2.2 Driving Situation Attributes

Driving situation attributes are the parameters that affect driving tasks, drivers' choice of

path or even whether or not they would like to drive. The weather conditions might highly affect the driver's task requirements and increase the risk of driving. Additionally, Google has noted that their self-driving prototypes have trouble interpreting data for a few road conditions, one of which is snow-covered roads (Official Google Blog, 2012). The road condition attribute represents the weather condition in the scenarios by considering the prevailing weather conditions in Alberta during different seasons. The task requirements are different for diverse road types (highway, arterial, etc.) and the driver/passenger may give up control to the vehicle on roads where less concentration is needed. Therefore, the effect of two different road types has been investigated in the scenarios: highway and arterial. Freeways provide largely uninterrupted travel and are designed for high speeds but arterials have frequent at-grade intersections with traffic lights. These two levels have been chosen based on the road characteristics in Calgary and Edmonton.

Another factor that can affect safety and comfort is the traffic congestion level on the roads. As the congestion increases, the driver needs to concentrate more. Also, if the driver is familiar with the road, they might pay less attention to the environment (Charlton & Starkey, 2011; Yanko & Spalek, 2013), so the risk will increase in case of an abrupt traffic incident. Familiarity with the road changes driving behavior and even the drive's choice of road. (Megens, 2015)

One of most important factors that affect people's choice is cost. Setting the price for AV purchase and usage has been the biggest challenge for the first part of the SP survey. Looking at previous studies and estimations of AV purchase and operating costs could help to come up with the fixed (per day) and variable (per 30 minute) part of the cost parameter.

In the study, "Emerging Technologies: Autonomous Cars-Not If, But When," (2014) IHS Automotive forecasts the purchase price of autonomous vehicles compared to present vehicles will increase from $7,000 to $10,000 in 2025, $5,000 in 2030 and $3,000 in 2035. Litman (2014) also forecasts the purchase, maintenance and service price of autonomous vehicles compared to present vehicles will increase $1,000 to $3,000 per year, but using AVs also decreases an average of 10% in fuel consumption and 30% in insurance fees. These two sets of research have a consistent estimation of AV purchase cost. On the other hand, existing vehicle operating and fixed costs range from 14.53 to 16.67 cents per km and $17.76 to $24.26 per day respectively, based on Canadian Automobile Association Driving Costs (2013) analysis for three different types of vehicles. Applying the likely car cost that AVs would introduce is shown in Table 3.

Table 3. Cost Range for different parameters in Autonomous Vehicles

Cost Type	***Automobile Cost Range***	***Cost Change***	***AV Cost Range***
Fuel	9.40 to 11.53 cents/km	10% reduction	8.46 to 10.38 cents per km
Insurance	$6.65 to $7.47 per day	30% reduction	$4.66 to $5.23 per day
Finance Expense	$2.3 to $3.57 per day	Adds $1,000 to $3,000 per year	$5 to $11.8 per day
Tires	1.86 to 2.56 cents/km	No Change	1.86 to 2.56 cents per km
Licence & Registration	$146.16 per year	No Change	$0.4 per day
Depreciation	$3,069 to $4,677 per year	No Change	$8.41 to $12.81 per day
AVs' Average Annual Ownership Cost		***$18.47 to $30.24 per day***	
AVs' Average Annual Operating Cost		***10.32 to 12.94 cents/km*** $\overset{\textit{Assumed speed: } 50\frac{km^*}{h}}{\Longleftrightarrow}$ ***$2.58 to $3.23 in 30 min***	

*City of Calgary Traffic Safety Tips

Price calculations show that for a driving speed of 50 km per hour (City of Calgary Traffic Safety Tips, 2016), the fixed cost range for AVs becomes $18 to $32 per day and the operating cost is approximately $3.5 per half an hour.

3.1.3 Second SP Part

AVs can also be used as shared autonomous vehicles (SAVs). In this case, people would share their ride to minimize their trip cost. The second part of the SP survey was designed to understand people perception and choice with the introduction of SAVs along with three other modes.

In this part, people's choice of mode is investigated only for commute trip purposes. Modes that are similar to SAV in providing door-to door service are: private automobile, taxi and Car2Go. Ideally, now that Uber is available in Calgary, it might have been a good mode to include as well; however, at the time the survey was conducted, people were still not familiar with it. SAVs can be considered as a public transit mode or a feeder service to mass public transit services such as subway or light rail transit (LRT). Table 4 and Table 5 summarize the SAV's attributes considered in Part II of the survey.

3.1.3.1 Trip Condition Attributes

Using SAVs can increase the total trip travel time because of: 1) the longer route to serve other passengers and 2) the resulting wait time for other passengers boarding/alighting. Therefore, this longer travel time might impact people's choice of this particular mode (Menon et al., 2014). Fagnant et al. (2014) have estimated a 10% increase in travel time (or distance) when using SAVs and this percentage is used in this study.

Burns (2012) estimated that SAVs would result in transportation cost savings and there will be a crossover between car-sharing programs (like Car2Go), taxi system and public transportation. While using SAVs would have the convenience of an automobile with door-to-door service, it also can eliminate the parking costs for users, specifically in CBDs.

Three levels of parking cost attributes were considered for the private auto: free, 4$ per hour and $20 per hour. These levels have been chosen based on parking prices in Calgary (Parking rates - CPA, 2016). As discussed, the weather condition, trip purpose and secondary tasks can also affect users' choice.

Table 4: Trip Condition Attribute and Attribute Levels for Commute trips

Attribute	**Travel Time**	**Weather Condition**	**Parking Cost for Automobile**	**Secondary Task**
Attribute Levels	Less than 15 min 15 to 40 min	Sunny Snowy	Free $4 per hour $20 per hour	Yes No

3.1.3.2 Transport Modes' Attributes

The four modes are different in some other aspects like safety, environmental impact, wait time and price (or fare). Figuring out the attribute levels has been an important challenge of designing this SP survey. The following sections will explain how these attribute levels have been chosen.

3.1.3.2.1 Cost

Burns et al. (2013) developed a SAV model in Ann Arbor (Michigan), Manhattan (New York), and Babcock Ranch, a new small town in Florida. They estimated that the cost per trip

mile falls from $0.18 to $.039 ($0.29 to $0.63 per km), depending on the demand and system fleet size. They stated that this cost is more affordable compared to the owning and operating cost of a vehicle. Zhang et al. (2015) opted for a higher trip cost compared to Burns et al. (2013), so they assumed a $0.4 per trip mile as the SAV travel cost. In another study, Fagnant and Kockelman (2014) also estimated the SAV cost. They stated that SAVs can reduce the taxi fare to one third, although it will still return 19% of the investment.

Based on the aforementioned literatures, SAVs' fare in this SP part of the survey has been chosen to be in the range of $0.29 to $0.63 per km (Burns et al., 2013; Zhang et al., 2015). This assumption also includes the fare equal to one third of that of a taxi service (Fagnant, & Kockelman, 2014). In order to have the SAV fare per time unit, these prices have been multiplied by SAV's average speed: 50 km per hour (City of Calgary Traffic Safety Tips, 2016). Therefore, the SAV fare will be in the range of $7 to $16 per 30 min. The 30-minute time unit is chosen to represent a more sensible time for commute trips. These price levels change by a $1.5 increment from $7 to $16 (Zoepf & Keith, 2016). Considering the fact that SAVs are not available in the market yet and these scenarios are hypothetical, in order to cover a wide range of prices and have an unbiased estimation result, some other price levels have been added to the mentioned range ($7 to $16 per 30 min) to cover public transit and taxi fares as well. Therefore, the price attribute ranges from $2 (near public transit fare) to $50 (more than taxi fare). It also includes some levels in between as shown in Table 5.

The process of figuring out the automobile cost is explained in the design of the first SP part, Table 3. Three price levels have been used for this part (Motion, 2016). The range minimum, average and maximum based on Table 3: $18 (fixed cost per day) + $3.4 per 30 min, $21(fixed cost per day) + $5 per 30 min and $23(fixed cost per day) + $5.5 per 30 min. The

Car2Go fare is $0.41 per minute which is $12 per 30 min (Car2Go website, 2016). Two other random and close to reality (Hess and Rose, 2009) price levels for Car2Go have been considered for a better estimation in our model: $7.5 and $16 per 30 minute.

Taxi regular fares have been calculated using “taxi fare finder” website in Calgary and Edmonton for different paths in which the travel time is almost 30 min. The average cost of $44 per 30 min is assumed for this study (TaxiFareFinder website, Calgary and Edmonton, 2015). Two other random and close to reality (Hess and Rose, 2009) price levels for Taxi fare have been considered for a better estimation in our model: $32.5 and $38.8 per 30 minute.

3.1.3.2.2 Waiting Time/Access Time

Wait time for and access time to a transit mode is one of the factors that define the quality of a service and that would be important factors for the users to consider when using SAVs. Larson (1987) states consumers believe wait time is considered as wasted time and can be used more productively.

Owning and using an automobile has the benefit of zero minutes of wait time which no other included modes have. Two levels have been chosen for wait time attributes for taxis: 10 and 18 minute because usually it takes longer for taxies to arrive for pick up in Alberta (Calgary Sun NEWS, 2013). In case of SAVs, two attribute levels of 5 minutes and 8 minutes were considered for wait time (Rigole, 2014; Lima Azevedo, et al., 2016). The same levels were chosen for the access time for Car2Go.

3.1.3.2.3 Environmental Impact

Environmental impact and safety impact are attributes that would encourage people to use SAVs. and should be included in this part of the SP. Safety impact has been reflected as "Reduction in Accidents" and the environmental impact as "CO_2 Emissions Reduction (compared to present vehicles)" in the SP scenarios.

In order to figure out the attribute levels for "CO_2 Emissions Reduction (compared to present vehicles)", we need to know the CO_2 emission and compare it to present automobiles. Therefore, this would be 0% for automobile and taxi because present vehicles are being used for taxis or automobile. In 2014, the CO_2 emissions for the average used cars on the road was analyzed and they concluded that it is 156.6 g/km (SMMT website Car2Go Report, 2016), but the CO_2 emissions for the SmartCar that is being used by Car2Go is 119 g/km. (Smart Fortwo, 2010) Calculations show that the attribute level for Car2Go will be approximately 24%.

Fagnant and Kockelman (2014) investigated the potential environmental impacts of introducing SAVs and found out that in comparison to average US light-duty vehicles, each SAVreduces the CO_2 emissions by 34%, which was the attribute level chosen for SAV in the SP. (Fagnant & Kockelman, 2014)

3.1.3.2.4 Safety

"Reduction in Accidents" has been chosen to reflect the safety improvements corresponding to SAV in SP scenarios. This attribute is set at 0% for automobile and Car2Go because no new technology or specific driver experience is applied to or needed for them. To be a taxi driver in Alberta, applicants should have experience and hold an advanced driving license. Deery (1999) has conducted a statistical analysis in how the age (experience) factor affects the

traffic crashes in Australia and concluded that young age drivers (ages 16 to 24) comprise about 35% of fatal and 50% of injury crashes. He also claimed that the situation in Canada (Transport Canada, 1984) and US is similar. Therefore, if taxi drivers are all experienced drivers and thus 24 years and older, the "Reduction in Accident" attribute level for taxis was chosen to be the lower bound range of 35%, as was the result in the study by Deery (1999). Using AVs (full automation) was assumed to result in crash reduction by 90%. This is justified by the fact that full automation would remove the driver error that accounts for 90% crash causes (John, 2002).

Table 5: Alternatives, Attributes and Attribute Levels for Commute trips

Attribute \ Alternative	**Automobile**	**Taxi**	**Car2Go**	**SAV**
Waiting Time/Access Time	0	10 min 18 min	5 min 8 min	5 min 8 min
Price (per 30 min) **Excluding Parking cost**	$18 (fixed cost per day) + $3.4 per 30 min $23(fixed cost per day) + $5.5 per 30 min $21(fixed cost per day) + $5 per 30 min	$32.5 $38.8 $44	$7.5 $12 $16.7	$2 $4 $7 $8.5 $10 $11.5 $13 $14.5 $16 $21 $32 $44 $50
Reduction in Accidents	0%	35%	0%	90%
CO_2 Emissions Reduction (compared to present vehicles)	0%	0%	24%	34%

After defining the alternatives in both SP parts of the survey and reducing the number of levels challenged, for the first part, a maximum of 1024 and 2808 scenarios could be created for Part I and II of the SP survey respectively. The next challenge would be to reduce the number of scenarios because then the number of responses needed would decrease. Two different designs

could be used: full factorial design and partial factorial design (Hensher, Rose, & Greene, 2005). In full factorial design, all the possible combinations of the attribute levels (factors) would be considered. In partial factorial design, a limited number of combinations of attribute levels would be considered. In other words, the construction of a partial factorial design is based upon the principle of proportional frequencies of the factor levels (Addelman, 1962). The subset (fraction) of a full factorial design should be carefully chosen and the orthogonality of the design should be observed. Orthogonality is a mathematical constraint requiring that all attribute levels vary statistically independent of one another (Hensher & Greene, 2002). The orthogonal coding permits uncorrelated estimates of all main effects (Addelman, 1962) and it guarantees that we can always estimate the effect of one attribute or interaction clear of any influence due to any other attribute or interaction (Davidson et al, 2014). Full factorial design satisfies the orthogonality. However, the number of scenarios will affect the orthogonality and in fractional factorial survey design the orthogonality of the design should be ensured. In this thesis, the orthogonal design was conducted using Ngene 1.1.2 software (ChoiceMetrics, 2012). The software can generate orthogonal design when there are no correlations between the levels of attributes within each alternative and across all available alternatives simultaneously by only using the code: ";orth = sim". In addition, when considering the relationship between different attributes, an interaction may arise. In other words, the effect of one attribute may depend on the level of the other attribute. Therefore, to eliminate correlated estimates by making all two-way interactions independent of all main effects, a foldover design was generated by applying the code ";foldover" in Ngene 1.1.2 software.

Ngene software generated 72 scenarios that have the orthogonal feature and eliminates two-way interactions for the first part of SP survey. Showing 72 scenario to every respondent

was not possible. Thus, for survey total time management purposes only 4 scenarios were shown to each respondent. As the blocking method allows us to show each decision maker a fraction of scenarios while providing the orthogonality feature (it splits the orthogonal design into smaller designs), it was applied to the Ngene 1.1.2 coding and increased the total number of scenarios to 288.

At the beginning of the second part of the SP survey, full factorial design was chosen but also the blocking method was used to show only 3 scenarios per person. However, getting responses became a big challenge over the time and after getting an inadequate total of 375 complete answers, the design of the second part also changed to an orthogonal partial factorial design and 72 scenarios overall were chosen in the blocks containing 4 scenarios for each respondent. Different samples of scenario cards are shown in Figure 1, Figure 2 and Figure 3.

Trip Purpose	Travel Time	Secondary Task
Commute	Less than 15 min	No

	Driving Situation I	Driving Situation II
Level of Automation	Level 3	Level 2
Road Type	Arterial	Arterial
Road Condition	Icy	Icy
Level of Congestion	Congested	Congested
Price	$30 (fixed cost per day) + $3.5 per 30 min	$24 (fixed cost per day) + $3.5 per 30 min

Figure 1. 1st SP Part Survey Scenario Sample for Commute Trip Purpose

Trip Purpose	Travel Destination	Secondary Task
Non-Commute	Outside the City	Yes

	Driving Situation I	Driving Situation II
Level of Automation	Level 4	Level 2
Road Type	Highway	Arterial
Road Condition	Icy	Icy
Familiarity with the Road	Not Familiar	Familiar
Price	$24 (fixed cost per day) + $3.5 per 30 min	$28 (fixed cost per day) + $3.5 per 30 min

Figure 2. 1st SP Part Survey Scenario Sample for Non-Commute Trip Purpose

Trip Purpose	Travel Time	Weather Condition	Parking Cost for Automobile	Secondary Task
Commute	**15 to 40 min**	**Snowy**	**$4 per hour**	**No**
	Automobile	**Taxi**	**Car2Go**	**Shared Autonomous Vehicle**
Waiting/Access Time	0	18 min	5 min	5 min
Price (per 30 min) Excluding Parking Cost	$23 (fixed cost per day) + $5.5 per 30 min	$44	$12	$7
Reduction in Accidents	0%	35%	0%	90%
CO2 Emissions Reduction (compared to present vehicle)	0%	0%	24%	34%

Figure 3. 2nd SP Part Survey Scenario Sample

3.1.4 Sample Size Calculation

The statistical significance of a model depends on the sample size of the survey. A large sample size might cost more but a small sample size can result in a poor model fit. Bartlett et al. (2001) have described the formula below for calculating the sample size:

$$N = Z^2 \frac{p(1-p)}{e^2}$$

Where:

N is the sample size

Z is the Z − value for the study confidence level (95%) which is 1.96 in our case

p is the sample proportion (variability in population)

e is the sampling error (5%)

The challenge of using this formula is the value of p (Tay, 2010), but in the worst case it can be assumed to be 0.5 because $p(1-p)$ can not exceed 0.25 and the sample size will be 384. But in our case, the sample proportion is the car (passenger plus driver) in both SP parts and it is 0.79 based on the travel survey in Calgary, 2011. Therefore, the sample size with a margin of error of ±0.05 at a 95% confidence level will be:

$$N = 1.96^2 \frac{0.79(1-0.79)}{0.05^2} \cong 255$$

However, a rule of thumb has been suggested by Long and Freese (2006) that at least 10 observations per parameter in the regression equation should be obtained which results in more than 400 responses needed. Both methods are satisfied with the number of responses gathered for this study. Long and Freese (2006) also indicates that a sample size over 500 seems adequate.

Data have been collected on various socio-economic attributes (e.g. age, occupation, gender, household and income level), trip making behavior, driving experience and driving behavior. In the next section the method of analysis will be discussed.

3.2 Analysis Approach

Potential users place weight on certain situations. In the case of this thesis, the situations are the levels of automation (1st SP part) and the introduction of new mode of transport SAV (2nd SP part) and the weight is known as "utility". In general, utility measures the preference of an "alternative" (Hensher, et al., 2005). In the following sections, a detailed explanation of maximum utility, logit choice modelling framework and the solution to calculate the model's power (maximum likelihood) is discussed.

3.2.1 Utility Function

The utility of an alternative in a choice situation for each person/response (a) is shown in the next two equations (Hensher & Greene, 2002).

$U_i = V_i + \varepsilon_i$

Where:

V_i is the measureable component

ε_i is the unmeasurable component (error) of the utility

$V_i = \varphi_0 + \varphi_1 \times X_{1i} + \varphi_2 \times X_{2i} + \cdots + \varphi_n \times X_{ni} + \cdots$

Where:

n is the index for attributes

φ_n is the utility function coefficient associated with attribute n

X_{ni} is the value if attribute n for alternative i

φ_0 is the choice specific constant term

φ_0 indicates on average the role of all unobserved sources of utility. It can be negative or positive and a bigger value for φ_0 shows that if all variables are kept the same, which choices have still the largest influence on the preference. We can also define $v_{ni} = \varphi_n \times X_{ni}$ as the partial utility associated with attribute n in alternative i.

The error term is assumed to vary according to identical and independent standard Gumbel distributions which is shown in this equation (Garrow, 2012):

$F(x) = P(X \leq x) = \exp\big(-exp\big(\lambda(x - \eta)\big)\big)$

Where:

λ is the scale parameter of the distribution

η is the location parameter of the distribution, which is also the mode of the distribution

3.2.2 Logit Choice Modelling

Each one of us make a choice every day for every single trip that we take. Different factors affect our choice based on trip characteristics such as trip purpose or travel time, mode characteristics, our personal preferences that can be a function of our socio-economic background, etc. To model these choices, logit choice modelling method is used. It is a mathematical model in which the attractiveness of the alternative among other existing alternatives and the attributes affecting it will be investigated (McFadden 1974). This model will estimate choice behavior by deriving the utility function from and considering the probability that a certain driving situation or a certain mode is chosen above the others. Ben Akiva and Lerman (1985) have defined the logit choice modeling as follows. In this model, the probability of having the highest utility for an alternative will be anticipated using this probability equation:

$$P_i = \frac{e^{U_i}}{\sum_i e^{U_i}}$$

Where:

P_i is the probability when alternative i is chosen

U_i is the utility associated with alternative i

Considering the probability equation, utility equation and the Gumbel distribution, the probability of a mode having the highest utility can be written as:

$$P_i = \frac{e^{\lambda \mathrm{V_i}}}{\sum_i e^{\lambda \mathrm{V_i}}}$$

Garrow (2012) have defined the likelihood as:

$$L = \prod_a P(i_a) = \prod_a \frac{e^{\lambda \mathrm{V_i}}}{\sum_i e^{\lambda \mathrm{V_i}}} = \prod_a \frac{e^{\lambda \varphi_0 + \sum_i \lambda \varphi_{ni} \times X_{ni}}}{\sum_i e^{\lambda \varphi_0 + \sum_i \lambda \varphi_{ni} \times X_{ni}}}$$

However, because the likelihood is between 0 and 1, the log-likelihood (LL) would be used for computational tractability to be able to have a better measurement of the likelihood:

$$LL = \ln(L) = \sum_{a} \ln(P(i_a)) = \sum_{a} ln\left(\frac{e^{\lambda\varphi_0+\sum_i \lambda\varphi_{ni}\times X_{ni}}}{\sum_i e^{\lambda\varphi_0+\sum_i \lambda\varphi_{ni}\times X_{ni}}}\right)$$

The LL function needs to be maximized in the modelling process. For this reason, the logit model software ALOGIT 4.3 (ALOGIT 2016) is used and will complete an iterative process which will maximize each P_i by determining all coefficients (φ) associated with alternative i. In order to understand the relative influence of each coefficient, we can compare them with respect to their unit. Statistical tests (t-ratio and t-statistic) will be performed on different coefficients to see whether or not the factors are statically important, how strong their effect is and the difference in significance in certain conditions. T-ratio represents the significance of a coefficient from 0 and the output file of the software provided the t-ratio values for all factors. The difference is said to be "significant" with a 95% confidence level if the absolute value of t-ratio or t-statistic is greater than 1.96. The logit model satisfies the axiom of "independent of irrelevant alternatives (IIA)". It means the ratio of two alternatives with non-zero probabilities is not affected by the presence or absence of a third alternative.

3.2.3 Tree-Structure Adjustment

The logit expression assumes the same error distribution (Weibull) with the same dispersion (λ_1) for all alternatives. In case similar alternatives are existing in the set of alternatives (Alt. b and Alt. c in Figure 4), the logit model assumes a different distribution (with different λ_2) for the error terms of the similar alternatives. In this model, the probability of having the highest utility for an alternative will be anticipated using this probability equation:

$$P_i = \frac{e^{\lambda_2 V_i}}{\sum_i e^{\lambda_i V_i}}$$

After making changes to the utility function with different λ, the model results in a θ value that equals $\frac{\lambda_1}{\lambda_2}$ that is applied to the basic tree structure and defines the nested structure (Figure 4). The θ value must be smaller than 1, otherwise the tree-structure assumed is not correct and the levels above θ represent the real elasticity among alternatives better. Therefore, θ should be set to 1 where all those alternatives corresponding to that tree level be considered to have equal elasticity (basic tree-structure).

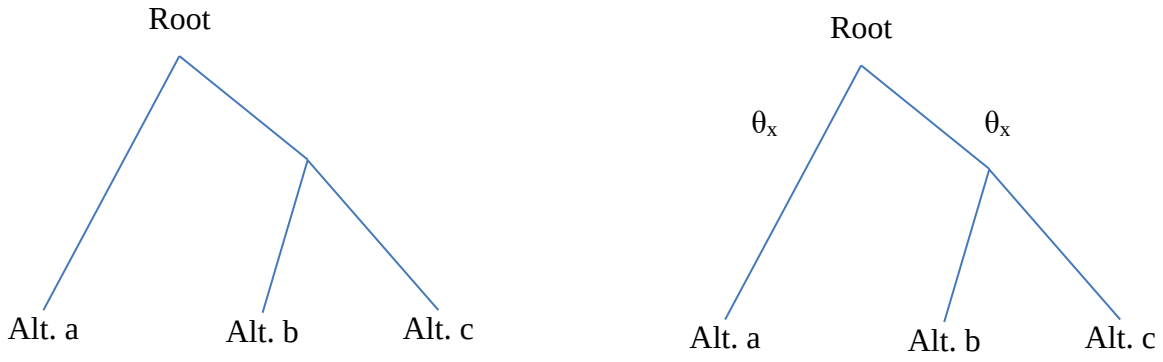

Figure 4. Adjusted vs. Unadjusted Tree Structure

3.2.4 Model's Goodness-of-Fit

Goodness-of-fit indicates whether or not the model predicts the data well and the quality of this prediction. This measurement can also help us compare models and find the better match for the data. As human behavior is complex, the estimation produced by the software is not perfect but goodness-of-fit can measure this error. There are different methods to measure the

goodness-of-fit of a model and one of them is maximum likelihood test which is the best one according to (Hunt & Abraham, 2007).

3.2.4.1 Maximum Likelihood

The maximum likelihood test is similar to R^2 test in linear regression. It is calculated using this formula:

$$\rho^2(0) = 1 - \frac{L(k^*)}{L(0)}$$

Where:

$L(k^*)$ *is the LL for model with estimated coefficients*

$L(0)$ *is* the LL for model when all coefficients are zero

$\rho^2(0)$ vary between 0 and 1 and the closer to 1, the better the fit is and it is the best way of representing the goodness-of-fit for logit models (Hunt & Abraham, 2007). There is also another maximum likelihood index that can examine the goodness-of-fit. This index compares the model with estimated coefficients with a model of a full set of $A - 1$ alternative specific constants. It will be calculate using this formula:

$$\rho^2(C) = 1 - \frac{L(k^*)}{L(C)}$$

Where:

$L(C)$ is the log-likelihood for model with a full set of $i - 1$ alternative specific constants.

3.2.5 Data Adjustment

Data obtained from the survey needs to be adjusted for different reasons. The most basic one would be to be a good representative for the population because we want to be able to draw conclusions regarding a city or region (Bhat et al., 1993). Sometimes the demographic distribution of the data does not match the demographic distribution of the population. For this adjustment, a weight factor (w_i) should be applied to the LL formula:

$$LL = \ln(L) = \sum_a w_i \ln(P(i_a)) = \sum_a w_i ln\left(\frac{e^{\lambda\varphi_0+\sum_i \lambda\varphi_{ni}\times X_{ni}}}{\sum_i e^{\lambda\varphi_0+\sum_i \lambda\varphi_{ni}\times X_{ni}}}\right)$$

The weight factor is the ratio of population share for each observation and is calculated by considering each respondent's age-gender, income and household category and comparing it to the real population data obtained from 2011 and 2014 census data (Statistics Canada, 2016).

Another adjustment needs to be done to the data, because in the SP section we ask more than one scenario question from one respondent. The maximum likelihood carries the fact that there is no correlation between different answers. But in our cases, there are correlations and therefore the error term associated with it should be applied to the model. The Jack-knife variance introduced by Tukey (1958) applies the maximum likelihood estimator on each of the original dataset and estimates their variance from the distribution of the estimates across the sample (Labbé et al., 2013). To find the Jack-knife estimate of a parameter; a subsample is defined while the ith observation is omitted. $\bar{x}_i$ is the average value of the parameter x_i in the subsample and $\bar{x}_.$ is the estimator based on all of the subsamples (Efron, & Stein, 1981).

$$\bar{x}_i = \frac{1}{N-1}\sum_{i=1}^{N} x_j$$

$$\bar{x}_{.} = \frac{1}{n}\sum_{i=1}^{N} \bar{x}_i$$

Where:

N is the total number of observations.

And the estimator variance is calculated using the Jack-knife technique.

$$Variance_{(Jack-knife)} = \frac{n-1}{n}\sum_{i=1}^{N} (\bar{x}_i - \bar{x}_{.})^2$$

In order to estimate the bias of a parameter in the sample and assuming $\hat{\varphi}$ as the average coefficient value: (the indexes' definition is consistent)

$$\hat{\varphi}_{.} = \frac{1}{N}\sum_{i}^{N} \hat{\varphi}_i$$

$$\widehat{Bias_{(\varphi)}} = (n-1)(\hat{\varphi}_{.} - \hat{\varphi})$$

Therefore, the formula to correct the estimated Jack-knife bias is:

$$\hat{\varphi}_{Jack-knife} = n\hat{\varphi} - (n-1)\hat{\varphi}_{.}$$

Fortunately, ALOGIT 4.3 (ALOGIT 2016) software has the option to apply Jack-knife method for data adjustment.

The purpose of this thesis is to investigate the influences of various factors on driving, when driver-less vehicles are available, through utilization of a logit choice model and the influence of different parameters on a set of modes that include SAVs.

Chapter Four: **Descriptive Statistics Results**

In this chapter, detailed properties of the survey sample and the data from RP survey is discussed. Statistical analysis on questions asked from respondents and the range of age, gender and income is investigated and compared to the Canadian 2011 census data (Statistics Canada, 2016) for Alberta.

Answers were obtained from respondents who are 18 years of age and older and live in two cities in Alberta, Canada: Edmonton and Calgary. The data was collected online using the Surveygizmo website and the link was posted on social media and emailed to different people and companies. There were also 100 responses collected in-person. 385 respondents answered the the questions in the beginning of the survey.

4.1 Study Area

As mentioned before, data was collected in Edmonton and Calgary, Alberta, Canada. The following provides a brief overview about Alberta including population, dwelling types from Census 2011, public transit characteristics and downtown parking costs in Calgary and Edmonton are provided. The 2016 population of Calgary was 1,392,609 and 1,321,426 in (Government of Alberta, 2017). There are 161 and 205 bus routes in Calgary (City of Calgary, 2017) and Edmonton (City of Edmonton, 2017), respectively and each city has a light rail transit (LRT) system. Parking costs range in downtown Calgary from free to $30 per two hours and in Edmonton it is from free to $15 per two hour (Parkopedia.ca, 2017). Also, Uber has recently become available in these two cities. Table 6 shows the distribution of occupied private dwellings by structural type in Alberta and Figure 5 shows the population density in Calgary and Edmonton, Alberta, Canada.

Table 6. Percentage Distribution of Occupied Private Dwellings by Structural Type. Source: Statistics Canada, 2016

Dwelling Type	Percentage	Dwelling Type	Percentage
Single-detached House	63.5	Moveable Dwelling	3.4
Apartment >5 Stories	4.2	Semi-detached House	5.2
Apartment Duplex	2.4	Row House	7.0
Apartment <5 Stories	14.2	Other single-attached House	0.1

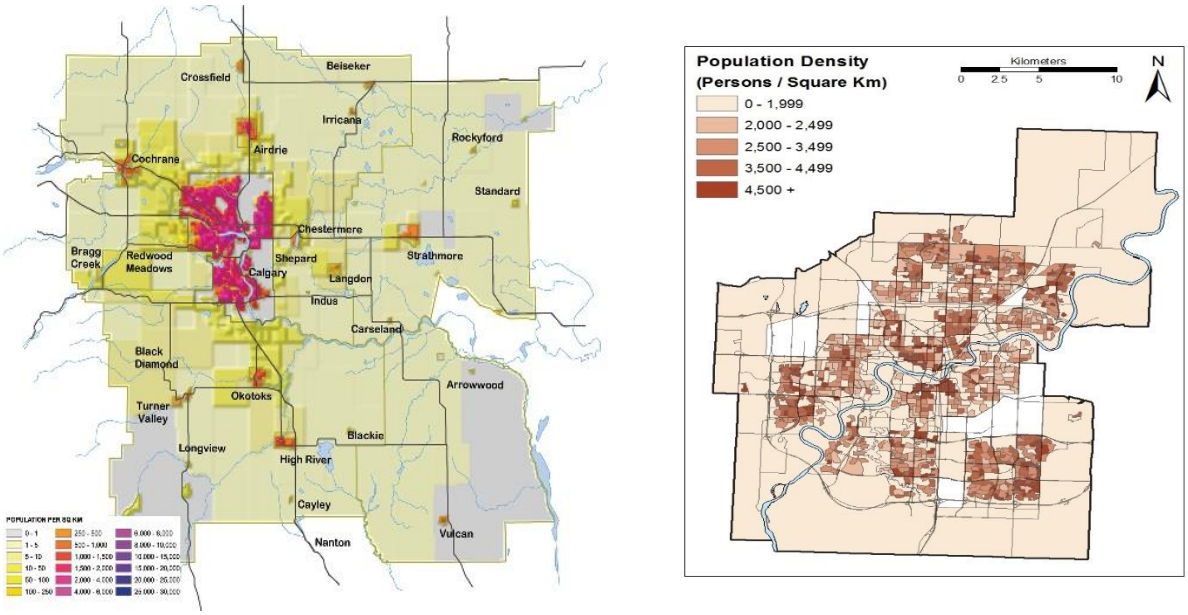

Figure 5. Calgary (left) and Edmonton (right) Population Density, Data Source: City of Calgary & Statistics Canada

4.2 Socio-Economic Attributes Distribution

Most of the interviewees provided their age range and gender, but 111 of them did not provide their income range. Overall, 49.1% of the respondents were female and 44.4% of them were male. This shows that using online tools for SP survey distribution might prevent the data from mostly being answered by males, which often occurs with face to face surveys (Hunt, 2008). Table 7 shows the sample description statistics of the data gathered for this survey.

Table 7. Sample Description Statistics

Alternative	Value	Sample Size	Percentage
Gender	Male	228	49.1%
	Female	206	44.4%
	No Answer	30	6.5%
Age	16 to 19	15	3.2%
	20 to 24	63	13.6%
	25 to 34	188	40.5%
	35 to 44	89	19.2%
	45 to 54	38	8.2%
	55 to 65	35	7.5%
	65 or over	6	1.3%
	No Answer	30	6.5%
Occupation	Employed full-time	229	49.4%
	Employed part-time	25	5.4%
	Full-time Student	133	28.7%
	Part-time Student	1	0.2%
	Retired	8	1.7%
	Not currently Employed	42	9.1%
	No Answer	26	5.6%
Household Composition	One-person	81	17.5%
	Multi-person, No children	191	41.2%
	Multi-person, with child(ren)	157	33.8%
	No Answer	35	7.5%
Number of Cars in Household	Zero	46	10.6%
	One	151	34.6%
	Two	165	37.8%
	More than two	74	17.0%
	No Answer	28	6.4%
Level of Education	Less than Bachelor Degree	75	16.2%
	Bachelor Degree	177	38.1%
	Graduate Degree	186	40.1%
	No Answer	26	5.6%
Annual Household Income	Under $15,000	12	2.6%
	$15,000-$24,999	33	7.1%
	$25,000-$34,999	31	6.7%
	$35,000-$49,999	31	6.7%
	$50,000-$74,999	64	13.8%
	$75,000-$99,999	42	9.1%
	$100,000 or more	140	30.2%
	No Answer	111	23.9%

4.3 Age-Gender Distribution

In Table 8 the percentage and number of male and female respondents and population from statistics Canada is shown. Figure 6 and Figure 7 show the age and gender distribution of the sample survey as compared to the population distribution in Table 8. These figures show that the percentage distribution by age group in the sample does not match well with the population. In order to validate the data, age-gender data for each survey participant was compared with the demographic distributions of the parameters in Alberta from the 2011 Canada census data (Statistics Canada, 2016). The total the gender parameter perfectly matched with the population data, but as age-gender data did not match well, a weight was assigned to the data to match the demographic distribution with population. The weight factor is equal to the percentage of the population data in the intended category (e.g. females who are 25 to 34 years old) so that each response gets a suitable portion of contribution to the results.

Table 8. Number and Percentage of the Sample and Population Age-Gender, Source: Statistics Canada, 2016.

Age Range	Male	Male%	Female	Female%	Pop. Male	Pop. Male%	Pop. Female	Pop. Female%
16 to 19 years	8	1.86%	7	1.62%	122065	3.35%	116145	3.19%
20 to 24 years	38	8.82%	25	5.80%	131510	3.61%	126965	3.48%
25 to 34 years	78	18.10%	109	25.29%	284930	7.82%	278200	7.63%
35 to 44 years	47	10.90%	40	9.28%	262440	7.20%	256215	7.03%
45 to 54 years	25	5.80%	13	3.02%	281945	7.73%	278395	7.64%
55 to 65 years	26	6.03%	9	2.09%	209725	5.75%	206215	5.66%
65 or over	6	1.39%	0	0.00%	184120	5.05%	221600	6.08%

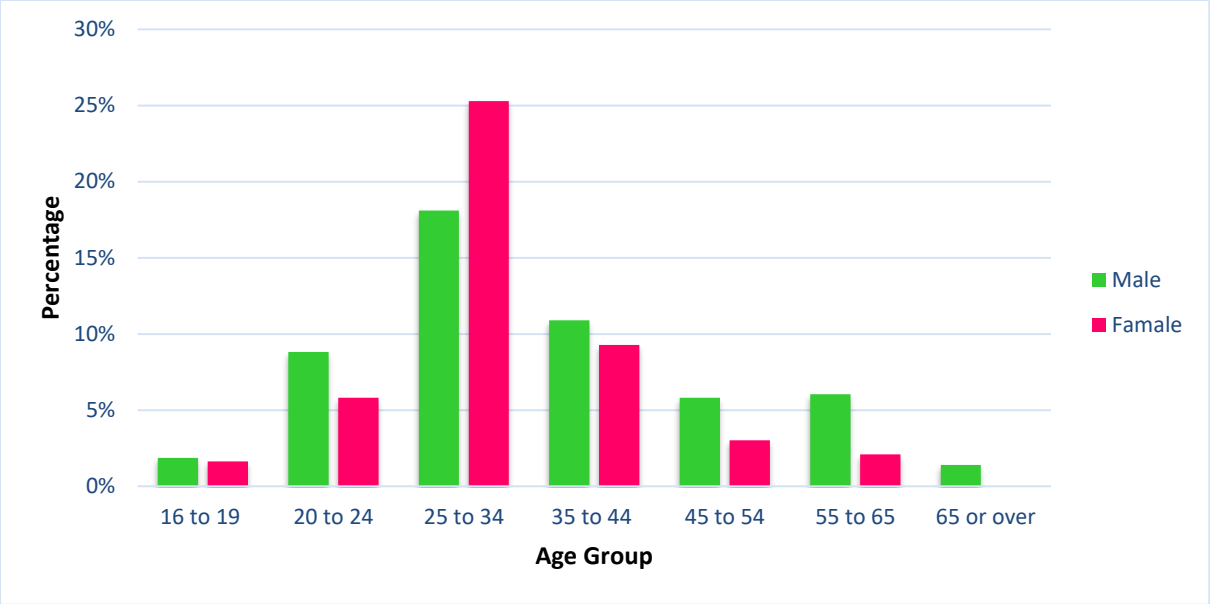

Figure 6. The Percentage of Male and Female Interviewees in Different Age Ranges

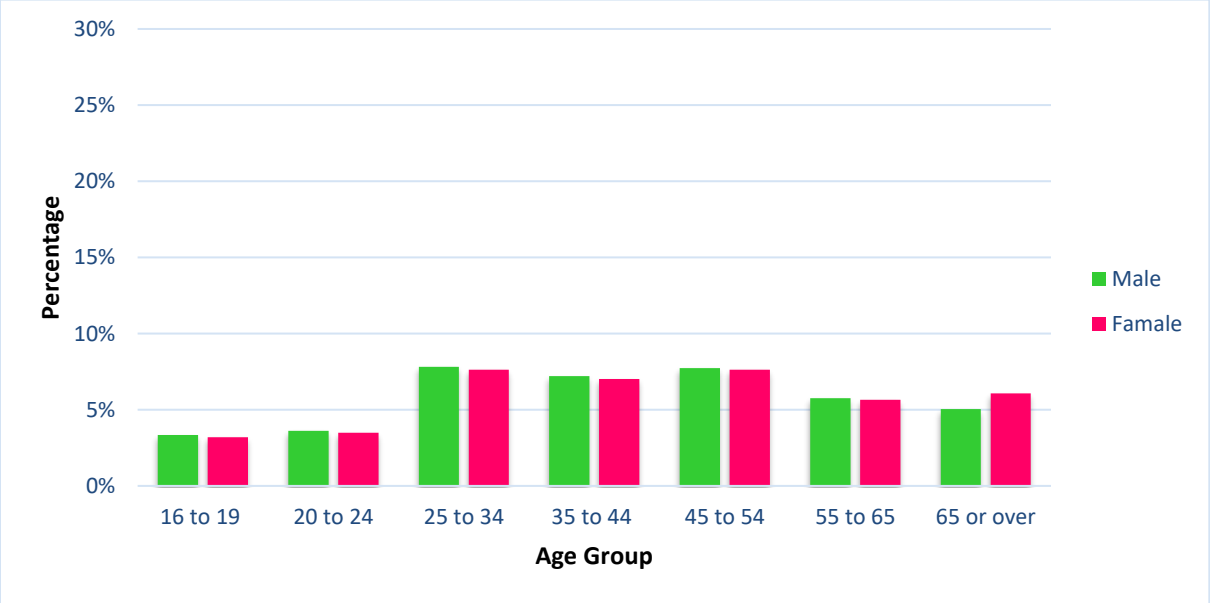

Figure 7. The Percentage of Male and Female Residents in Alberta in Different Age Ranges. Source: Statistics Canada, 2016.

4.4 Annual Household Income Distribution

The number and percentage of annual household income ranges for the interviewees and population is divided to two parts: one-person household and multi-person household which is shown in Table 9 and Table 10, respectively. Figure 8 and Figure 9 depict the data in the tables and show that the distribution of household income in the survey does not match the one in population, based on Statistics Canada, 2016.

Table 9. Number and Percentage of the Sample and Population Annual Household Income for One-Person Household in Alberta, (Statistics Canada, 2016)

Annual Household Income Range	Number of Respondents	Respondents%	Population	Population%
Under $15,000	8	11.27%	547,450	18.35%
$15,000-$24,999	17	23.94%	423,580	14.20%
$25,000-$34,999	6	8.45%	326,840	10.96%
$35,000-$49,999	5	7.04%	421,140	14.12%
$50,000-$74,999	19	26.76%	504,870	16.92%
$75,000-$99,999	10	14.08%	310,300	10.40%
$100,000 or more	6	8.45%	448,930	15.05%

Table 10. Number and Percentage of the Sample and Population Annual Household Income for Multi-Person Household in Canada, (Statistics Canada, 2016)

Annual Household Income Range	Number of Respondents	Respondents%	Population	Population%
Under $15,000	4	1.42%	257,500	3.07%
$15,000-$24,999	16	5.67%	269,230	3.21%
$25,000-$34,999	25	8.87%	561,420	6.70%
$35,000-$49,999	26	9.22%	924,220	11.03%
$50,000-$74,999	45	15.96%	1,522,330	18.16%
$75,000-$99,999	32	11.35%	1,369,110	16.33%
$100,000 or more	134	47.52%	3,478,310	41.50%

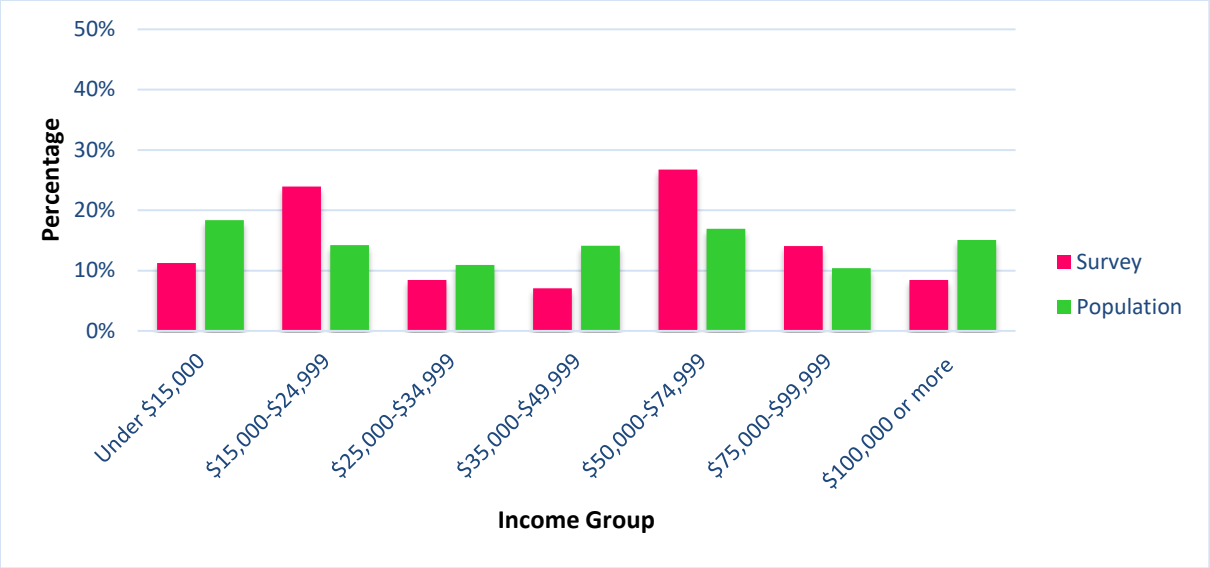

Figure 8. Respondents' Annual One-Person Household Income Percentage. Source: Statistics Canada, 2016.

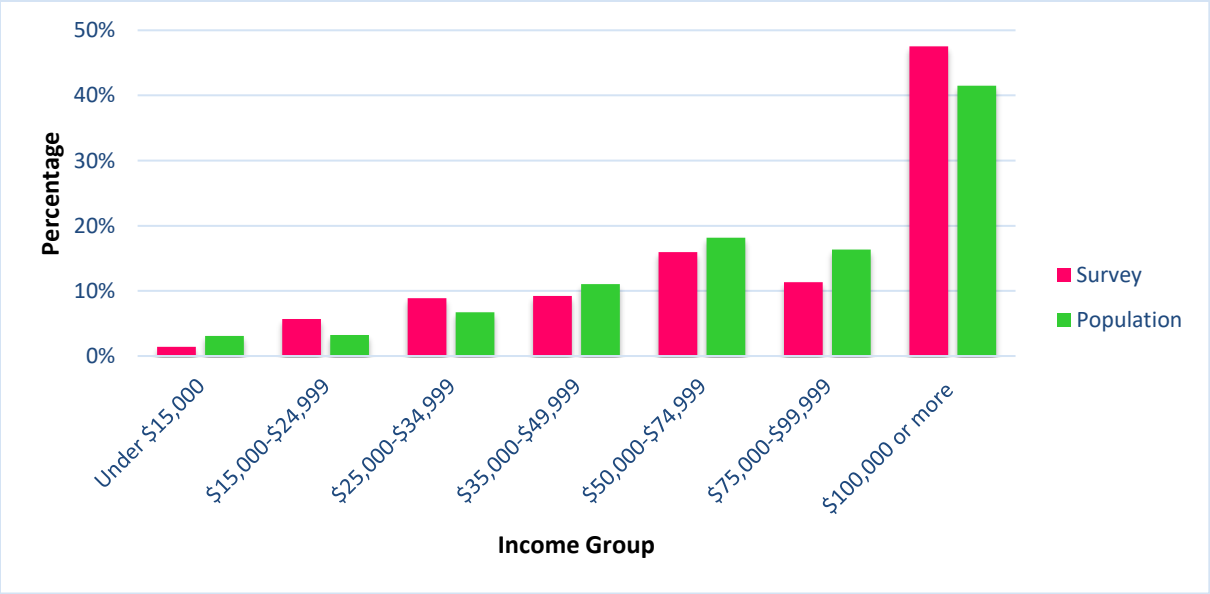

Figure 9. Respondents' Annual Multi-Person Household Income Percentage. Source: Statistics Canada, 2016.

Thus, a weight factor has been defined to reflect the demographic distribution of the population data. The weight factor is determined based on the percentage of the population data in the intended category (e.g. a multi-person household with $35,000-$49,999 income range) so that each response gets a suitable portion of contribution to the results. These weights, as discussed in this section and Section 4.3, will be included in the ALOGIT 4.3 software (ALOGIT 2016) coding.

4.5 Descriptive Statistics Results

As discussed in section 3.1, at the beginning of the survey, respondents answer general questions about their attitude and perception toward AVs. 87% of the respondents reported having heard about driver-less vehicles before taking the survey; however, in the case where AVs are available to use, only 36% of the respondents stated that they would sit and feel safe without looking at the road when the vehicle is driving itself. In the following sections, the information about the survey samples driving experience, driving behavior and attitudes toward AVs will be discussed.

4.6 Sample Driving Experience and Behaviour

Respondents have indicated the first three transportation modes they use (Figure 10). The data from Calgary (City of Calgary, 2013) in 2011 has been compared with the first ranked mode used by the survey sample in Figure 11. In our sample, we have more people that use auto passenger and walk mode and less people using other modes when compared to the 2011 data from the city of Calgary. This might be because many respondents were university students and it may cause a biased result in the second SP part when in commute trips' mode choice.

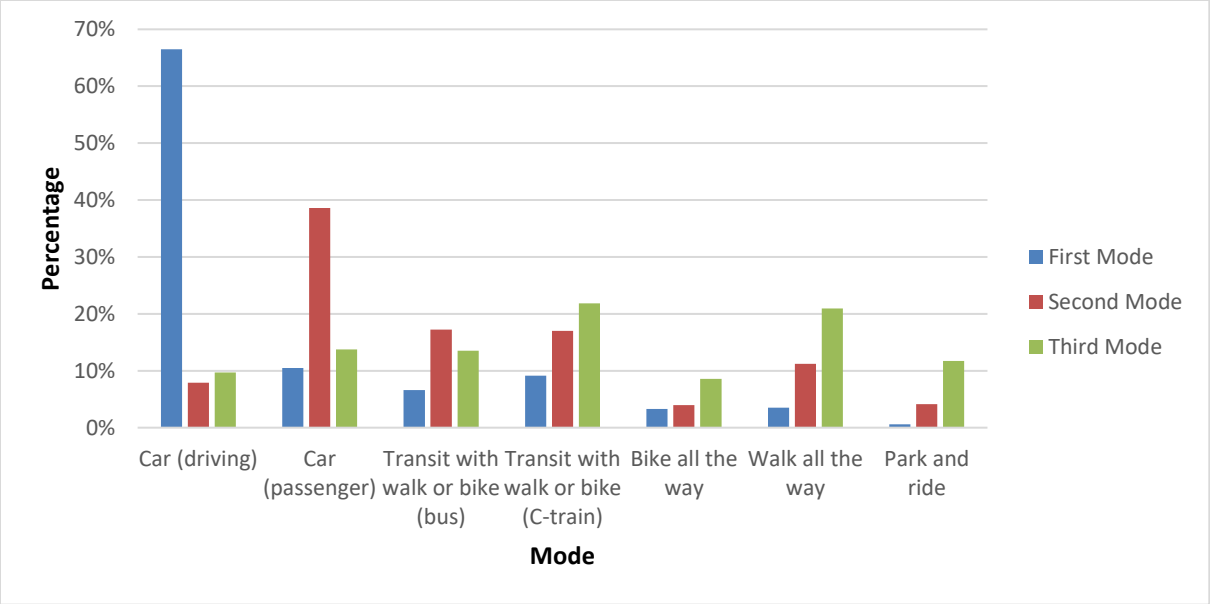

Figure 10. First Three Modes Respondents Use

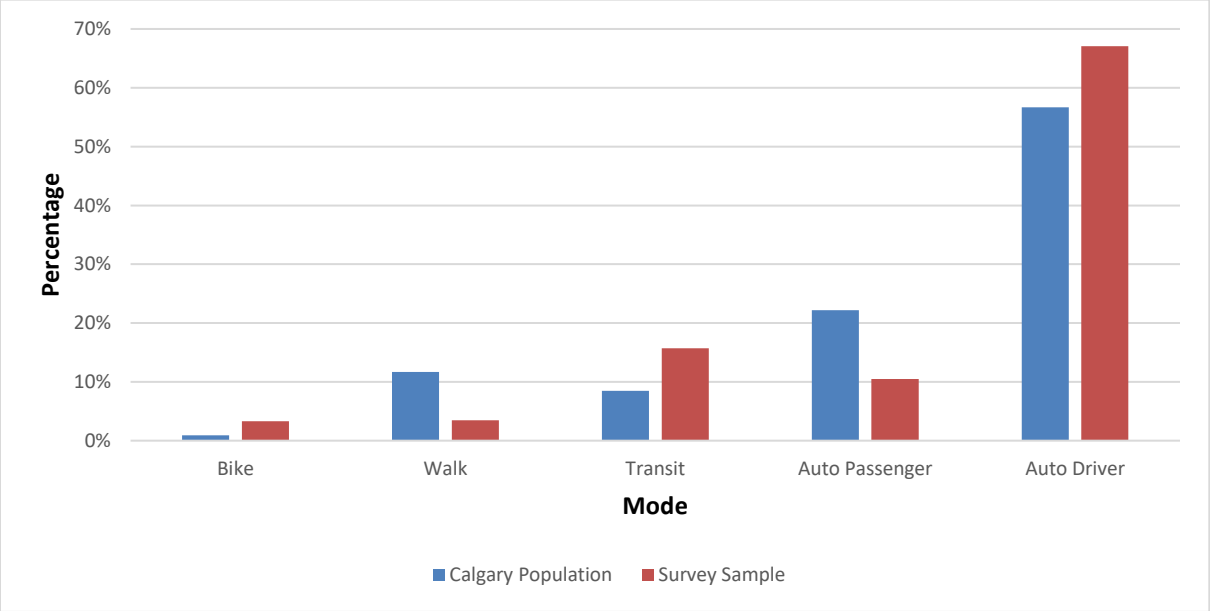

Figure 11. Comparing Mode Share from Calgary Population (2011) and Survey Sample. Source: The City of Calgary, 2016

Respondents' driving experience is shown in Figure 12. More than 55% of drivers drive less than 10 hours per week and only 7% of them drive more than 20 hours per week. Also 87.3% of them own the car they drive.

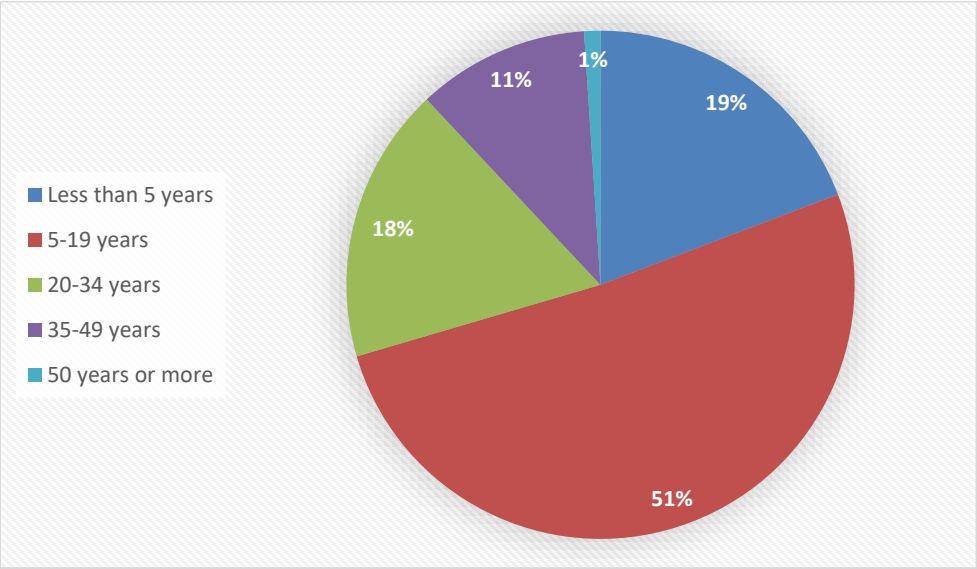

Figure 12. Survey Sample Driving Experience

Drivers were asked about their driving attitudes, which are summarized in Table 11. Results show that drivers in our survey sample are mostly careful drivers that drive at the speed limit and more than half of them stated that they enjoy driving. Only a small portion of the sample drivers use their horn while driving but more than half of them will use aggressive driving to get through the traffic fast.

This data will be used in other sections to see how people's driving behaviour might affect their willingness to give up control to an AV and in mode choice.

Table 11. Survey Sample Driving Behaviour

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Drive Carefully	32%	50%	14%	4%	1%
Like to Drive at Speed Limit	8%	30%	38%	17%	6%
Sensible to Fuel Consumption	24%	42%	24%	4%	5%
Respond Quickly in Certain Conditions	19%	50%	21%	8%	2%
Enjoy Driving	27%	36%	25%	48%	9%
Drive Aggressively (get through traffic faster)	18%	44%	20%	14%	4%
Drive Aggressively (use horn)	1%	9%	18%	30%	42%

4.7 Attitude and Perception toward AVs

People have expressed their concerns about AVs in different situations, such as in poor weather condition, unexpected situations (for instance when a kid jumps in front of the vehicle), interacting with non-AVs, or interacting with pedestrian and cyclists. The biggest concerns were about the potential for AVs to malfunction in unexpected situations and their ability to interact with pedestrians and cyclists. Although respondents did seem to have more trust in AVs interacting with manual driven vehicles, only 6% to 8% of the respondents would trust the AVs completely in all situations. More than half of the respondents, however, are highly willing to use AVs if more tests are conducted to confirm their reliability and safety performance. Therefore, showing the results of the reliability tests for AVs to people would increase their willingness to use them.

As AVs are expected to result in increased safety and reduced traffic congestion, these technologies can also result in increased comfort and convenience for their users and less insurance expenditures for their owners. In the first part of the survey, people expressed their perception and opinion towards these possible benefits as summarized in Figure 13.

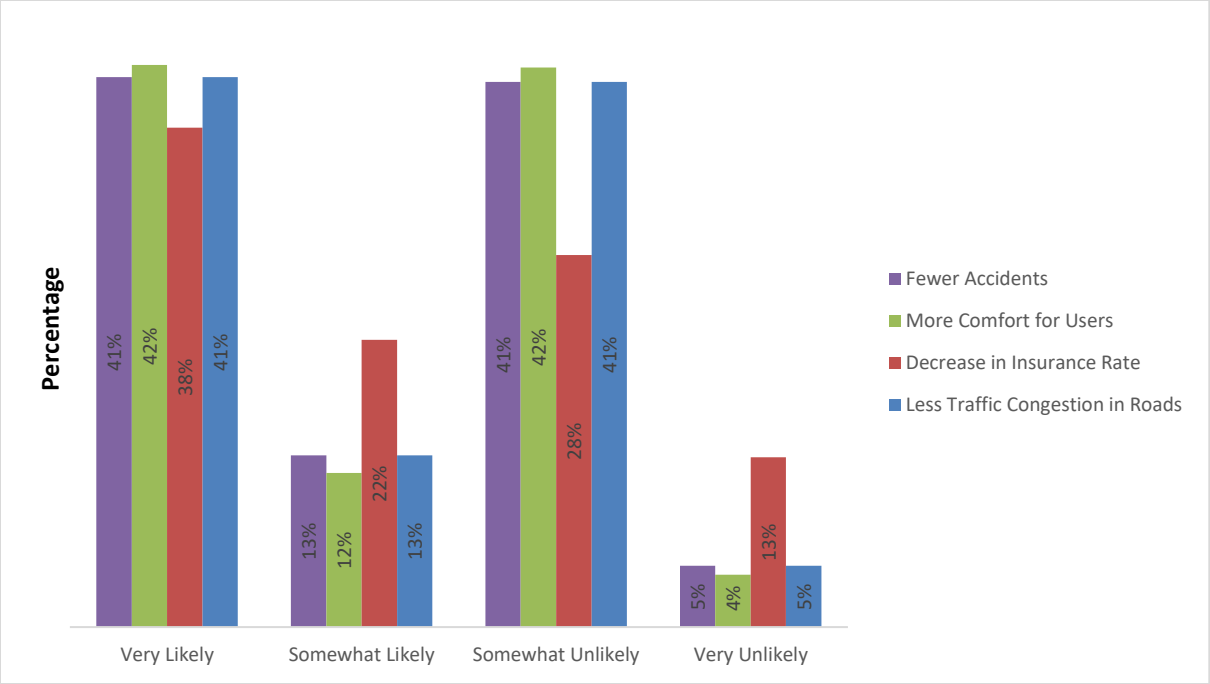

Figure 13. Respondents' Opinions about Benefits Associated with AVs.

There are also risks associated with using AVs, with security failure being the most important one. 68% of the respondents thought security failure is likely to happen. In another question, interviewees were asked about the extent they are willing to give up control of every required driving task to the vehicle. The tasks have been chosen based on the definition of different automation levels. With 36% of the respondents stating that they are likely to sit feeling safe and not look at the road when the vehicle is driving itself, these respondents are considered as those who will give up control of every task to a very high degree. The driver's willingness to give up control for various tasks is summarized in Figure 14.

AVs are expected to provide their occupants the opportunity to use their time more productively while travelling. In case AVs are available, Figure 15 shows what people stated

they would do while riding in an AV. It is interesting to see that 22.5% of respondents stated that they would still be watching the roads.

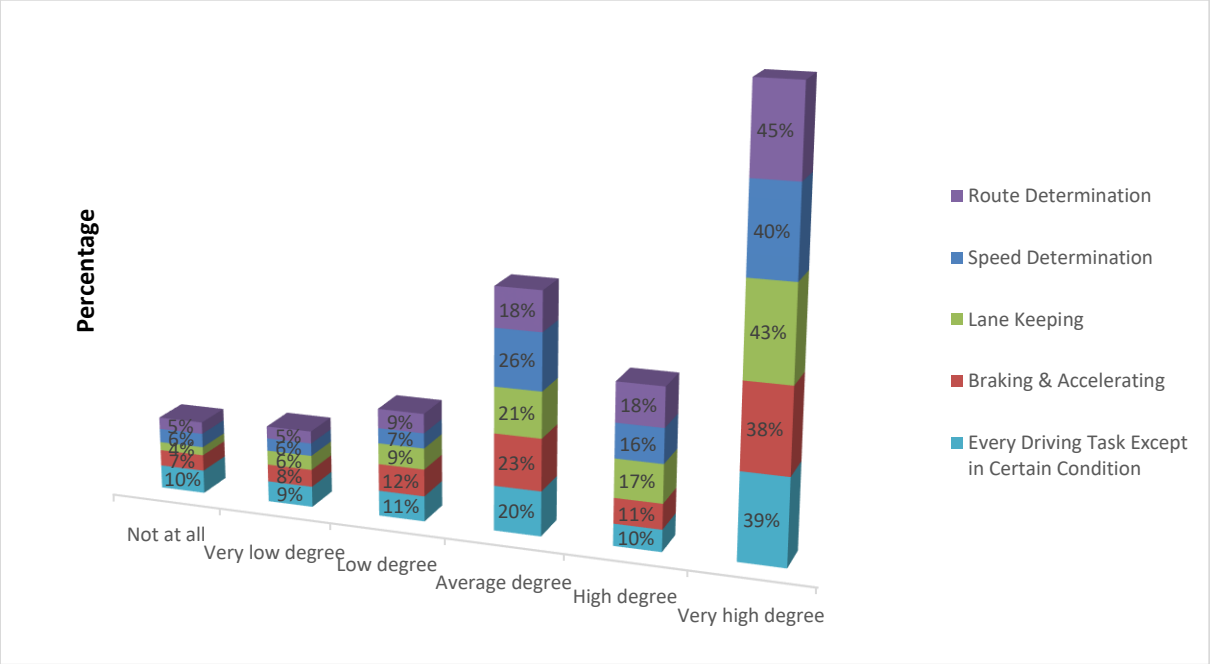

Figure 14. Driver's Willingness to give up the Control to the Vehicle in Different Tasks

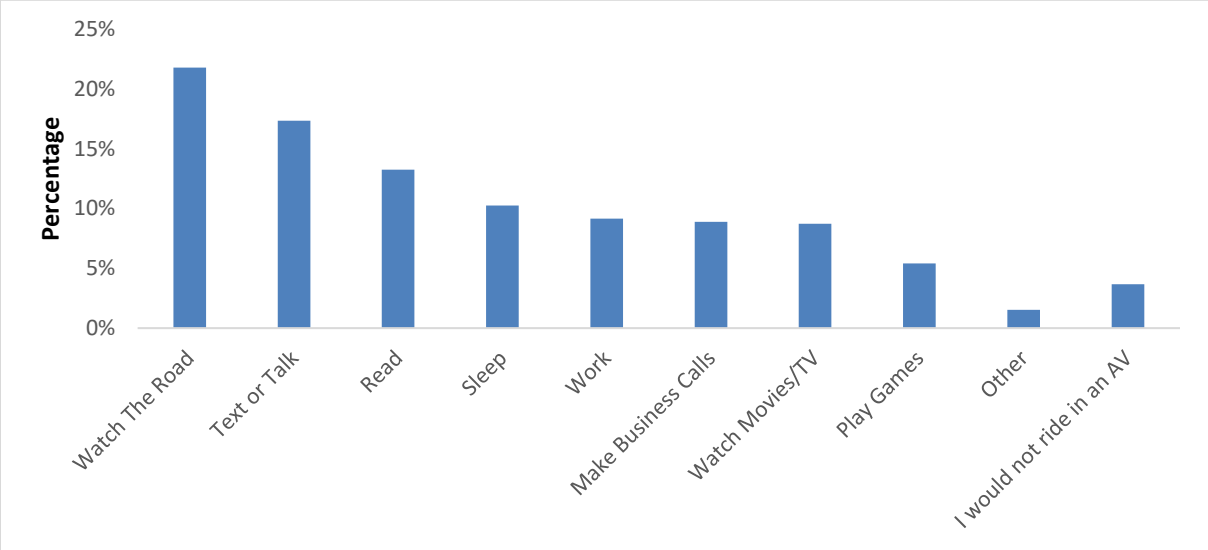

Figure 15. What People Do While Riding in AVs?

Chapter Five: **Results for Using AVs as a Private Transport Mode**

In this chapter, detailed analysis of the data obtained from the first SP part of the survey is discussed. Only drivers have filled this part of the SP survey, with a total of 359 commute trip and 364 non-commute trip filled answers, respectively. For each trip purpose in the first SP part of the online survey, respondents answered two scenarios each.

The first SP part of the survey has been analyzed using logit choice modeling. Different utility functions for measuring the utility of driving were considered using a combination of different socio-economic attributes for both commute and non-commute trips. In the following, each attribute sign, value, T-ratio and T-statistic values is discussed in the context of level of automation and willingness to pay (WTP). The section starts with parameter estimation representing the average population attitudes as summarized in tables and graphs for better visualization of the results. To characterize the results for the population, data is weighted for each respondent based on their age-gender and annual household income group as determined from 2011 and 2014 census data (Statistics Canada, 2016).

5.1 Baseline Function

The utility function with the combination of variables mentioned in Table 2 and considering the weight factor for matching the survey data with real population data was modeled in ALOGIT 4.3 software (ALOGIT 2016).

The baseline function demonstrates the overall average attitude of the sample with the coefficients. The coefficients obtained through this logit analysis are used to develop inferences about the statistical significance of the attributes on driving. The data is used to predict the attractiveness of various levels of automation and other attributes. Analyzing the baseline

function for commute trips shows that there are no t-ratios' absolute value lower than 1.96 (95% level of confidence), which indicates that all attributes are statically significant. Similarly, T-statistic analysis showed that none of the attribute levels should be combined. However, for non-commute trips, though each attribute level is statically significant, the T-statistic test shows that Levels 2, 3 and 4 are not statistically different from each other and thus should be combined. Their combination Level 2,3,4 still has a T-ratio value higher than 1.96. It means drivers have dealt similarly with these three levels in all other conditions (travel time, road condition, pricing, etc.), which is expected as non-commute trips are more flexible in terms of arrival time and have a lower value placed on travel time. So, for non-commute trips the levels of automation have been limited to Level 1 and Level 2,3,4. Table 12 shows the attributes' notation and their definition in this part. For the purpose of analysis, some attribute levels are set to zero (Hensher, Rose, & Greene, 2005). Analysis results for baseline functions in both commute and non-commute trip purposes are shown in Table 13 and Table 14.

Table 12. Attributes' Notation and Definition

Attribute	Notation	Definition
Level of Automation	**Level1**	Automation Level 1-Always set to zero
	Level2	Automation Level 2
	Level3	Automation Level 3
	Level4	Automation Level 4
Road Type	**Highway**	Highway road- Always set to zero
	Arterial	Arterial road
Road Condition	**Norm**	Normal road condition- Always set to zero
	Icy	Icy road condition
Congestion Level	**Uncong**	Uncongested road- Always set to zero
	Cong	Congested road
Familiarity with the Road	**Famil**	Familiar with the road- Always set to zero
	NFamil	Not familiar with the road
Price	**Price**	Cost associated with driving

Table 13. Baseline Function Analysis Result for Commute Trips

Attribute	Coefficient	Std. Error	T-Ratio
Level1	0	0	0
Level2	0.5959	0.0177	33.7
Level3	0.4543	0.0166	27.3
Level4	0.7344	0.0168	43.6
Highway	0	0	0
Arterial	-0.1469	0.013	-11.3
Norm	0	0	0
Icy	-0.9289	0.0132	-70.4
Uncong	0	0	0
Cong	-0.2775	0.0122	-22.7
Price	-0.06163	0.00141	-43.6
Model's Goodness of Fit			
Initial Log-Likelihood = -42529.2944		Final Log-Likelihood = -37677.4179	
"ρ^2" with respect to Zero = 0.1141			

Table 14. Baseline Function Analysis Result for Non-Commute Trips

Attribute	Coefficient	Std. Error	T-Ratio
Level1	0	0	0
Level2	0.1646	0.0158	10.4
Level3	0.1392	0.0156	8.9
Level4	0.1507	0.0163	9.3
Highway	0	0	0
Arterial	-0.1884	0.012	-15.7
Norm	0	0	0
Icy	-0.6236	0.0141	-44.2
Famil	0	0	0
NFamil	-0.1656	0.0138	-12
Price	-0.06126	0.00134	-45.6
Model's Goodness of Fit			
Initial Log-Likelihood = -42671.7738		Final Log-Likelihood = -39781.8620	
"ρ^2" with respect to Zero = 0.0677			

All attributes' signs are consistent with expectations when no demographic covariate is applied. For both trip purposes, price and the icy road condition show a negative impact on the utility of driving by having a negative sign. In commute trips, congestion has a negative sign and

in non-commute trips, not being familiar with the road has a negative sign as well. The disutility of icy road condition is 3.77 times more than non-familiarity with the road and 3.35 times more than congestion.

Two attributes (price and level of automation) were presented as discrete samples of continuous variables while other variables are coded as dummy parameters. The resulting partial utility is shown in Table 15/Figure 16 and Figure 17. The standard error for the statistical estimator is displayed using a small bar at the top of the bars/points. This error value represents the degree of accuracy of the estimation process for that particular attribute (Hunt, 2010).

Results from the plot of coefficients on the price variable shows positive values in some levels (mostly in non-commute trips) while the coefficient value for the first level is set to zero. In this case, three price level coefficients are positive: $20, $22 and $24 per day. However, for the levels higher than $24 per day, all partial utility values are negative. In commute trips, only the $20 per day level has a positive coefficient.

These findings might indicate that people are showing a rational reaction to the cost of driving with AVs and thus are willing to pay for improved comfort and service levels and for the opportunity to spend more time with their family or friends or any other service that AVs can provide. Another plausible explanation is that drivers might have chosen neither of the scenarios or one scenario with a higher price level because of other attributes included in the scenario, or they have a disability, or simply not all the price levels have been shown to them.

Interestingly, the level of automation has a positive effect on the driver's choice of driving situation in both trip purposes. The positive sign indicates the added utility of the automation levels; and is attributed to the increased comfort and opportunity to spend more quality time with friends and family while driving. However, Level 3 has a smaller positive

effect, which is expected and can be explained by the additional features in Level 3 that respondents do not see as valuable as compared to Level 2 or 4. In other words, in Level 3, all the driving tasks cede to the vehicle but the driver should react in certain conditions, which is defined as sudden conditions and mostly dangerous ones. The added level of automation in Level 3 is risky and is not attractive enough compared to Level 2, as drivers even while paying more still must always be alert in case an unexpected event occurs. Thus, drivers seem to prefer to be clearer on the level of control in Levels 2 and 4 as compared to Level 3. The results direct us to skip Level 3 automation in the market and move directly to fully autonomous vehicles. This will be investigated further when considering the effect of different socio-demographic differences in the following sections.

Table 15. Partial Utility of Price Levels ($ per day) Including Standard Error and T-Ratio in Baseline Function for Different Trip Purposes.

Price Level	$18	$20	$22	$24	$26	$28	$30	$32
Commute Trip Purpose								
Estimate	0	0.08858	-0.01511	-0.6165	-0.3642	-0.5058	-0.5228	-1.003
Std. Error	0	0.0247	0.0243	0.0265	0.0243	0.0239	0.0246	0.0267
T-Ratio	0	3.6	-0.6	-23.2	-15	-21.2	-21.2	-37.6
Non-Commute Trip Purpose								
Estimate	0	0.5871	0.08901	0.5896	-0.2162	-0.02295	-0.3076	-0.6915
Std. Error	0	0.0259	0.0246	0.0267	0.0272	0.0249	0.0258	0.0259
T-Ratio	0	22.7	3.6	22	-7.9	-0.9	-11.9	-26.7

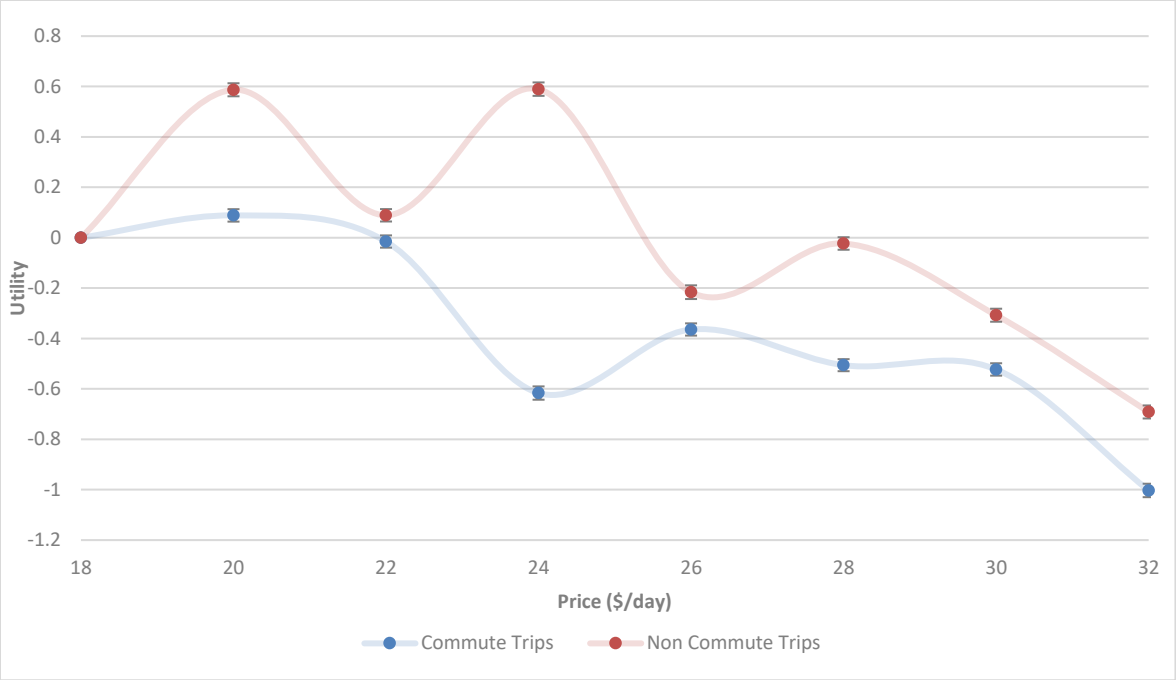

Figure 16. Partial Utility of Price Levels in Baseline Function for Different Trip Purposes. The bars show the variations in the utility of different modes upon change in the attribute.

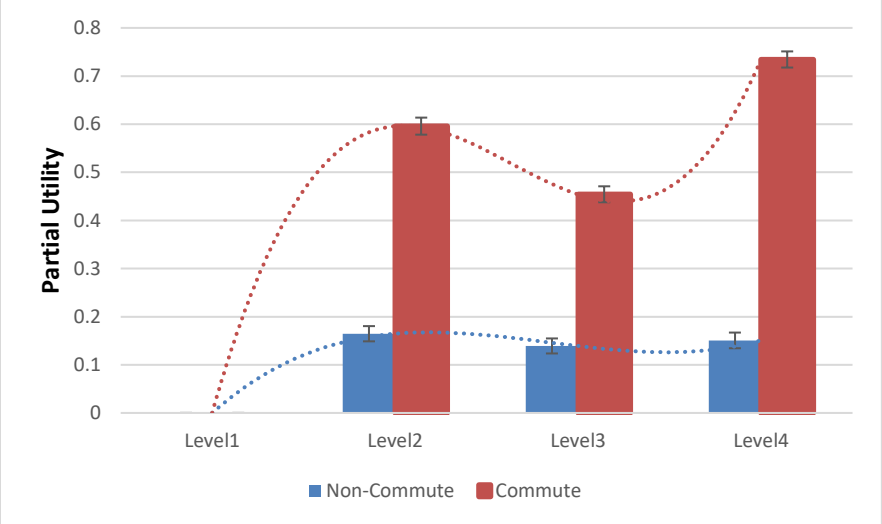

Figure 17. Partial Utility of Levels of Automation in Baseline Function for Commute and Non-Commute Trip Purposes. The bars show the variations in the utility of different modes upon change in the attribute.

The drivers have also expressed the most influential factor affecting their decisions in driving situation. Road condition (icy or normal) was the most important factor in choosing the driving situation scenario followed by automation level, then price, familiarity and congestion. Almost all drivers have also expressed the second and third rank factor that has affected their decisions. Figure 18 shows the factors and how many decisions have been influenced by them.

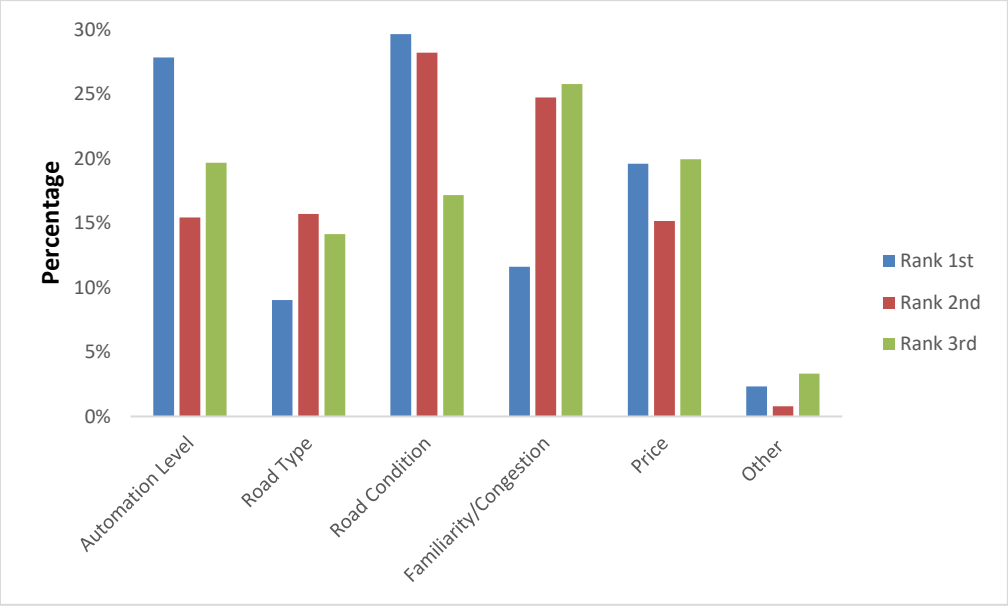

Figure 18. Most Influential Factors Affecting Drivers' Decision in Driving Situation

5.2 Level of Automation Sensitivity

One of the main purposes of this part of the SP survey is to find out if and how drivers would react to different levels of automation. Are they going to give up control of different tasks to the vehicle and to what level?

As discussed, drivers stated that they would react differently to automation levels depending on the trips purpose. In order to investigate the reason and effect of diverse socio-economic features on drivers' level of automation choice, ALOGIT codes (ALOGIT 2016) were modified and run for each feature. In the following section, the effects and results are discussed for both trip purposes.

The result of the analysis shows that drivers' willingness to use higher levels of automation is mainly attributed to their demographic differences and perceptions towards AVs. For instance, Level 3 and Level 4 automation has a high disutility for the drivers who are concerned with an AVs' malfunction due to poor weather condition, in unexpected situations or security failure. Some conflicting responses were also observed. As expected, respondents who attribute AV's to fewer accidents, decrease in insurance rate, comfort and less congestion, seem to be less resistant towards added automation levels.

Since higher levels of automation are associated with less fuel consumption (Fagnant & Kockelman, 2014), respondents who are conscious of fuel consumption were shown to be more likely to use these levels. As expected, respondents who stated to be either aggressive drivers, confident in their response time to manoeuvres, or who enjoy driving or dangerous driving, are shown to be less willing to give up the control of the tasks to the vehicle. Similarly, respondents who stated to be very careful drivers are shown to be less willing to trust higher levels of automation; although, the utility of driving with higher automation is shown to be correlated with drivers who are compliant with the speed limit.

5.2.1 Commute Trips

In commute trips, different levels of automation are shown to be more sensitive to the travel time. In the following, travel time is divided into two levels: short trips (i.e. less than 15 minute) and long trips (i.e. 15 to 40 minute).

Choosing each level (2, 3 and 4) in longer travel time is statistically different from those corresponding to shorter travel time. Results demonstrate that drivers are more willing to cede control for shorter trips as shown for automation Levels 3 and 4 that differ significantly. Interestingly, for shorter trips, Level 3 is more attractive than Level 2. This result can be explained by the fact that drivers have less exposure to unexpected conditions during a short commute trip. In addition, for longer trips, Levels 2 and 4 are not statistically different from each other.

Figure 19 shows the coefficients for each level of automation for short and long trips. All levels are statistically different from each other whether or not there is a secondary task for the driver to perform. However, the existence or absence of a secondary task is shown to have a statistically significant effect on different automation levels. The existence of secondary tasks makes Level 3 less desirable for drivers compared to Level 2 and 4. Therefore the absence of a secondary task made Level 3 more attractive to vehicle users.

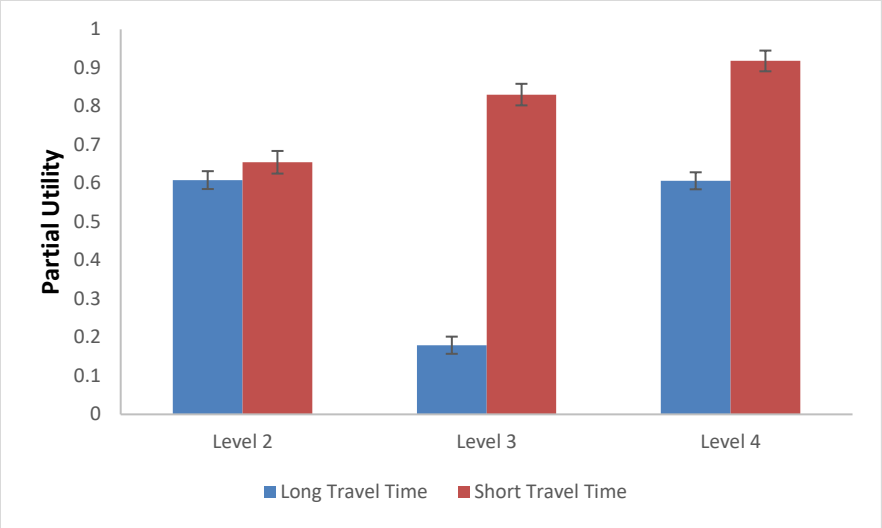

Figure 19. Coefficients for Different Automation Levels in Short and Long Travel Time in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute.

Analyzing the effect of gender in drivers' willingness to give up control to the vehicle resulted interesting findings. All levels have an absolute T-ratio of more than 1.96 for both genders. However, for female respondents, Levels 2 and 3 are not statistically different from each other, which means as long and there is more than one task (but not all tasks) assigned to the vehicle, their utility of level of automation will not change significantly. On the other hand, for male respondents, the utility of Level 3 coefficient is even less than for Levels 2 and 4. This finding can be explained by the fact that the majority of male respondents do not like to expect and react to only certain conditions in their commute trips. However, the positive sign of Level 3 coefficient indicates that it still has a positive effect on the utility of driving. The finding from investigating the effect of gender on willingness to give up the control in different levels of automation confirms that Level 3 automation should be skipped in the market. Figure 20 shows

the coefficients for different levels of automation for male and female drivers for commute trip purpose.

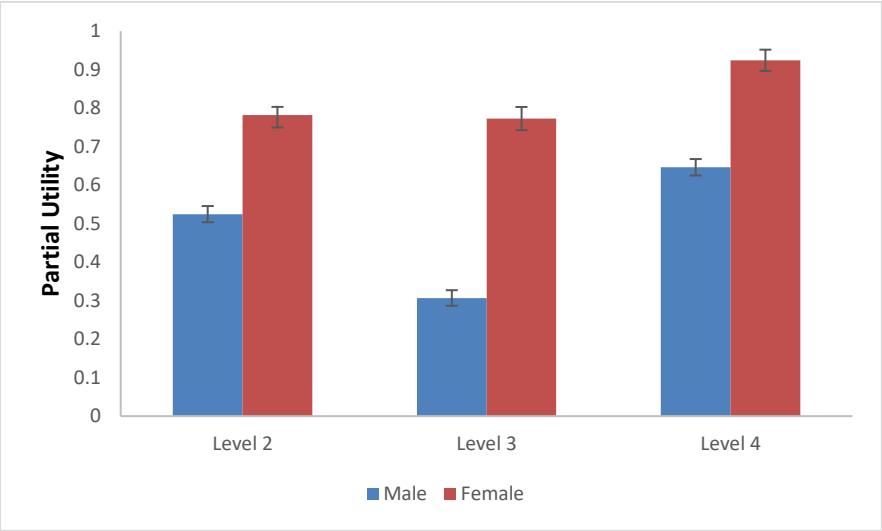

Figure 20. Coefficients for Different Automation Levels for Male and Female Drivers in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute.

Drivers corresponding to different age categories reacted opposite to levels of automation. Three age groups have been defined: under 35 years old, 35 to 50 years old and over 50 years old. All levels are statistically significant for all age groups. T-statistic test shows that in automation Level 2 and 3, only the reaction of drivers of group 35 years and younger is statistically different from the rest. It means respondents corresponding to the age group of 35 to 50 years old and the age group of 50 years old and above reacted statically similar to Levels 2 and 3. But in Level 4, the feedback of drivers who are in the age group of 50 years of age and above is statistically different from the rest. In other words, respondents in the age groups of 35 years and younger and 35 to 50 years reacted statistically similar to Level 4.

On the other hand, if we only look at one age group at a time, for all examined age groups, all levels of automation are statistically different from each other and for the younger and older age group, Level 3 has a smaller positive effect as compared to Level 2 on their utility of driving. Analysis of the respondents in the age group of 35 to 50 years, shows a decrease in the partial utility of automation level with higher level of automation. Comparing the coefficients show that respondents in this age group seem to be the least willing to cede full control of the vehicle.

The most interesting finding of analyzing automation levels for different age groups is that the coefficient corresponding to Level 4 automation for the age group of 50 and above has a positive value of 2.24. It means when fully autonomous vehicles are available; drivers 50 years old and older would be more willing to own and drive them for commute trips. The finding from investigating the effect of age on willingness to give up control in different levels of automation almost direct us to skip Level 3 automation in the market and move directly to fully autonomous vehicles. Figure 21 shows the coefficients for different levels of automation for drivers with different age groups in commute trip purpose.

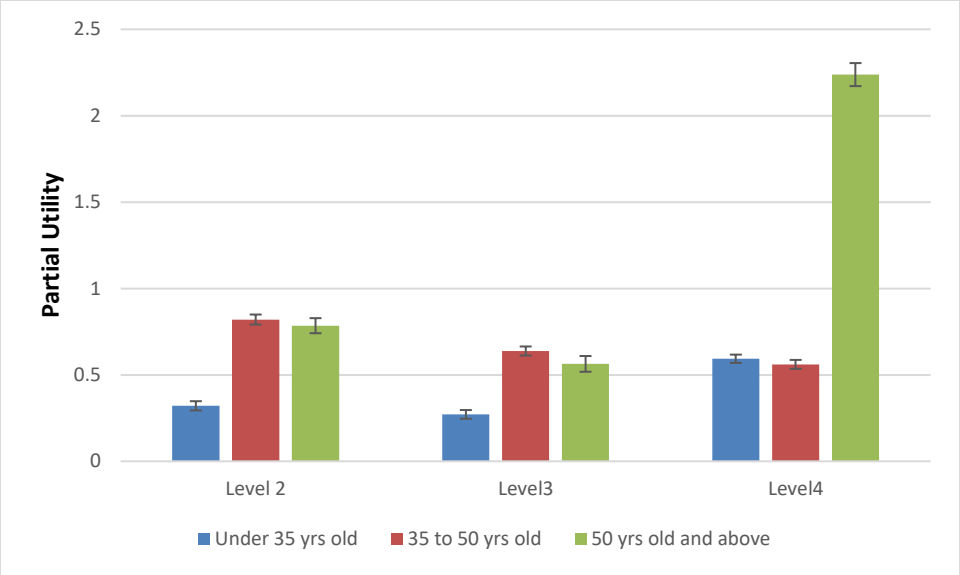

Figure 21. Coefficients for Different Automation Levels for Drivers in Different Age Groups in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute.

The analysis of how level of education affects drivers in response to higher levels of automation interestingly shows that driver's attitude toward each level of automation is different. For Level 2, drivers who have a university degree have a positive attitude toward it, but for drivers who do not have a college degree, Level 2 has a negative effect on their utility of driving. All drivers have a positive attitude toward automation Level 3 and 4. Drivers with no university degree are not reacting statistically different toward Level 3 and Level 4, and Level 3 would attract drivers with a bachelor degree twice as much as the rest. Also, drivers with a bachelor degree are open to Level 4 the most.

The results also showed that years of driving experiences have different impacts on automation levels. Four levels of driving experience were defined for the respondents to choose: less than 5 years, 5 to 19 years, 20 to 34 years, 35 years and more. Respondents with less than 5

years of driving experience have negative attitude toward different levels of automation; are shown to be the most resistant toward Level 4 automation and least resistant toward Level 3. This finding can be attributed to the fact that respondents with few years of driving experience do not trust the vehicle to drive itself in certain conditions (Level 4). Drivers with more than 5 years experience are more open toward added levels of automation; however, drivers who have 5 to 35 years of driving experience trust Level 3 the least. Drivers with more than 35 years of experience are the most open drivers toward Level 4 automation. Their utility of driving increases as the level rises. Figure 22 demonstrates all levels of automation coefficients for different levels of driving experience.

Respondents who drive between 10 to 20 hours per week are approximately three time more willing to give up control to the vehicle compared to the ones who drive less than 10 hours per week.

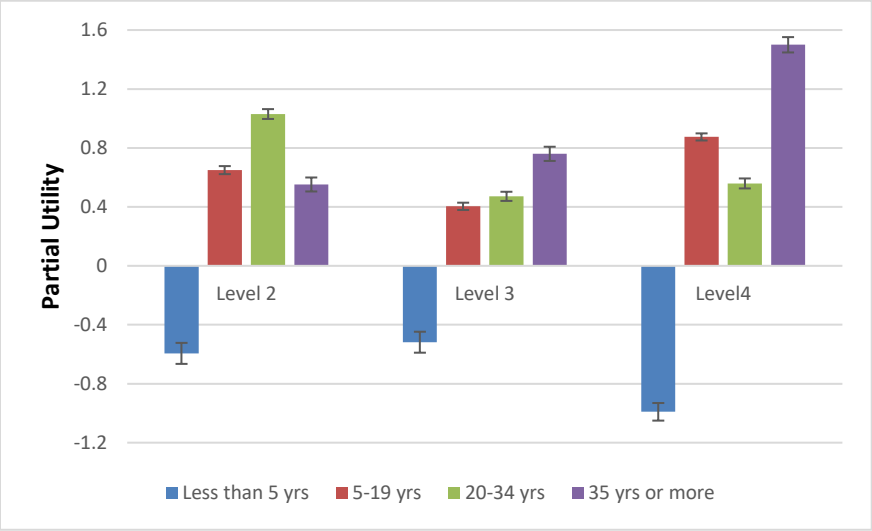

Figure 22. Coefficients for Different Automation Levels for Drivers with Different Driving Experiences in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute.

The type of car that respondents use implies a very interesting finding. Drivers who use a free car made available for them (for instance a family member who uses another family members', his/her parents', vehicle without paying for it) are much more open to giving up control to the vehicle. Level 4 is approximately 13 times and 9 times more attractive to them than those respondents who drive an owned car or a leased car, respectively. Figure 23 shows different coefficients for levels of automation in case of driving an owned, leased or free car made available. It shows that respondents who usually use a leased car have a negative attitude toward automation Level 3 unlike Level 2 and 4. The reason may be due to age and family situation that the respondents with an available free car are in. They might be from a young age group, single, and usually attending to college. Therefore, they may not feel the same responsibility for the safety of the passengers as a person in an older age bracket with a family.

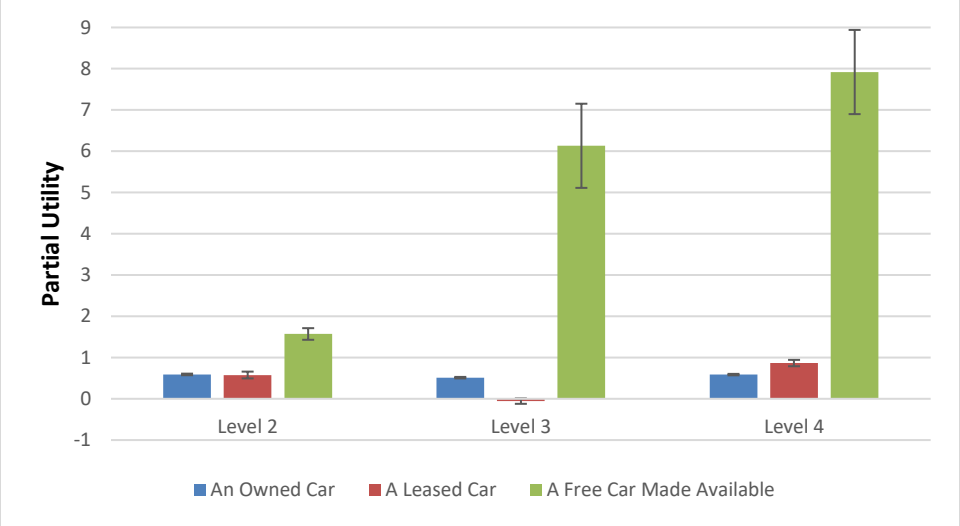

Figure 23. Coefficients for Different Automation Levels for Different Kind of Cars Driven in Commute Trips. The bars show the variations in the utility of different modes upon change in the attribute.

Also, for households that have children, Level 2 automation is the most desired one and their attitude toward Level 3 and 4 is not statistically different. It might be because they feel responsible for their child or children and they do not trust the vehicle driving itself, but they like the comfort that Level 2 automation will provide them with.

5.2.2 Non-Commute Trips

For this section, because there are only two levels available, the explanation does not include any graphs. Analyzing the sensitivity of Level 2,3,4 to travel time in non-commute trips demonstrates that with a travel destination within the city, people are less willing to give up control to the vehicle. Level 2,3,4 for a travel destination within the city is statistically different from a travel destination outside the city. In fact, although the sign for levels of automation has always been positive and it had a positive effect on the utility of driving, for a non-commute trip within the city Level 2,3,4 has a negative sign. This means drivers enjoy driving to destinations inside the city for their recreational or shopping trips. But as expected, drivers like to cede the control to the vehicle for trip destinations outside the city so that they can use their time more efficiently.

In case respondents are presented with the opportunity to do a "secondary task" during their trip, the willingness to give up control increases as well. Thus, the presence of a secondary task made Level 2,3,4 or ceding any control task more attractive. Interestingly, when respondents were not presented with a secondary task on their trip, the sign of Level 2,3,4 was negative, which indicates that giving up control at any level would be a disutility for the driver.

Male and female drivers are both sensitive to the increase in levels of automation, but for female drivers, as the level of automation increases, the utility of driving decreases and Level

2,3,4 has a negative sign. For male drivers Level 2,3,4 has a positive sign and the utility of driving increases with levels of automation. The age factor also affected drivers' willingness to give up control to the vehicle. Drivers who are more than 35 years old are not willing to use higher levels of automation and Level 2,3,4 has a negative effect on their utility of driving in non-commute trips. In other words, drivers within the age group of 35 years old and above would like to handle the driving tasks all by themselves. Level 2,3,4 has a positive effect on the utility of driving of the drivers who are less than 35 years old.

The effect of education level was also investigated on levels of automation and it seems like drivers with graduate degree are less resistant to higher levels of automation in their vehicles. Other respondents seem to have a negative attitude toward Level 2,3,4. The reason can be because educating people has a positive correlation with use of science and trust in new technology; and more educated people are more curious about new technologies.

Level 2,3,4 is the most likely to be used by drivers with less than 5 years of experience in non-commute trips, and the least likely to be used by drivers with more than 35 years of experience. Drivers with 20 to 34 years of experience stated that they would not use this level as shown in the negative effect on their utility of driving. Respondents who spend more time (more than 10 hours) driving per week have a negative attitude toward automation for non-commute trips. This can be explained by the fact that increased travel time means increased possible exposure to unforeseen events and thus decreased trust in ceding the control.

As the levels increase, the utility of driving also increases for households with no children for both trip purposes. It may be because they trust AVs more and feel safer compared to the families who have children. Willingness to give up control to the vehicle is almost 28 time more for drivers who drive a borrowed car, from a family member, than those who drive their

own vehicle. Level 2,3,4 is not attractive for people who lease a car for their non-commute trips and has a negative sign.

5.3 WTP for Different Automation Levels

Another key interest and finding of this thesis was the WTP for the fixed cost associated with AVs that includes the purchase cost, maintenance and service price with different levels of automation. The approach used for estimating WTP uses the model coefficients that are expressed in terms of utility. The coefficients can be divided by one another based on their units to understand exactly how much of an improvement in one attribute is needed to compensate for a loss in another (Zoepf & Keith, 2016). The utility function in our case has the form shown in the following formula; each sub sentence should have the $utils$ (the measure of happiness) unit to have a correct unit for the function. As defined before, X_{price} has the unit of $\frac{\$}{day}$, consequently, the price coefficient φ_{price} would have the unit of $\frac{utils}{\$/day}$. Following the same rule, the level of automation coefficient φ_{level} would have the unit of $utils$. Then WTP can be calculated by dividing these two coefficients. It will be in terms of price with the unit of $\frac{\$}{day}$.

$$U_{driving} = \varphi_{level} \times X_{level} + \cdots + \varphi_{price} \times X_{price}$$

The price coefficient in Table 13 has a negative sign and the value of 0.06163 and 0.06126 for commute and non-commute trips, respectively. Using these values results in WTP for each level of automation for each trip purpose can be determined and are shown in Table 16.

Table 16. WTP for Different Levels of Automation (Price Coefficient in Table 13 is Used)

	Level 2	**Level 3**	**Level 4**	$\frac{\beta_{level}}{\beta_{price}} \times 365$
Commute Trips	$\frac{0.5959}{-0.06163} \times 365 = \frac{\$3529}{year}$	$\frac{0.4543}{-0.06163} \times 365 = \frac{\$2691}{year}$	$\frac{0.7344}{-0.06163} \times 365 = \frac{\$4349}{year}$	
Non-Commute Trips	$\frac{0.1664}{-0.06126} \times 365 = \frac{\$980}{year}$	$\frac{0.1392}{-0.06126} \times 365 = \frac{\$829}{year}$	$\frac{0.7344}{-0.06126} \times 365 = \frac{\$898}{year}$	

As discussed before, for non-commute trips the three automation levels are not statistically different from each other. Therefore, from now on, WTP will only be calculated for Level 2,3,4 and represents the WTP for each of the three levels.

In order to analyze the effect of different demographic features and personal characteristics on WTP for different levels of automation, two sets of utility functions were considered. In the first set, price and level of automation parameters have been split by each socio-economic attribute and in the second set, only the price was split by personal characteristics. The first set was chosen for analysis because its error terms were smaller. Also, as we divide the partial utility of levels by price coefficient to find WTP, the outcome would be more reliable when both levels of automation and price were split by different personal characteristics. Splitting all the parameters may increase the error terms (Hassanvand, 2012).

Indirect utility observation of price demonstrates that it is sensitive to different socio-economic parameters. This impact was investigated using ALOGIT 4.3 (ALOGIT 2016) software in both commute and non-commute trip purposes. These influences will be discussed in the following section.

5.3.1 Gender Effect

People with different genders are statistically different in their attitude toward price or levels of automation. In commute trips, both genders have positive attitude toward levels of automation and negative attitude toward the price. But in non-commute trips, female respondents have a negative attitude toward Level 2,3,4, so the WTP has a negative sign. The WTP was calculated for different genders and is shown in **Table 17.** WTP ($ per year) for People with Different Genders in Different Levels of Automation in both Trip PurposesTable 17. The results show that male respondents are more willing to pay for different levels of automation, sometimes almost as much as twice the WTP for women for commute trips. As for non-commute trips, female respondents seem to not be willing to pay. In addition, Level 3 is associated with the lowest WTP for both males and females.

Table 17. WTP ($ per year) for People with Different Genders in Different Levels of Automation in both Trip Purposes

Gender	Automation Level	Commute Trip Purpose	Non-Commute Trip Purpose
Male	Level 2	$5,124/year	$2682/year
	Level 3	$3,489/year	
	Level 4	$6,013/year	
Female	Level 2	$3,091/year	-$922/year
	Level 3	$2,586/year	
	Level 4	$3,265/year	

5.3.2 Age Effect

Drivers with different ages react contrarily to WTP. Drivers over 50 years of age are much less resistant to pay for different automation levels compared with other drivers. For commute trips, drivers who are 50 and over have a positive attitude toward the price. This might

be associated with the increase need for driving assistance and comfort provided with AVs. The WTP was assumed to be the maximum price for people with positive attitude toward the price.

However, for non-commute trips, drivers under 35 years of age are approximately 1.5 times more open toward spending their money on different levels of automation and drivers in the age range between 35 and 50 are not willing to pay for Level 2,3,4 because it is not attractive to them. The amount of WTP has been calculated for different age groups and is shown in Table 18.

Table 18. WTP ($ per year) for People with Different Age Groups in Different Levels of Automation in both Trip Purposes

Age Level	Automation Level	Commute Trip Purpose	Non-Commute Trip Purpose
Under 35 years of age	Level 2	$1,432/year	$2,576/year
	Level 3	$845/year	
	Level 4	$2,449/year	
35 to 50 years of age	Level 2	$5,463/year	-$643/year
	Level 3	$4,161/year	
	Level 4	$3,694/year	
Over 50 years of age	Level 2	**$11,680/year**	$1,469/year
	Level 3		
	Level 4		

5.3.2.1 Income Effect

As expected, income level also had significant effects on WTP. Low income level drivers are not going to pay for Level 2,3,4 and Level 2 in non-commute and commute trips, respectively because these levels are not attractive to them. Middle income level drivers are not shown to be willing to pay for Levels 3 and 4 in their commute trips. High income level drivers

are the most willing to pay for different levels of automation specifically in their commute trips. The amount of WTP has been calculated for different income levels and is shown in Table 19.

Table 19. WTP ($ per year) for People with Different Income Levels in Different Levels of Automation in both Trip Purposes

Income Level	Automation Level	Commute Trip Purpose	Non-Commute Trip Purpose
Low Income (Under $50K)	Level 2	-$27/year	-$1252/year
	Level 3	$1,268/year	
	Level 4	$1,758/year	
Middle Income ($50K to $100K)	Level 2	$709/year	$1,032/year
	Level 3	-$682/year	
	Level 4	$24/year	
High Income (Over $100K))	Level 2	$6,238/year	$1,295/year
	Level 3	$5,180/year	
	Level 4	$7,541/year	

5.4 Price Sensitivity Analysis

In this section, people's sensitivity toward price will be analyzed for different conditions. For this reason, only the price parameter has been split by different conditions in the set of utility functions.

The first condition is travel time/destination (based on the trip purpose). Travel time/destination has a significant effect on disutility of costs associated with different automation levels. Disutility of spending money for driving rises 2.6 when travel time is less than 15-minutes in commute trips. Also, in the case of travel destinations within the city, drivers are 1.6 times less open to pay for AVs with different levels of automation.

The existence of a secondary task for a driver decreases the disutility of paying for AVs by more than $\frac{1}{3}$ in non-commute trips but not in commute trips. This inconsistency might be

because people usually do not have to do a secondary task in their commute trips and they just assumed their own daily experience when responding to the scenarios.

Disutility of price varies for people with different employment statuses. T-statistic test shows statistical differences between people with different employment statuses. Respondents who are retired, not employed or students are more resistant toward paying for different levels of automation; and this is expected. In non-commute trips, the partial utility of price for retired people is -1.379 $\frac{utils}{\$/day}$ that can be because they have a lower income comparing to others. But in commute trips, students are the most resistant toward the price. It can be explained when considering that students need to make commute trips almost every day to school and with the income they receive; they cannot afford to use AVs.

In both trip purposes, all household compositions are reacting statistically different toward the price. The multi person households with children are more open to spending their money on AVs compared with one person households or multi person households without children. This can be because when one of the parents or even both are working during the weekdays, they would like to spend more time with their children and AVs give them the opportunity to do so.

In commute trips, respondents who own more than one car and the ones who do not own a car, react statistically similar to the price and are shown to be less resistant to pay for AVs compared to respondents who own only one car. A plausible explanation can be because those who own more than one car have a higher income level and those who do not own a car are willing to buy one. In non-commute trips, their response is statistically different but they are still more willing in spending money on AVs.

For both trip purposes, disutility of price decreases when people spend more time driving. For instance, respondents who report spending more than 20 hours per week driving have even a more positive attitude toward the price in their commute trips. It means they are happy with the service AVs would provide as they can have more time to spend on leisure, reading or even working instead of driving.

The respondents were asked to choose what kind of car they drive the most and the options were: an owned car, a leased car or a free car made available (a borrowed car from a family member). In case of commute trips, the respondents who lease a car (example car2go) have a positive attitude toward paying to use AVs, which is expected. However, the respondents who usually borrow a car from another household member are the most resistant, which is also expected as this group is not used to spending money for car use. In non-commute trips, it is vice versa. One of the plausible reasons for this finding is that drivers who lease a car usually do not own a vehicle and in their recreational trips they would like to enjoy the driving and are not willing to spend money on AVs. But maybe in case of the 3rd group, they have the free car made available for them for their commute trips and not for non-commute ones and that is why they are willing to pay more money for AVs for their recreational trips.

The analysis shows that the increased disutility of the price is due to demographics, differences in perceived benefits and concerns, and perceptions associated with AVs. For commute trip purpose, respondents who are willing to give up control to the vehicle in speed determination, braking and accelerating, lane keeping and route determination to a very high degree, are shown to be more willing to pay to receive those added benefits. In addition, respondents who attribute added automation with fewer accidents, decrease in insurance rate,

comfort, reduced congestion and think that security failure is less likely to happen, are less resistant toward paying for AVs.

Chapter Six: **Results for Using AVs as a Shared Transport Mode**

In this chapter, detailed analysis on the data obtained from the second SP part of the survey is discussed. The survey has been analyzed using logit choice modeling with 464 complete responses where each person surveyed experienced three scenarios. Different utility functions have been considered for estimating the utility of each mode (Automobile, Taxi, Car2Go and SAV). The utilities were examined based on socio-economic factors, trip characteristics and mode attributes. In the following section each attribute sign, value, T-ratio and T-statistic values are discussed and the effect of socio-economic factors on the mode choice will be investigated. For modelling purpose, the model constant associated with Automobile mode has been set to zero (Hensher, Rose, & Greene, 2005). Table 20 below summarizes attributes' notations and their definitions as used in this chapter.

Table 20. Attributes' Notations and Definitions

Mode	Notation	Definition
Automobile	**APricF**	Auto Fixed Cost
	APricO	Automobile Operating Cost
	Park	Parking Cost
Taxi	**TWit**	Waiting Time associate with Taxi
	TPric	Cost associated with Taxi
	TCONS	Model Constant for Taxi Mode
Car2Go	**CAcc**	Access Time associate with Car2Go
	CPric	Cost associated with Car2Go
	CCONS	Model Constant for Car2Go Mode
SAV	**SWit**	Waiting Time associate with SAV
	SPric	Cost associated with SAV
	SCONS	Model Constant for SAV Mode
All Modes	**RinAc**	Reduction in Accident
	CO_2	CO_2 Emission Reduction (compared to present vehicle)
Combined Attributes	**TCWA**	Taxi Waiting Time and Car2Go Access Time Combined

The section starts with a parameter estimation with the baseline function and the analysis and policy recommendations will be discussed after adjusting the model and considering different socio-economic factors and people's attitude toward AVs.

6.1 Baseline Function Analysis

The utility functions with the combination of variables listed in Table 4 and Table 5 were modeled in ALOGIT 4.3 software (ALOGIT 2016). The weight factor provides an adjustment to remove the biasness of the sample to reflect the population distribution in terms of age, gender and household annual income. The coefficients resulted from the baseline function analysis help us to understand the overall average attitudes of the respondents. The coefficients obtained through this logit analysis were used to draw inferences about the statistical significance of the considered attributes in each mode. For this part of the SP survey, respondents were asked to rank different modes based on the condition they see in the scenario and it was stated that the mode they rank first represents the mode they have chosen. ALOGIT 4.3 (ALOGIT 2016) has the option of doing ordered logit analysis with both choice and rank (i.e. ordered logit) options. Therefore, two different models were developed and compared. The model with the better goodness of fit of $\rho^2(0)$ that corresponds to the choice model was chosen. The results for the rank approach are shown in Appendix D:.

In addition, different nested tree structure scenarios, with the weight adjustment factors applied, have been modeled and tested with ALOGIT 4.3 software (ALOGIT 2016). Analysis (Appendix E:) shows that all the nested structures cannot be included because the results show a θ value more than 1, which reflects the independence of the choices from the respondents'

perspective. Therefore, the basic tree structure (Figure 24) is the best structure for modelling the mode choice.

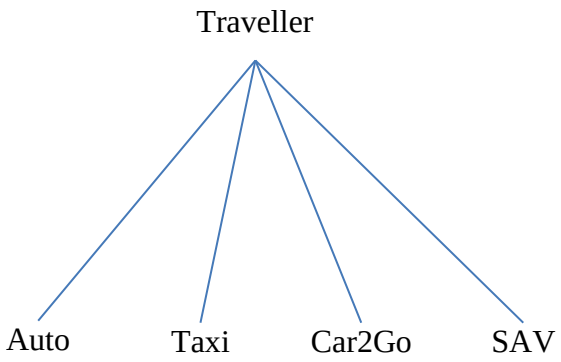

Figure 24. Basic (Unadjusted Tree) Structure for the Second SP Part

This tree structure gives us the opportunity to use this model for future models based on IIA axiom. Matching this tree structure with the data can mean either these four modes are very similar or very different from each other. The first case is not true based on the previous mode share studies in Alberta, Canada, such as Hassanvand, 2012. As there are no studies on Car2Go and SAV mode share in this province or Canada as a whole, the resulted tree-structure indicates that people look at these four modes in very different ways. For planning purpose the mode share results can be used in an independent way from other modes based on IIA axiom, which is a benefit (Hunt, 2014). Therefore, when the model is used to generate predictions involving new alternatives, the estimated parameter values would be no different with or without the new alternative, so that the values found during calibration still apply. However, future studies might be needed to compare these modes with public transit modes in order to use them for planning purposes.

Analyzing the baseline function showed a very high correlation between RinAc and CO2 with the model constants. Therefore, all coefficients cannot be estimated simultaneously (Daly 1992). As the model constants represent all the effects that have not been considered in the study, eliminating them creates a violation of the regression model as it causes correlation between the independent variables and the error term. However, the two attributes, RinAc and CO2, can be estimated in another run when the model constants are set to zero (ALOGIT Support, 2016). In this process, the actual values of all other parameters and the model's goodness of fit stayed the same.

After all, analyzing the baseline function (Table 21) shows that there are no t-ratios' absolute value lower than 1.96 (95% level of confidence). Analysis of the results shows the expected signs for all the coefficients except for the wait time parameter associated with SAV mode and automobile operating cost. The price was expected to have a negative sign, but in this case t is positive and is correlated to respondents who choose automobile mode, own an automobile or have a vehicle available for them to use. The operating cost is much smaller than the fixed cost associated with the automobile mode. Therefore, this positive sign indicates that respondents are willing to pay even more for the operating cost because of the comfort that the automobile would provide them with. These findings were supported with earlier research by Hassanvand (2012) and Winter et al. (2015) who also found a positive sign for the auto price.

The unexpected positive sign for SAV wait time's can be due to the complex experimental set-up (Winter et al, 2017). In our case, there were four alternatives with four attributes in addition to three condition attributes (shown in section 3.1.3) that the respondent was supposed to consider and choose. It can be concluded, in this complicate choice-set, that overall the wait time attribute had less influence on the participants' choice and it caused the

respondents not to observe and consider this parameter in a proper way. A possible explanation for this positive wait time coefficients can be explained by the fact that in the case of SAV, wait time might be considered more reliable and takes place at home and is not considered as disutility, as people can be productive while waiting. There is also correlation between the wait time and mode cost. It means people might decide to wait if they find the mode more desirable from a cost point of view. However, this non-observance will be investigated further when considering the effect of socio-demographic differences in the following sections.

T-statistic test shows that respondents have the same disutility towards waiting for a Taxi to pick them up or walking to access Car2Go. Therefore, these two coefficients have the same value. All price parameters and other wait time attributes are statistically different from each other.

The model constants associated with Taxi and Car2Go show a positive value when Automobile mode constant is set to zero. Both modes have advantages compared to Automobile mode that is associated with purchase, maintenance and operating costs. Using these modes also eliminates the concern and time needed to look and pay for a parking spot. In addition, when using a Taxi, the passenger can use the travel time in a more productive way and people who cannot drive (for any reason) are able to use a Taxi. Using Car2Go provides the joy of driving without including the additional cost disadvantages of vehicle ownership and parking costs. However, the SAV constant was found to be negative. This can be explained by the disadvantage of sharing a ride with strangers in a SAV which affects people privacy and results in extra riding time and possible extra wait time depending on the SAV fleet size to serve other passengers (Azevedo et al., 2016).

The Jack-Knife (JK) data adjustment for considering the effect of showing more than one scenario to a respondent was processed for the chosen model. Generally, the JK method would reduce the error in estimation; however, after applying the JK data adjustment lower t-ratio values are expected. As seen in Table 21, this method seems to have no significant effect on the estimated values of parameters or the constants; however, t-ratio values have changed significantly. The t-ratio values that were very large in the chosen model showed a decrease after the JK data adjustment. In most cases, the drop of the t-ratio value was below 1.96 which made the value of the parameters not significant with a 95% confidence interval. Also, the randomness of the JK process and the possibility of the true standard errors to be close to the naive ones needs to be considered as reasons for such discrepancies in the results (Mina Hassanvand, 2012). This problem could also be due to the noise in the JK random process (Daly, 2011).

Table 21. Baseline Function Analysis Results

Mode	**Attributes**	**Original Estimates**			**Jack-Knife Estimate**		
		Coefficient	**Std. Error**	**T-Ratio**	**Coefficient**	**Std. Error**	**T-Ratio**
Automobile	**APricF**	-1.063	0.0178	-59.7	-1.0549	0.316	-3.34
	APricO	0.09659	0.032	3	0.102	0.435	0.23
	Park	-0.03262	0.00063	-51.8	-0.0327	0.012	-2.66
Taxi	**TCWA**	-0.0397	0.0025	-15.9	-0.0396	0.039	-1.02
	TPric	-0.04474	0.00231	-19.4	-0.0432	0.052	-0.83
	TCONS	1.593	0.0945	16.9	1.5309	1.946	0.79
Car2Go	**CPric**	-0.1719	0.00444	-38.7	-0.1636	0.082	-2
	CCONS	1.521	0.065	23.4	1.433	1.128	1.27
SAV	**SWit**	0.03343	0.00563	5.9	0.0338	0.077	0.44
	SPric	-0.001146	0.000616	-2	-0.0001	0.012	-0.01
	SCONS	-1.868	0.0501	-37.3	-1.8525	0.645	-2.87
All Modes	**RinAc**	4.552	0.27	16.9	4.3743	5.56	0.79
	CO2	6.337	0.271	23.4	5.9711	4.698	1.27
Model's Goodness of Fit							
Initial Log-Likelihood = -207558.5989				Final Log-Likelihood = -186593.9914			
"ρ^2" with respect to Zero = 0.1010							

The effect of weather and time travel conditions on different modes has been investigated by dividing the travel time into a binary categorization: short trip (travel time less than 15 minute) and long trip (travel time 15 to 40 minutes). Results indicate that people have more of a negative attitude toward SAVs in a snowy weather condition. The reason may be because they do not trust the car driving itself in adverse weather condition, which has also been proved by aforementioned analysis. In addition, for long trips, people have shown a smaller negative attitude toward SAVs compared to shorter trips. This may be because SAVs give them the option of using their travel time in a more productive way when they are supposed to spend a considerable portion of time commuting.

Two attributes in the SAV mode (price and wait time parameters) were presented as discrete samples of continuous variables. The partial utility of the price variable can be seen in Table 22 and Figure 25. The standard error for the statistical estimator is displayed as an interval on the points. This error value represents the degree of accuracy of the estimation process for that particular attribute. (Hunt, 2010)

Results from the plot of coefficients on SAV price variable shows expected negative values in all levels while the coefficient value for the first level is set to zero. A couple of jumps and positive values in Figure 25 are unexpected but can be explained considering the fact that not all the scenarios with all the price level combinations have been shown to same respondents. SAVs are typically priced cheaper than most other vehicles (Burns et al., 2013; Zhang et al., 2015; Fagnant, & Kockelman, 2014), so users looking for the cheapest modes will frequently choose SAVs. Interestingly, respondents showed a rational positive reaction to the cost of traveling with SAVs for up to $7 per half an hour. It means they think this price is a good deal for such a service. The Car2Go cost is now $12 per half an hour. Comparing our finding with

Car2Go cost shows that if SAVs come to market with a less than $7 per half an hour fare, Car2Go users might switch to SAVs.

Table 22. Partial Utility of Price Levels Including Standard Error and T-Ratio in Baseline Function

Price Level	Estimate	Std. Error	T-Ratio
$2	0	0	0
$4	0.02621	0.0411	0.6
$7	0.2684	0.0386	6.9
$8.50	-0.5018	0.0435	-11.5
$10	-0.321	0.0422	-7.6
$11.50	-1.323	0.0529	-25
$13	-0.6324	0.0438	-14.4
$14.50	-0.03494	0.0427	-0.8
$16	-1.777	0.0566	-31.4
$21	-0.6798	0.0433	-15.7
$32	-0.09754	0.0396	-2.5
$44	-0.3702	0.043	-8.6
$50	-0.1711	0.0431	-4

Figure 25. Partial Utility of SAV Price Levels. The bars show the variations in the utility of different modes upon change in the attribute.

The respondents have also expressed the most influential factors affecting their decision in mode choice among the four considered modes. Wait/access time and price ranked as the most important factors. Almost 40% of drivers have expressed their second most influential factor as reduction in accidents. Figure 26 shows the factors and how many decisions have been influenced by them.

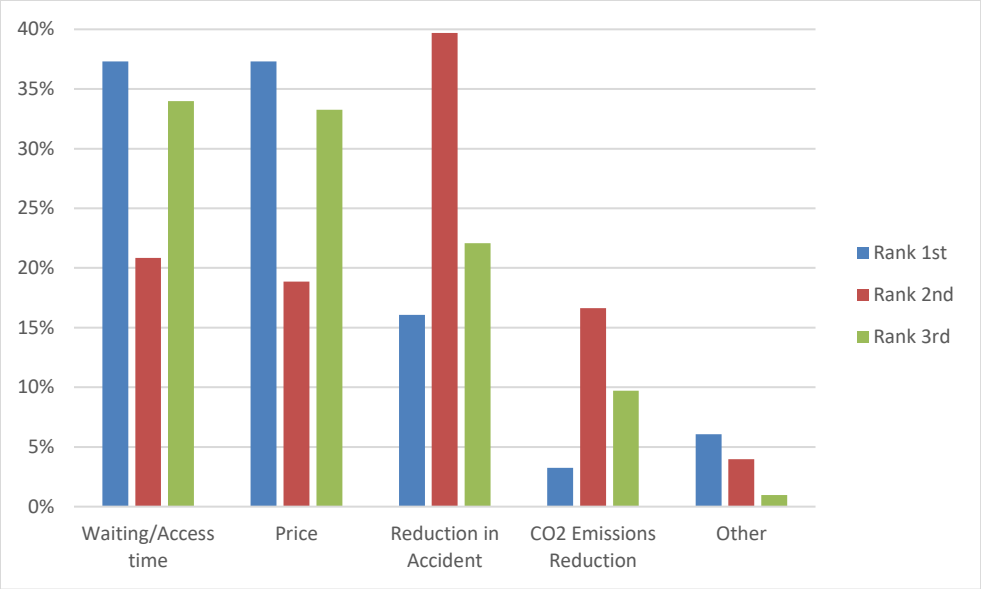

Figure 26. Most Influential Factors Affecting Respondents' Mode Choice

25% and 50% of the respondents mentioned that they will definitely and probably sell one of their automobiles when SAVs become available, respectively. This is an important finding showing the impact of SAV on potentially reducing auto ownership; thus, the demand for residential parking.

The effect of respondents' attitude and perception toward AVs on their mode choice has been investigated. For this purpose, the ordinal expression of likelihood and concern has been divided into a binary categorization. concerns or benefits that were chosen as somewhat likely and very likely to happen were considered as being "likely to happen" in the technology, while all others were treated as being "unlikely to happen". Also, individuals who expressed their level of concern for AVs in different situations have been considered "concerned" if they have chosen the levels slightly concerned, moderately concerned and very concerned; and they have been considered "not concerned" if they have chosen the level, not at all concerned. To find out the effect of respondents' attitude and perception toward AVs on mode choice and the cost

associated with SAVs, in this part, different utility functions with separate parameters based on respondent's binary attitude categorization have been analysed.

Results indicate that, respondents' perception have not impacted their mode choice in some cases. For instance, the disutility of price for respondents who think security failure/more comfort is unlikely/likely to happen with AVs, is even greater than the ones who do not think this concern/benefit are likely/unlikely to happen! However, respondents who think fewer crashes and less congestion is likely to happen with AVs, have a positive attitude toward paying for SAVs. This indicates that they are willing to pay even more to receive these benefits from SAVs. Also, those who are not concerned about the AVs' interaction with regular vehicles or bikes and pedestrian have a positive attitude toward paying for SAVs.

Investigating the effect of people's attitude toward AVs shows that the SAV constant has a smaller negative value for the respondents who think fewer crashes, less congestion and more comfort is likely to happen with AVs. Also, the SAV constant has a smaller negative value for the respondents who are not concerned about AVs' interacting with regular vehicles, bikes and pedestrian. This means these factors have affected people's choice and in order to attract more people to use SAVs, factories can do more tests on AVs' security and congestion impact. They can reveal their results to social media to emphasize these factors and change people's minds about AVs before the system comes to the market. In addition, people who enjoy driving have a higher disutility toward using SAVs compared to people who do not or are neutral toward the joy of driving.

Indirect utility observation of SAV fare demonstrates that it is sensitive to different socio-economic parameters. The main purpose of this part of the SP survey is to examine how respondents react to SAVs by investigating their reaction to the wait time, fare and model

constant associated with this mode. Therefore, a set of functions were developed with different wait time, fare and model constant parameters associated with SAV mode (and occasionally other modes) based on socio-economic attributes (gender, income, age, presence of disability, perception and membership in a car-sharing program such as Car2Go).

6.2 Gender Effect

In order to examine the effect of gender on choosing SAVs, SAV utility function with separate parameters (including constants) based on different genders were developed and summarized in Table 23. The notation "M" and "F" after the SAV's wait time, price and constant coefficients in Table 23 is representing the parameters for Males and Females, respectively.

T-ratio test shows that all parameters are statistically important for all age groups. And t-statistic test results in statistically significant difference in each parameter for males and females. The model shows a positive sign in wait time for females only. As mentioned before, this unexpected sign can be due to the complex experimental set-up in this choice-set, the wait time attribute had less influence on the female participants' choice. Therefore, the problem in the general wait time sign is due to the non-observance of this parameter by female respondents. It can also be because female respondents feel the waiting time for SAVs can be used in a more productive way.

SAV fare has a negative impact on females' utility of using SAVs. However, males have an unexpected positive attitude toward paying for SAVs. This positive sign for SAV cost may be because males are showing a rational reaction to the cost of traveling with SAVs and are willing to pay more to get a good service. The same statement about the complexity of the choice-set and parameter non-observance can also be true for males regarding the SAV cost. In addition, we

observe expected negative values for constant in both gender groups. In addition, the results show a higher value of time for males when riding in an SAV simply because SAV fare has a much smaller value for male respondents. However, SAV constant shows that the disadvantage of sharing a ride with strangers is higher for female users. When comparing the Taxi mode constant for female users with SAV mode constant, we can conclude that the disadvantage of using SAVs for females is because they do not feel safe sharing a ride with strangers. In addition, as the SAV mode constant has a smaller negative amount for male respondents, they might be the early adaptors of this system.

Table 23. Analysis Result: Gender Effect on SAV's Attributes

Attributes	Coefficient	Standard Error	T-Ratio
TCONSM	1.615	0.0947	17.1
TCONSF	1.936	0.0958	20.2
SWitM	-0.03818	0.00666	-5.5
SWitF	0.1805	0.00996	18.1
SPricM	0.006793	0.000699	9.7
SPricF	-0.02819	0.0014	-20.1
SCONSM	-1.526	0.0568	-26.9
SCONSF	-2.585	0.0777	-33.3

6.3 Age Effect

In order to find out the effect of age on choosing SAVs, SAV utility function with separate parameters (including constants) based on different age groups have been analyzed. The notation "Y", "M" and "O" after the SAV's wait time, price and constant parameters in Table 24 are representing the parameters for Young, Middle and Old age group, respectively. These three age groups have been defined: under 35 years old (Y), 35 to 50 years old (M) and over 50 years old (O).

T-ratio test shows that all parameters are statistically important for all age groups. Disutility of waiting for an SAV to arrive is much higher for respondents in the 50 and above age group compared with those in the 35 years and younger age group. However, the model shows a positive sign in wait time for middle age respondents (35 to 50 years old). This can be interpreted in different ways: first, it can be implied that people within this age group do not mind waiting even longer for SAVs which may be because SAVs offer door-to-door service and their time can be used productively. The same justification related to the complexity of the choice-set can be true and it can be concluded that SAV wait time attribute had less influence on the participants' choice who are between 35 and 50 years old and it has caused a non-observance of this parameter.

SAV fare has a negative impact on people's utility of using SAVs who are in the young and middle age groups. Also, the t-statistic test shows that this disutility is not statistically different for the 35 years and younger age groups and the 35 to 50 year old age group. However, people in the 50 years old and over age group have a positive attitude toward paying for SAVs. This positive sign for SAV cost can be because people within this age group are showing a rational reaction to the cost of traveling with SAVs and are willing to pay more to get a good service. Also, seniors that are not able to drive are included in this age group and SAVs can provide them with good service that is less costly than the Taxi mode. The same statement about the complexity of the choice-set and parameter non-observance can also be true for people within this age group regarding the SAV cost. T-statistic test shows that people in the under 50 years old age group are statistically different from people in the 50 years old and above age group in their feeling about paying for SAVs.

We observe expected negative values for constant in all age groups while the constant is not statistically different for people who are in the 35 to 50 years old age group with the constant for people in the 50 years old and above age group. T-statistic test shows that SAV constant is statistically different for people in the under 35 year old age group and people in the 35 years old and above age group. However, SAV constant shows that the disadvantage of sharing a ride with strangers is higher for the user over the age of 35 years. In addition, as the SAV mode constant has a smaller negative amount for people under 35 years of age, they might be the early adaptors of this system.

Table 24. Analysis Result: Age Effect on SAV's attributes

Attributes	Coefficient	Standard Error	T-Ratio
SWitY	-0.02195	0.00729	-3
SWitM	0.1434	0.0118	12.1
SWitO	-0.142	0.0272	-5.2
SPricY	-0.00664	0.000818	-8.1
SPricM	-0.00514	0.00127	-4.1
SPricO	0.0468	0.00247	19
SCONSY	-1.13	0.0547	-20.6
SCONSM	-1.987	0.0846	-23.5
SCONSO	-1.745	0.197	-8.9

6.4 Income Effect

In order to find out the effect of income on choosing SAVs, SAV utility function with separate parameters (including constants) based on different income groups have been analyzed. The notations "L", "M" and "H" after SAV's waiting time, price and constant in Table 25 is representing the parameters for Low, Middle and High income group, respectively. These three

income groups have been defined: under $50K (L), $50K to $100K (M) and over $100K (H). T-ratio test shows that all parameters are statistically significant for all income groups.

SAV fare has a negative impact on people's utility of using SAVs for those who have an annual income of over $50K. However, people with the annual income of $50K or under have a positive attitude toward paying for SAVs. This positive sign for SAV cost can be because people with this income group are usually students and they do not own a car and they are showing a rational reaction to the cost of traveling with SAVs because SAVs can provide them with a good service that is less costly than the Taxi or Car2Go modes. The same explanation related to the complexity of the choice-set and parameter non-observance can also be true for people within this income group regarding the SAV cost. We observe expected negative values for constant in all income groups, as well. T-statistic test results show a statistically significant difference of all parameters for all income groups except in the SAV constant for people with the low and high income group. The popularity of SAVs (compared to Automobile) is 50% less for people in the low and high income groups compared to the middle-income group.

Table 25. Analysis Result: Income Effect on SAV's attributes

Attributes	Coefficient	Standard Error	T-Ratio
SWitL	0.03538	0.0149	2.4
SWitM	0.1284	0.014	9.2
SWitH	0.01329	0.00681	2
SPricL	0.01539	0.00152	10.1
SPricM	-0.00707	0.0017	-4.2
SPricH	-0.00311	0.000739	-4.2
SCONSY	-1.856	0.104	-17.8
SCONSM	-2.637	0.105	-25
SCONSO	-1.738	0.057	-30.5

6.5 Carsharing Program Membership Effect

18% of survey respondents were members of a car-sharing program like Car2Go. To find out the effect of car-sharing membership on choosing SAVs, SAV and Car2Go utility function with separate parameters (including constants) based on respondent's membership in a car-sharing program have been analyzed. The notation "Y", "N" after Car2Go and SAV's wait time, price and constant in

Table 26 is representing the parameters for respondents who are a car-sharing program member (Y) and who are not (N). T-statistic test results show a statistically significant difference of all parameters for all car-sharing program membership situations. Comparative analysis of the results for car-sharing program members shows that they have negative attitude toward the access time associated with Car2Go but a positive sign appeared for SAV wait time. As stated before, the reason may be because car-sharing members are happy with their situation and it has caused parameter non-observance about SAV wait time. Even though both Car2Go and SAV cost has a negative impact on car-sharing program members' choice, disutility of paying for SAVs is twice as much as that of paying for Car2Go. We observe smaller negative value for SAV constant and a positive value for Car2Go constant for car-sharing program members which can be legitimatized by considering the joy that driving provides for some respondents and the advantage of not sharing a ride with strangers. Also, comparing SAV constant for both members and non-members of a car-sharing program shows that non-members show 6 times more negative perception towards SAVs compared to car-sharing members if all other variables are maintained constant. This is an important finding as it shows that making people more familiar with the idea of shared mobility indicates less resistance to use other forms of these systems and car-sharing members might be the early adaptors of SAV system.

Table 26. Analysis Result: Carsharing Membership Effect on Car2Go & SAV's Attributes

Attributes	Coefficient	Standard Error	T-Ratio
CAccY	-0.1522	0.0098	-15.5
CAccN	-0.01553	0.00442	-3.5
CPricY	-0.116	0.00864	-13.4
CPricN	-0.1837	0.00515	-35.6
CCONSY	2.04	0.118	17.3
CCONSN	1.773	0.0741	23.9
SWitY	0.1801	0.0163	11.1
SWitN	0.01726	0.00611	2.8
SPricY	-0.2332	0.006	-38.9
SPricN	0.008026	0.000631	12.7
SCONSY	-0.2738	0.123	-2.2
SCONSN	-1.608	0.0516	-31.2

6.6 Disability Effect

1.7% of the respondents had a problem that prevents them from driving (e.g. disabilities, vision problems, etc.). However, statistical data from 2012 shows that 12.5% of people in Alberta are struggling with disabilities (Statistics Canada, 2016). Therefore, the findings in this section might not be a good representation of the population. To find out the effect of respondents' disability on choosing SAVs, SAV and Taxi utility function with separate parameters (including constants) based on respondent's answer to the question about whether they have a disability that prevents them from driving or not have been analyzed. The notation "Y", "N" after Car2Go and SAV's wait time, price and constant in Table 27 is representing the parameters for respondents who have a disability (Y) and who do not (N).

T-statistic test results show no statistically significant difference for people with a disability between the disutility of Taxi and SAV cost. Comparative analysis shows that people with a disability have a negative attitude toward the access time associated with Car2Go but a

positive sign appeared for SAV wait time. As stated before, the reason may be because they are happier with the assistance that a taxi driver can offer and the privacy that they are provided with when using Taxi, which has caused parameter non-observance about SAV wait time. We observe a large negative value for SAV constant and a positive value for Taxi constant for people with disabilities which can be legitimatized by considering the privacy that Taxi provides. Also, feeling more comfortable with human interaction and the existence of a driver who might assist them might be an important consideration for them.

Table 27. Analysis Result: Disability Effect on SAV's Attributes

Attributes	Coefficient	Standard Error	T-Ratio
TWitY	-1.917	0.186	-10.3
TWitN	-0.03252	0.00321	-10.1
TPricY	-2.873	0.288	-10
TPricN	-0.04728	0.00245	-19.3
TCONSY	142.1	13.7	10.4
TCONSN	1.65	0.0949	17.4
SWitY	13.52	1.64	8.2
SWitN	0.02858	0.00566	5
SPricY	-3.496	0.422	-8.3
SPricN	-0.00027	0.000617	-0.4
SCONSY	-60.2	7.37	-8.2
SCONSN	-1.789	0.0504	-35.5

6.7 Demand Estimation

After estimating the coefficients of the logit model for SAVs, the demand for this system can be estimated applying the coefficients to different scenarios with different attribute levels or even new levels (Catalano et al., 2008). The coefficients applied to the utility functions and the demand for shared autonomous vehicles has been estimated using the probability equation explained in Section 3.2.2. Analysis resulted in a demand more than 6% for this system. Figure

27 shows the mode share for SAVs with different fares and based on different parking costs. This figure shows that if we want to reduce automobile use in downtown areas, the policy of increasing the parking cost can make people switch from automobile to SAVs when they are available. The demand for different modes based on the parking cost is demonstrated in Figure 28.

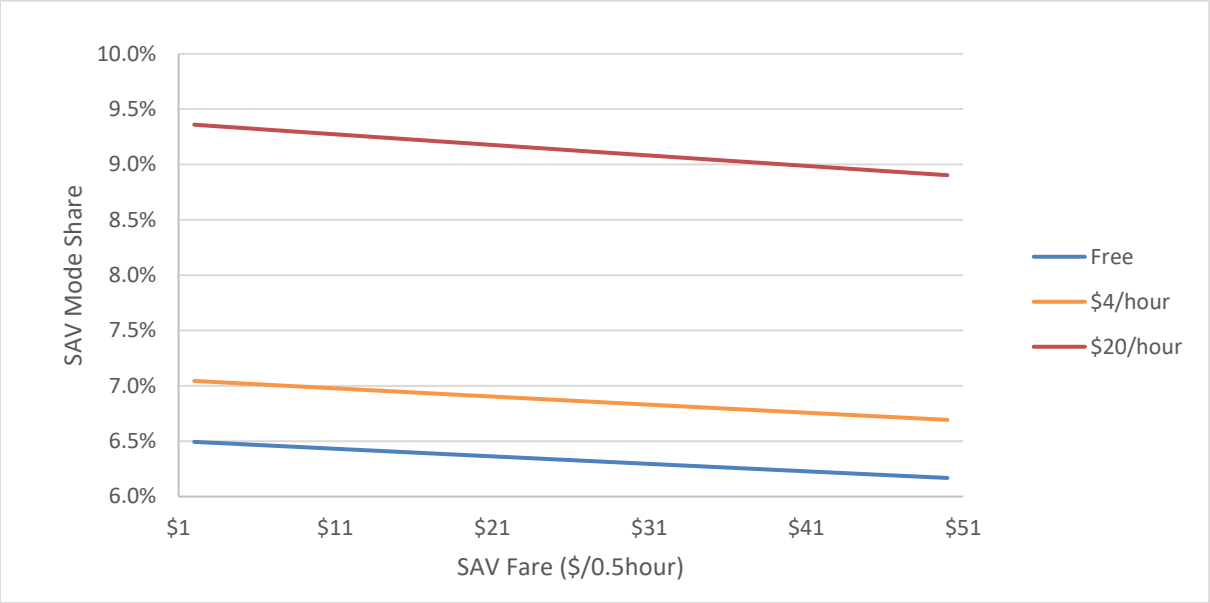

Figure 27. The Variation of SAV Mode Share Depending on its Fare Based on Different Automobile Parking Costs

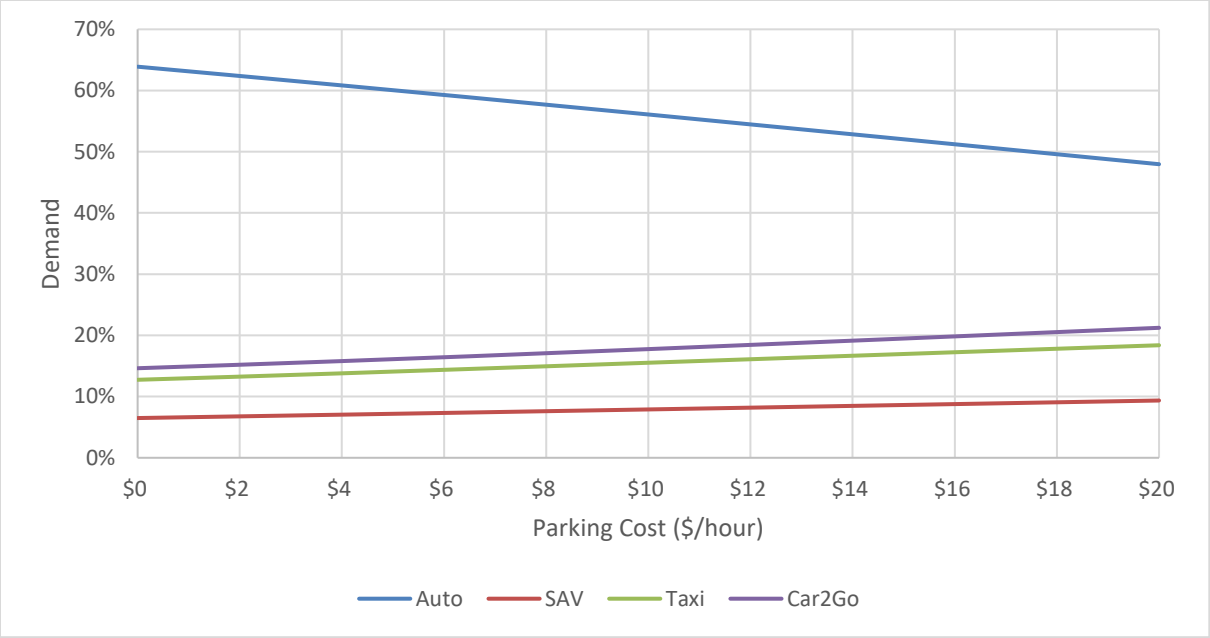

Figure 28. Demand for Different Modes Based on Different Parking Costs

Chapter Seven: **Conclusion**

A variety of factors were considered in the evaluation of driving with different levels of automation among residents of Alberta and in their willingness to use shared autonomous vehicles for commuting. The parameters were combined based on the similarity of the parameter type and statistical significance with 95% level of confidence. After adjusting the weight factor to remove the biasness of the sample and reflect the population distribution in terms of age, gender and household annual income, the utility of driving and using SAVs was analysed. Table 28 summarizes the attribute signs and the explanation for the findings and unexpected cases.

7.1 Results Summary

When analysing the utility of driving with an autonomous vehicle, results show that the level of automation has a positive effect on the driver's choice of driving situation for both trip purposes (commute and non-commute). The positive sign indicates the added utility of the automation levels; and is attributed to the increased comfort and opportunity to spend more quality time with friends and family while driving. However, Level 3 has a smaller positive effect. This finding is expected and is explained by the additional features in Level 3 that respondents do not see as valuable as compared to Levels 2 or 4. In other words, in Level 3, all of the driving tasks cede to the vehicle but the driver should react in certain conditions, which is defined as sudden and mostly dangerous. The added level of automation in Level 3 is risky and is not attractive enough as compared to Level 2, as drivers must be always alert in case an unexpected event prevails but are still paying more. Thus, drivers seem to prefer to be more clear regarding the level of control as in Levels 2 and 4 as compared to Level 3. In further analysis, price and levels of automation were compared for various socio-economic differences, driving

experience and behaviour, and respondent's opinion about the benefits and concerns associated with AVs. The key findings were that socio-economic factors affected people's willingness to use and pay for different levels of automation. For female respondents on commute trips, as long as there is more than one task (but not all tasks) assigned to the vehicle, their utility of level of automation will not change significantly. Although both genders have positive attitude toward level of automation, for male respondents, the partial utility of Level 3 coefficient is even less than Levels 2 and 4. In non-commute trips, male and female drivers are both sensitive to the increase in levels of automation, but for female drivers, as the level of automation increases, the utility of driving decreases and Level 2,3,4 has a negative sign. For male drivers Level 2,3,4 has a positive sign and the utility of driving increases with levels of automation. In addition, when fully autonomous vehicles are available; drivers 50 years and older would be more willing to drive them for commute trips.

Drivers' willingness to use higher levels of automation is attributed to both their demographic differences and perceptions towards AVs. For instance, Level 3 and Level 4 automation has a high disutility for the drivers concerned about AVs' malfunction due to poor weather conditions, in unexpected situations, or security failure. Some conflicting responses were observed. Respondents who attribute AV's to fewer accidents, decrease in insurance rate, comfort and less congestion, seem to be less resistant towards added automation levels. Also, respondents who stated to be either aggressive drivers, confident about their response time, or enjoy driving or dangerous driving, are shown to be less willing to give up control of the tasks to the vehicle. Similarly, respondents who stated to be very careful drivers are shown to be less willing to trust higher levels of automation; although, the utility of driving with higher automation is shown to be more correlated with drivers who are compliant with the speed limit.

Table 28 shows the summary of the findings of this thesis in attribute signs and if unexpected, the explanation is included.

People's willingness to pay to own different levels of automation in their own vehicle is 3 to 5 times more in commute trips compared to non-commute trips. It shows that people enjoy driving for their recreational trips and not only is the technology less desirable for them but also they are not willing to pay for it as much as with their commute trips.

The analysis shows that the increased in disutility of the price is also due to demographic differences in benefits and concerns perceptions associated with AVs. For commute trip purposes, respondents who are willing to give up control to the vehicle in speed determination, braking and accelerating, lane keeping and route determination to a very high degree, are more willing to pay to receive those added benefits. In addition, respondents who think a decrease in accidents, insurance rate, comfort and less congestion is more likely or security failure is less likely to happen, are less resistant toward paying for AVs.

When analysing the utility of using a shared autonomous vehicle for commuting, car-sharing program members had a negative attitude toward the access time associated with Car2Go but a positive sign appeared for SAV wait time. This shows that when they can wait at home (or work) for a ride and can get other things done in that time, makes the wait time desirable and more productive. Also, even though both Car2Go and SAV cost has a negative impact on car-sharing program members' choice, disutility of paying for SAVs is twice as much as that of paying for Car2Go. We observed a smaller negative value for SAV constant and a positive value for Car2Go constant which can be legitimatized by considering the joy that driving provides for people. Also, comparing SAV constant for both members and non-members of a car-sharing program shows that non-members show 6 times more negative perception towards SAVs than

the members. This is an important finding as it shows that making people more familiar with the idea of shared mobility makes them less resistance toward other forms of these systems. It might also indicate that car-sharing members might be the early adaptors of SAVs. Therefore, expanding the home area of Car2Go can make more people ready for shared autonomous vehicles.

The idea of sharing a ride with strangers and riding in an autonomous vehicle has more disutility for female users and people who are in the age group of 35 years and over. Males and people within the age group of 35 years and younger are the least resistant toward the idea of shared autonomous vehicles and they might be the early adaptors of this system. Interestingly, respondents showed a rational positive reaction to the cost of traveling with SAVs for up to $7 per half an hour. It means they think this price is a good deal for such service.

T-statistic test results show no statistically significant difference for people with a disability between the disutility of Taxi and SAV cost. Comparing analysis results in people with disabilities shows a large negative value for SAV constant and a positive value for Taxi constant for people with disabilities which may be because of the privacy that a Taxi provides them with. Also, feeling more comfortable with human interaction and the existence of a driver who might assist them might be an important consideration for them. However, data from Statistics Canada in 2012 indicates that 12.5% of the people in Alberta are struggling with disabilities (Statistics Canada, 2016) and in our survey sample only 1.7% of the respondents had a problem that prevents them from driving. Therefore, the findings might not be a good representation of the population.

Table 28. Finding Summary-Attribute Sign and Explanation

Attribute	Attribute Sign	Explanation
Using AVs as a Private Transport Mode		
Automation Level	Positive	Interesting finding. It is attributed to the increased comfort and opportunity to spend more quality time with friends and family while driving. However, level 3 has a smaller positive effect. This finding is expected and is explained by the additional features in level 3 that respondents do not see them valuable as compared to levels 2 or 4. In level 3, the driver should react in certain conditions (sudden conditions and mostly dangerous ones). Thus, drivers seem to prefer to be clearer to the level of controls as in levels 2 and 4 as compared to level 3.
Road Type (Arterial)	Negative	Expected.
Road Condition (Icy)	Negative	Expected.
Congestion Existence	Negative	Expected.
Not-Familiar with the Road	Negative	Expected.
Price	Negative	Expected.
Using AVs as a Shared Transport Mode		
Automobile Fixed Cost	Negative	Expected.
Automobile Operating Cost	Positive	Unexpected. It is correlated to respondents who choose automobile mode, own an automobile or have a vehicle available for them to use. Respondents are willing to pay even more for the operating cost (comparing to auto fixed cost) because of the comfort that automobile would provide them with.
Parking Cost	Negative	Expected.
Taxi Waiting Time	Negative	Expected.
Cost associated with Taxi	Negative	Expected.
Model Constant for Taxi	Positive	This mode has advantages compared to automobile mode that is associated with purchase, maintenance and operating cost. Using these modes also eliminates the concern and time needed looking and paying for a parking spot. When using a Taxi, the passenger can use the travel time in a more productive way. Also, people who cannot drive (for any reason) are able to use Taxi.
Car2Go Access Time	Negative	Expected.
Cost associated with Car2Go	Negative	Expected.
Model Constant for Car2Go	Positive	This mode has advantages compared to automobile mode that is associated with purchase, maintenance and operating cost. Using these modes also eliminates the concern and time needed looking and paying for a parking spot. Using Car2Go provides the joy of driving while not including the additional cost disadvantages of vehicle ownership and parking cost.
SAV Waiting Time	Positive	Unexpected. It can be due to the complex experimental set-up (four alternatives with four attributes in addition to three condition attributes). In this complicate choice-set, the waiting time attribute had less influence on the participants' choice and it has caused the respondents not to observe and consider this parameter in a proper way. Also, waiting time for SAV might be considered more reliable and takes place at home and is not considered as disutility as people can keep productive while waiting considering the correlation between the waiting time and mode cost (people might decide to wait if they find the mode more desirable from the cost point of view). However, this non-observance is due to the answers by female respondents and the ones in the age group of 35 to 50 years old.
Cost associated with SAV	Negative	Expected.
Model Constant for SAV	Negative	This can be explained by the disadvantage of sharing a ride with strangers in a SAV which affects people privacy and results in extra riding time and possible extra waiting time (depending on the SAV fleet size) to serve other passengers.
Reduction in Accidents	Positive	Expected.
CO_2 Emission Reduction (compared to present vehicle)	Positive	Expected.

Investigating the effect of people's attitude toward AVs shows that the SAV constant has a smaller negative value for the respondents who think fewer crashes, less congestion and more comfort is likely to happen with AVs. Also, the SAV constant has a smaller negative value for the respondents who are not concerned about AVs' interacting with regular vehicles, bikes and pedestrian. This means that these factors have affected people's choice and to attract more people to SAVs, factories can do more tests on AVs' security and impact on congestion and reveal their results to social media to emphasize these factors and change people's minds about AVs before the system comes to market. As most of the respondents expressed that they will trust this technology if more safety tests would be done, one of the first steps toward bringing in this new technology would be to inform people about the benefits of AVs and prove it to them. In addition, analysis shows that if we want to reduce automobile use in downtown areas, the policy of increasing the parking cost can make people switch from automobile to SAVs when they are available.

7.2 Contributions

Studies on autonomous vehicles have been implemented in recent years, but this study is unique in Canada. The study contributions are:

- ✓ First study in Canada to include SP survey on autonomous and shared autonomous vehicles
- ✓ Identifying the factors contributing to willingness to pay for autonomous vehicle purchase
- ✓ Estimating the demand for shared autonomous vehicles
- ✓ Estimating factors that affect AVs' and SAV's adaption by Canadian people

- ✓ Estimating the effect of weather condition, improved safety and more environmental friendly system in autonomous vehicle technology on people's willingness to use SAVs
- ✓ Recognizing the effect of trip purpose on people's willingness to use different levels of automation

7.3 Important Findings and Recommendations

- ❖ Level 3 automation should be skipped and the market should move directly to fully autonomous vehicles.
- ❖ The early owners of autonomous vehicles are males over 50 years old.
- ❖ Willingness to use higher levels of automation is attributed to people's perceptions towards autonomous vehicles. Therefore, one of the first steps toward bringing in this new technology would be to inform people about the benefits of AVs and prove it to them.
- ❖ Expanding the home area of Car2Go can make more people ready for shared autonomous vehicles.
- ❖ Car-sharing members might be the early adaptors of SAVs.
- ❖ Males younger than 35 years old are the early adaptors of SAVs.
- ❖ The idea of owning an autonomous vehicle might be more desirable for people with disabilities compared to the shared autonomous vehicles.
- ❖ To reduce automobile use in downtown areas, the policy of increasing the parking cost can make people switch from automobile to SAVs (up to 3%) when they are available.

7.4 Future Studies

Since studying on autonomous vehicles is a new subject in transportation studies and this study is the first demand modelling study in Canada, a variety of studies can be done in the future:

- Conducting a stated preference survey and including public transit and autonomous vehicle ownership.
- Investigating the effect of shared autonomous vehicles on urban sprawl, car ownership and parking in Alberta, Canada.
- Investigating the penetration rate of autonomous vehicles and shared autonomous vehicles in Alberta, Canada.
- Estimating the fleet size needed to serve people with shared autonomous vehicles in different level of service scenarios.

APPENDIX A: ETHICS APPROVAL

Conjoint Faculties Research Ethics Board
Research Services Office
3rd Floor MacKimmie Library Tower (MLT 300)
2500 University Drive, NW
Calgary AB T2N 1N4
Telephone: (403) 220-3782
cfreb@ucalgary.ca

December 4, 2015

Ethics ID: REB15-2693

Lina Kattan

Civil Engineering

Dear Lina Kattan:

RE: Autonomous Vehicles in Alberta

The above named research protocol has been granted ethical approval by the Conjoint Faculties Research Ethics Board for the University of Calgary. Please make a note of the conditions stated on the Certification. In the event the research is funded, you should notify the sponsor of the research and provide them with a copy for their records. The Conjoint Faculties Research Ethics Board will retain a copy of the clearance on your file.
Please note, a renewal or final report must be filed with the CFREB within 30 days prior to the expiry date on your certification. You can complete your renewal or closure request in IRISS.
In closing, let me take this opportunity to wish you the best of luck in your research endeavor.

Sincerely,

Christopher R. Sears, PhD, Chair, CFREB

APPENDIX B: NGENE SOFTWARE CODING

B.1. 1st SP Part

```
Design
? This will generate a fractional factorial design
; alts=alt1, alt2
; rows=72
; orth=sim
; foldover
; block=32
; model:
U(alt1)=b1+b2*A[1,2,3,4]+b3*B[1,2]+b4*C[1,2]+b5*D[1,2]+b6*E[18,20,22,24,26,28,30,32]+b8*G[1,2]+b9*H[1,
2]/
U(alt2)=b2*A[1,2,3,4]+b3*B[1,2]+b4*C[1,2]+b5*D[1,2]+b6*E[18,20,22,24,26,28,30,32]
$
```

B.2. 2nd SP Part

B.2.1. Full factorial

```
Design
? This will generate a fractional factorial design
; alts=Automobile, Taxi, Car2Go, SAV
; rows=all
; fact
;model:
U (Automobile) =b1+b3*B1 [1] +b4*C1 [1] +b5*D [1] +b6*E [1]/
U (Taxi) =b7+b3*B2 [1] +b4*C2 [1] +b5*D [1] +b6*E [1]/
U(Car2Go)=b8+b3*B3[1,2]+b4*C3[1]+b5*D[1]+b6*E[1]/
U(SAV)=b3*B4[1,2]+b4*C4[2,4,7,8.5,10,11.5,13,14.5,16,21,32,44,50]+b5*D[1]+b6*E[1]
$
```

B.2.2. Partial Factorial

```
Design
? This will generate a fractional factorial design
; alts=Automobile, Taxi, Car2Go, SAV
; rows=72
; orth=sim
; block=18
; foldover
; model:
U(Automobile)=b1+b3*B[1,2]+b4*C[1,2,3]+b8*D[1,2,3]+b9*E[1,2]+b10*F[1,2]+b11*G[1,2]/
U (Taxi) =b7+b3*B [1, 2] +b4*C [1, 2, 3]/
U (Car2Go) =b8+b3*B [1, 2] +b4*C [1, 2, 3]/
U(SAV)=b3*B[1,2]+b4*C1[1,2,3,4,5,6,7,8,9,10,11,12]
$
```

APPENDIX C: SAMPLE ALOGIT INPUT (1ST SP PART)

C.1. Commute Trip ALOGIT 4.3 Code:

```
$TITLE Individual Commute AV - Linear All Parameters
----------Coefficients-------
$ESTIMATE
- Level of Automation Sensitivity
   11 Level1 T 0.0
   12 Level2 F 0.0
   13 Level3 F 0.0
   14 Level4 F 0.0
- Road Type Sensitivities
   21 Highway T 0.0
   22 Arterial     F 0.0
- Road Condition Sensitivities
   31 Norm   T 0.0
   32 Icy       F 0.0
- Crowding Sensitivities
   41 Uncong T 0.0
   42 Cong     F 0.0
- Price Sensitivity
   50 Price F 0.0
----------Data Input----
File (name=AVIC.txt) Data01 - Data49
----------Transformations----
- Level of Automation Transforms
Level11 = ifeq (Data04, 1)
Level21 = ifeq (Data04, 2)
Level31 = ifeq (Data04, 3)
Level41 = ifeq (Data04, 4)
Level12 = ifeq (Data09, 1)
Level22 = ifeq (Data09, 2)
Level32 = ifeq (Data09, 3)
Level42 = ifeq (Data09, 4)
- Road Type Transforms
Highway1 = ifeq (Data05, 1)
Arterial1 = ifeq (Data05, 2)
Highway2 = ifeq (Data10, 1)
Arterial2 = ifeq (Data10, 2)
- Road Condition Transforms
Norm1 = ifeq (Data06, 1)
Icy1   = ifeq (Data06, 2)
Norm2 = ifeq (Data11, 1)
Icy2   = ifeq (Data11, 2)
- Crowding Transforms
Uncong1 = ifeq (Data07, 1)
Cong1   = ifeq (Data07, 2)
Uncong2 = ifeq (Data12, 1)
Cong2   = ifeq (Data12, 2)
Weight = Data48*Data49*10000
----------Nesting Structure----
$NEST root () 1 2
```

----------Choice or Ranking----
CHOICE = Recode (Data14 1, 2)
----------Excluded Observations----
Exclude (1) = ifeq (Data14, 0)
----------Available Alternatives----
AVAIL (1) = IF (Data14)
AVAIL (2) = IF (Data14)
----------Utility Functions----
U (1) = p11*Level11 + p12*Level21 + p13*Level31 + p14*Level41 + p21*Highway1 + p22*Arterial1 + p31*Norm1 + p32*Icy1 + p41*Uncong1 + p42*Cong1 + p50*Data08
U (2) = p11*Level12 + p12*Level22 + p13*Level32 + p14*Level42 + p21*Highway2 + p22*Arterial2 + p31*Norm2 + p32*Icy2 + p41*Uncong2 + p42*Cong2 + p50*Data13

C.2. Non-Commute Trip ALOGIT 4.3 Code:

$TITLE Individual Non-Commute AV - Linear All Parameters
----------Coefficients----
$ESTIMATE
- Level of Automation Sensitivity
  11 Level1 T 0.0
  12 Level2 F 0.0
  13 Level3 F 0.0
  14 Level4 F 0.0
- Road Type Sensitivities
  21 Highway T 0.0
  22 Arterial F 0.0
- Road Condition Sensitivities
  31 Norm T 0.0
  32 Icy F 0.0
- Familiarity with the Road Sensitivities
  41 Famil T 0.0
  42 NFamil F 0.0
- Price Sensitivity
  50 Price F 0.0
----------Data Input----
File (name=AVINC.txt) Data01 - Data49
----------Transformations----
- Level of Automation Transforms
Level11 = ifeq (Data04, 1)
Level21 = ifeq (Data04, 2)
Level31 = ifeq (Data04, 3)
Level41 = ifeq (Data04, 4)
Level12 = ifeq (Data09, 1)
Level22 = ifeq (Data09, 2)
Level32 = ifeq (Data09, 3)
Level42 = ifeq (Data09, 4)
- Road Type Transforms
Highway1 = ifeq (Data05, 1)
Arterial1 = ifeq (Data05, 2)
Highway2 = ifeq (Data10, 1)
Arterial2 = ifeq (Data10, 2)
- Road Condition Transforms
Norm1 = ifeq (Data06, 1)
Icy1 = ifeq (Data06, 2)

Norm2 = ifeq (Data11, 1)
Icy2 = ifeq (Data11, 2)
- Familiarity Transforms
Famil1 = ifeq (Data07, 1)
NFamil1 = ifeq (Data07, 2)
Famil2 = ifeq (Data11, 1)
NFamil2 = ifeq (Data11, 2)
Weight = Data48*Data49
----------Nesting Structure----
$NEST root () 1 2
----------Choice or Ranking----
CHOICE = Recode (Data14 1, 2)
----------Excluded Observations----
Exclude (1) = ifeq (Data14, 0)
----------Available Alternatives----
AVAIL (1) = IF (Data14)
AVAIL (2) = IF (Data14)
----------Utility Functions----
U (1) = p11*Level11 + p12*Level21 + p13*Level31 + p14*Level41 + p21*Highway1 + p22*Arterial1 + p31*Norm1 + p32*Icy1 + p41*Famil1 + p42*NFamil1 + p50*Data08
U (2) = p11*Level12 + p12*Level22 + p13*Level32 + p14*Level42 + p21*Highway2 + p22*Arterial2 + p31*Norm2 + p32*Icy2 + p41*Famil2 + p42*NFamil2 + p50*Data13

APPENDIX D: SECOND SP PART- BASELINE FUNCTION ANALYSIS FOR RANKING APPROACH

Table 29. Baseline Function Analysis Result for Rank Model

Mode	Attributes	Coefficient	Standard Error	T-Ratio
Automobile	**APricF**	-0.5334	0.0184	-29
	APricO	0.4035	0.0264	15.3
	Park	-0.00904	0.000688	-13.2
Taxi	**TWit**	-0.02119	0.00304	-7
	TPric	0.01438	0.00279	5.1
	TCONS	2.503	0.112	22.3
Car2Go	**CAcc**	-0.05926	0.00374	-15.9
	CPric	-0.1052	0.00413	-25.4
	CCONS	-0.0008666	0.0617	0
SAV	**SWit**	-0.02425	0.00362	-6.7
	SPric	-0.00368	0.000406	-9.1
	SCONS	-10.35	0.0369	-280.3
Model's Goodness of Fit				
Initial Log-Likelihood = -533444.5938			Final Log-Likelihood = -211813.1572	
"ρ^2" with respect to Zero = 0.0140				

APPENDIX E: SECOND SP PART-RANKING APPROACH

Table 30. Nest Coefficients for Plausible Nested Structures

Nest Structure	Nest Coefficient (θ)	Nest Structure	Nest Coefficient (θ)
1. Auto 2. Taxi, Car2Go, SAV	9.38	1. SAV 2. Auto, Taxi, Car2Go	3.568
1. Auto 2. Car2Go 3. Taxi, SAV	2.549	1. Taxi 2. Car2Go 3. Auto, SAV	1.2061
1. Auto 2. Taxi 3. Car2Go, SAV	5.859	1. Taxi 2. Auto, Car2Go 3. SAV	1.342
1. Auto 2. Taxi, Car2Go 3. SAV	1.797	1. Car2Go 2. Auto, Taxi 3. SAV	1.493
2. Auto, Car2Go 3. Taxi, SAV	1.355 2.331	2. Auto, SAV 3. Taxi, Car2Go	1.2034 1.816

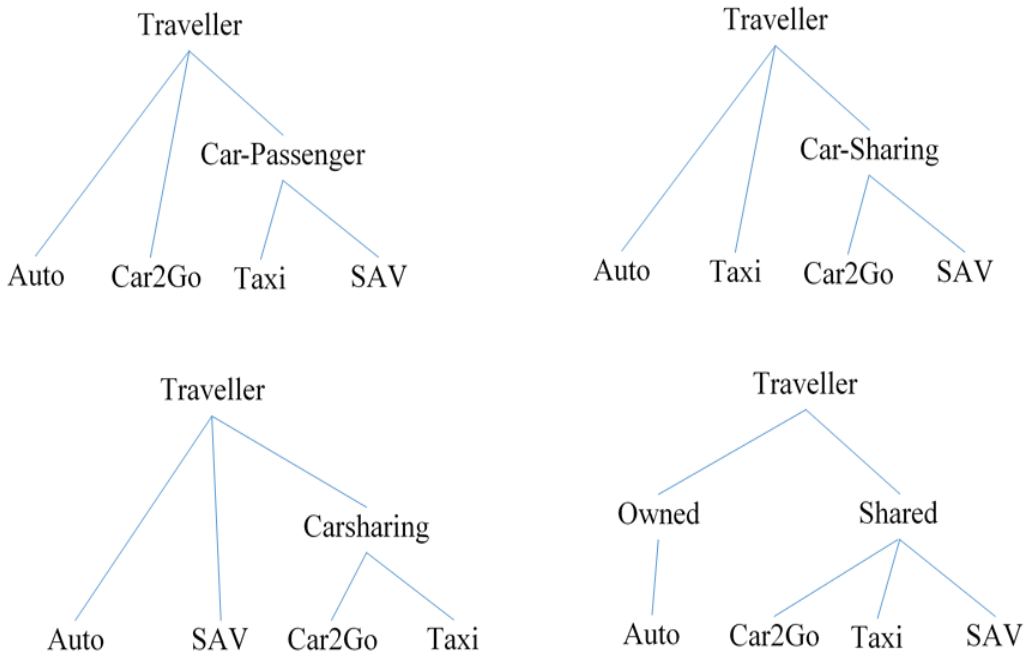

Figure 29. Examples of Plausible Tree-Structures

References

1. Megens, I. C. H. M. (2015) Vehicle Users' Preferences Concerning Automated Driving.
2. Schoettle, B., & Sivak, M. (2014). *A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia* (No. UMTRI-2014-21).
3. Schoettle, B., & Sivak, M. (2014). Public opinion about self-driving vehicles in China, India, Japan, the US, the UK, and Australia. Ann Arbor: The University of Michigan Transportation Research Institute: Transportation Research Institute.
4. Howard, D., & Dai, D. (2014). Public perceptions of self-driving cars: The case of Berkeley, California. In Transportation Research Board 93rd Annual Meeting (No. 14-4502).
5. Zmud, J., Sener, I. N., & Wagner, J. (2016). Self-Driving Vehicles: Determinants of Adoption and Conditions of Usage. In Transportation Research Board 95th Annual Meeting (No. 16-1832).
6. Menon, N., Pinjari, A. R., Zhang, Y., & Zou, L. (2016). Consumer Perception and Intended Adoption of Autonomous-Vehicle Technology: Findings from a University Population Survey. In Transportation Research Board 95th Annual Meeting (No. 16-5998).
7. Fraedrich, E., & Lenz, B. (2014, January). Automated Driving–Individual and Societal Aspects Entering the Debate. In Transportation Research Record: Journal of the Transportation Research Board (TRR). 93nd Annual Meeting Transportation Research Board (TRB) (Vol. 12, p. 16).
8. Horner, M. W., & Richard, A. (2016). Social Data Mining for Understanding Public Perceptions of Autonomous Vehicles: National Trends and the Case of Florida. In Transportation Research Board 95th Annual Meeting (No. 16-3786).
9. Silberg, G., Wallace, R., Matuszak, G., Plessers, J., Brower, C., & Subramanian, D. (2012). Self-driving cars: The next revolution. White paper, KPMG LLP & Center of Automotive Research.

10. Shaheen, S., Camel, M., & Ullom, W. M. (2014). Survey of US Transportation Officials on the Future of Integrated and Active Transportation Systems. In Transportation Research Board 93rd Annual Meeting (No. 14-3400).
11. KPMG (2015b) Automobile insurance in the era of autonomous vehicles [online] Available from https://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/automobile-insurancein-the-era-of-autonomous-vehicles-survey-results-june-2015.pdf
12. Bansal, P., & Kockelman, K. M. (2016). Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies. In Transportation Research Board 95th Annual Meeting (No. 16-1871).
13. Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. Transportation Research Part C: Emerging Technologies, 67, 1-14.
14. Milakis, D., Snelder, M., Van Arem, B., Van Wee, G. P., & Homem De Almeida Rodriguez Correia, G. (2016, January). Scenarios about development and implications of automated vehicles in the Netherlands. In 95th Annual Meeting Transportation Research Board, Washington, USA, 10-14 January 2016; Authors version. TRB.
15. Lavasani, M., Jin, X., & Du, Y. (2016). Market Penetration Model for Autonomous Vehicles Based on Previous Technology Adoption Experiences. In Transportation Research Board 95th Annual Meeting (No. 16-2284).
16. Chen, R. B., & Armington, W. (2016). Household Activity and Travel Patterns with Autonomous Vehicles: In-vehicle Activity Decisions. In Transportation Research Board 95th Annual Meeting (No. 16-3672).

17. Kim K. H., Yook, D. H., KO, Y. S., & Kim D. H. An Analysis of Expected Effects of the Autonomous Vehicles on Transport and Land Use IN Korea.
18. Schoettle, B., & Sivak, M. (2015). Potential impact of self-driving vehicles on household vehicle demand and usage. The University of Michigan Transportation Research Institute.
19. Blau, M. A. (2015). Driverless Vehicles' Potential Influence on Cyclist and Pedestrian Facility Preferences (Doctoral dissertation, The Ohio State University).
20. Sivak, M., & Schoettle, B. (2015). Road safety with self-driving vehicles: General limitations and road sharing with conventional vehicles. Ann Arbor, MI: University of Michigan Transportation Research Institute.
21. Official Google Blog, 2012
22. Kockelman, K. M., & Li, T. (2016). Valuing the Safety Benefits of Connected and Automated Vehicle Technologies. In Transportation Research Board 95th Annual Meeting (No. 16-1468).
23. Markit, I. (2016). IHS Markit industry experts. Retrieved November 18, 2016, from http://press.ihs.com/press-release/automotive/self-driving-cars-moving-industrys-drivers-seat (2014)
24. City of Calgary Traffic Safety Tips, 2016
25. Litman, T. (2014). Autonomous Vehicle Implementation Predictions. Victoria Transport Policy Institute, 28.
26. Ben-Akiva, M. E., & Lerman, S. R. (1985). Discrete choice analysis: theory and application to travel demand (Vol. 9). MIT press.
27. Charlton, S. G., & Starkey, N. J. (2011). Driving without awareness: The effects of practice and automaticity on attention and driving. Transportation research part F: traffic psychology and behaviour, 14(6), 456-471.

28. Yanko, M. R., & Spalek, T. M. (2013). Route familiarity breeds inattention: A driving simulator study. Accident Analysis & Prevention, 57, 80-86.
29. Najm, W. G., Koopmann, J., Smith, J. D., & Brewer, J. (2010). *Frequency of target crashes for intellidrive safety systems* (No. HS-811 381).
30. Lari, A., Douma, F., & Onyiah, I. (2014). Self-driving vehicles: Current status of autonomous vehicle development and Minnesota policy implications.
31. Brownell, C. K. (2013). Shared Autonomous Taxi Networks: An Analysis of Transportation Demand in NJ and a 21 st Century Solution for Congestion (Doctoral dissertation, Princeton University).
32. Katarzyna Anna Marczuk, Harold Soh Soon Hong, Carlos Miguel Lima De Azevedo, Emilio Frazzoli, Der-Horng Lee "Impact of rebalancing on the performance of automated mobility on demand systems." 18th Euro Working Group on Transportation, EWGT 2015. 126.
33. Burns, Lawrence D., William C. Jordan, and Bonnie A. Scarborough. "Transforming personal mobility." The Earth Institute (2013).
34. Rigole, P. J. (2014). Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.
35. Zachariah, J., Gao, J., Kornhauser, A., & Mufti, T. (2014). Uncongested Mobility for All: A Proposal for an Area Wide Autonomous Taxi System in New Jersey. In Transportation Research Board 93rd Annual Meeting (No. 14-2373).
36. Khan, A. M., Bacchus, A., & Erwin, S. (2012). Policy challenges of increasing automation in driving. IATSS research, 35(2), 79-89.

37. Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Adoption of Shared Autonomous Vehicles--A Hybrid Choice Modeling Approach Based on a Stated-Choice Survey. In Transportation Research Board 95th Annual Meeting (No. 16-2257).
38. Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. Transportation research part F: traffic psychology and behaviour, 27, 252-263.
39. Clark, B., Parkhurst, G., & Ricci, M. (2016). Understanding the socioeconomic adoption scenarios for autonomous vehicles: A literature review.
40. Lima Azevedo, C., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., & Ben-Akiva, M. (2016). Microsimulation of Demand and Supply of Autonomous Mobility On-Demand. In Transportation Research Board 95th Annual Meeting (No. 16-5455).
41. Fagnant, D. J., & Kockelman, K. (2014). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. In Transportation Research Board 93rd Annual Meeting (No. 14-1281).
42. Fagnant, D. J., & Kockelman, K. M. (2015). Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In Transportation Research Board 94th Annual Meeting (No. 15-1962).
43. LaMondia, J. J., Fagnant, D. J., Qu, H., Barrett, J., & Kockelman, K. (2016). Long-Distance Travel Mode-Shifts Due to Automated Vehicles: A Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis. In Transportation Research Board 95th Annual Meeting (No. 16-3905).

44. Shaheen, S. A., & Cohen, A. P. (2013). Carsharing and personal vehicle services: worldwide market developments and emerging trends. International Journal of Sustainable Transportation, 7(1), 5-34.
45. Brook, D. (2004, January). Carsharing–Start Up Issues and New Operational Models. In Transportation Research Board Annual Meeting.
46. Costain, C., Ardron, C., & Habib, K. N. (2012). Synopsis of users' behaviour of a carsharing program: A case study in Toronto. Transportation Research Part A: Policy and Practice, 46(3), 421-434.
47. Jorge, D., & Correia, G. (2013). Carsharing systems demand estimation and defined operations: a literature review. European Journal of Transport and Infrastructure Research, 13(3), 201-220.
48. Cervero, R. (2003). City CarShare: First-year travel demand impacts. Transportation Research Record: Journal of the Transportation Research Board, (1839), 159-166.v
49. Richardson, A. J., Ampt, E. S., & Meyburg, A. H. (1995). Survey methods for transport planning (p. 314). Melbourne: Eucalyptus Press.
50. Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market. Transportation Research Record: Journal of the Transportation Research Board, (2536), 98-106.
51. Chen, Donna, and Kara M. Kockelman (2015). "Management of a Shared, Autonomous, Electric Vehicle Fleet: Charging and Pricing Strategies." IATBR 2015-WINDSOR.
52. Segal, M., & Kockelman, K. M. (2016). Design and Implementation of a Shared Autonomous Vehicle System for Austin, Texas. In Transportation Research Board 95th Annual Meeting (No. 16-1837).

53. Levin, M. W., Li, T., Boyles, S. D., & Kockelman, K. M. (2016). A general framework for modeling shared autonomous vehicles. In 95th Annual Meeting of the Transportation Research Board.
54. Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies, 40, 1-13.
55. Zoepf, S. M., & Keith, D. R. (2016). User decision-making and technology choices in the US carsharing market. Transport Policy.
56. Car2Go website, 2016
57. Retrieved November 18, 2015, from http://57.http://www.smmt.co.uk/co2report
58. Daimler updates Smart Fortwo line, lowers CO2 emissions". green.autoblog.com, Eric Loveday, Jul 22nd 2010-https://en.wikipedia.org/wiki/Smart_Fortwo
59. US DOT, Research and innovative technology administration, Focus, John A. Volpe National Transportation Systems Centre, May 2002.
60. Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: a primer. Cambridge University Press.
61. Government of Canada. (2013, June 26). Commuting to work. Retrieved November 18, 2015, from https://www12.statcan.gc.ca/nhs-enm/2011/as-sa/99-012-x/99-012-x2011003_1-eng.cfm
62. TaxiFareFinder website, Calgary and Edmonton, 2015
63. Parking rates - CPA. Retrieved November 18, 2015, from https://www.calgaryparking.com/findparking/parkingrates
64. Leclerc, F., Schmitt, B. H., & Dube, L. (1995). Waiting time and decision making: Is time like money. Journal of Consumer Research, 22(1), 110-119.

65. Motion, A. (2016). CAA national. Retrieved November 18, 2016, from https://www.caa.ca/

66. Hunt, J.D. (2010). Stated Preference Examination of Factors Influencing Residential Attraction, In Pagliara, F., Preston, J., & Simmonds, D. (Eds.), Residential Location Choice Models and Applications (p. 21-59). Springer.

67. ALOGIT 4.3 serial 4402 (2016). Alogit Software and Analysis Ltd, available at the website: www.alogit.com Accessed 2016

68. Hassanvand Mina, (2012). Factors Affecting Utility of Passenger Modes in Calgary. University of Calgary, Calgary, AB.

69. Hunt, J. D., and Abraham, J. E. (2007). Influences on bicycle use. Transportation 34 (4), 453-470.

70. de Blaeij, A., Florax, R.J.G.M., Rietveld, P., and Verhoef, E. (2000). The Value of Statistical Life in Road Safety: A Meta Analysis. Tinbergen Institute Discussion Paper No. 2000-089/3

71. Addelman, S., 1962. Orthogonal main-effects plans for asymmetrical factorial experiments. Technometrics, Volume 4, pp. 21-46.

72. Bhat, C. R., Schofer, J.L., Koppelman, F. S., & Bautch, R. C. (1993). Driver Recruitability for Advanced Traveler Information System Experiments. Transportation Research, 4C, 265-274.

73. Long. J.S., Freese, J. (2006). Regression Models for Categorical Dependent Variables Using Stata. Texas: Stata Press.

74. Garrow, L. A. (2012). Discrete Choice Modelling and Air Travel Demand: Theory and Applications. Ashgate Publishing, Ltd.

75. Labbé, M., Laporte, G., Tanczos, K., & Toint, P. (Eds.). (2013). *Operations research and decision aid methodologies in traffic and transportation management* (Vol. 166). Springer Science & Business Media.

76. Cirillo, C., Daly, A. J., & Lindveld, K. (1996). Eliminating bias due to the repeated measurements problem in SP data. In Transportation Planning Methods. Proceedings of Seminar D Held at the PTRC European Transport Forum, Brunel University, England, 2-6 September 1996. Volume P404-1.
77. Efron, B., & Stein, C. (1981). The jackknife estimate of variance. *The Annals of Statistics*, 586-596.
78. Catalano, M., Lo Casto, B., & Migliore, M. (2008). Car sharing demand estimation and urban transport demand modelling using stated preference techniques
79. Shen, Y., Zhang, H., & Zhao, J. (2017). Embedding Autonomous Vehicle Sharing in Public Transit System: An Example of Last Mile Problem. *TRB 2017 Annual Meeting*
80. Yang, J., Dong, J., & Wang, W. (2017). A Simulation Model for Performance Analysis of Electric Autonomous Taxi Systems. *TRB 2017 Annual Meeting*
81. Zhang, W., & Guhathakurta, S. (2017). Parking Spaces in the Age of Shared Autonomous Vehicles: How Much Parking Will We Need and Where? *TRB 2017 Annual Meeting*
82. Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies.
83. Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B., & Coughlin, J. F. (2017). Autonomous Vehicles, Trust, and Driving Alternatives: A survey of consumer preferences.
84. Cools, M., Rongy, C., & Limbourg, S. (2017). Can Autonomous Vehicles Reduce Car Mobility? Evidence from a Stated Adaption Eeperiment in Belgium. *TRB 2017 Annual Meeting*

85. Lavasani, M., Jin, X., & Pinjari, A. (2017). Investigating the Willingness to Pay for Autonomous Vehicles and the Likelihood of Residential Relocation. *TRB 2017 Annual Meeting*
86. Kloostra, B., & Roorda, M. J. (2017). Fully Autonomous Vehicles: Analyzing Transportation Network Performance and Operating Scenarios in the Greater Toronto Area, Canada. *TRB 2017 Annual Meeting*
87. Winter, K., Cats, O., Martens, K., & van Arem, B. (2017). A Stated Choice Experiment on Mode Choice in an Era of Free-Floating Carsharing and Shared Autonomous Vehicles. *TRB 2017 Annual Meeting*
88. Truong, L. T., De Gruyter, C., Currie, G., & Delbosc, A. (2017). Estimating the Trip Generation Impacts of Autonomous Vehicles on Car Travel in Victoria, Australia. *TRB 2017 Annual Meeting*.
89. Nord, A., Sperling, E., & Tobey, M. (2017). Policies to Support the Integration of Autonomous Vehicles. *TRB 2017 Annual Meeting*
90. Hunt, J. D. (2014, October). ENCI 707. Transportation Modelling Class Lecture. University of Calgary. Calgary, Canada.
91. "Changing Travel Behaviour in the Calgary Region". Calgary.ca. (2013)
92. Hess, S., & Rose, J. M. (2009, October). Some lessons in stated choice survey design. In *European Transport Conference* (Vol. 2009).
93. Platt, M. (2013, December 29). Excuses keep coming for Calgary's taxi 'service' even when the cabs themselves clearly aren't. Retrieved February, 2015, from http://www.calgarysun.com/2013/12/29/excuses-keep-coming-for-calgarys-taxi-service-even-when-the-cabs-themselves-clearly-arent

94. Davidson, P., Teye, C., & Culley, R. (2014). Developing a Successful Stated Preference Methodology for Determining Destination Choice Coefficients and Using it to Investigate its Empirical Structural Relationship with Toll Route Choice. *Transportation Research Procedia*, *1*(1), 36-48.
95. ChoiceMetrics (2012) Ngene 1.1.2 User Manual & Reference Guide, Australia.
96. "2016 Census Population and Dwelling Counts". http://www.finance.alberta.ca/ *(2017)*
97. "The City of Calgary - Transit Maps Downloads". *Calgary.ca*., 2017. Web. 29 Feb. 2017.
98. "System Maps". *Edmonton.ca*., 2017. Web. 29 Feb. 2017.
99. Parkopedia". *parkipedia.ca*., 2017. Web. 29 Feb. 2017.
100. Cody Battershill. "Calgary Population and Employment Growth Forecast". *Best Calgary Homes,* 2013. Web. 29 Feb. 2017.
101. Michael Miller, University of British Columbia. "Data & Methodology". *Ibis.geog.ubc.ca*., 2012. Web. 29 Feb. 2017.
102. NHTSA (National Highway Traffic Safety Administration), 2013. Preliminary Statement of Policy Concerning Automated Vehicles. Washington, D.C. <http:// www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf> (October 15, 2014).