Autonomous Vehicles: Understanding Adoption Potential in the Greater Toronto and Hamilton Area

by

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Author's declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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

Abstract

Many Autonomous Vehicle (AV) researchers have done surveys and interviews to assess the relationships between some population or land use characteristics and people's intention to adopt private AVs (PAVs) and shared AVs (SAVs). Their findings provide clues on where in the urban area, there exists higher or lower PAV or SAV adoption potential. However, no scholar has created a model to index or score the PAV and SAV adoption potential and map it for a region. This thesis addresses these gaps. Through the literature review, variables that are strongly associated with a PAV or SAV adoption, and their index weights are identified. Then, using ArcMap 10.5.1, the PAV and SAV adoption potential is mapped out at the census tract level in the study area: the Greater Toronto and Hamilton Area (GTHA). Findings are then generated to inform planning and policy development.

Some highlights of the findings are as follows. Frist, The areas with high PAV adoption potential tends to be in the inner suburb, while the areas with low PAV adoption potential are often in the central city (Toronto). All of the areas with high SAV adoption potential are in the central city (Toronto), and most of the areas with low SAV adoption potential are in the outer suburb. Second, each of the four types of areas has some special land use characteristics. Third, in the park-and-ride and kiss-and-ride service areas of the GO train stations in the GTHA overall, there is discernably lower PAV adoption potential, and obviously higher SAV adoption potential. However, the overall potential of PAV and SAV adoption varies from line to line, and from station to station. Last but not least, changing the price of SAVs would unlikely change the PAV and SAV adoption potential in an area.

All of the findings expand the understanding of planners and policy makers in identifying areas with high or low PAV or SAV adoption potential. Knowing these locations and their characteristics would help planners and policy makers develop their plans and policies on PAVs and SAVs. The findings on the GO train services provide some background knowledge for Metrolinx staff to prepare a redesign of its parking spaces for GO train passengers, and the use of SAVs to help its passengers to access its GO train stations.

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List of Abbreviations

Abbreviation	Meaning
AV	Autonomous vehicle
Ave	Avenue
CAV	Connected autonomous vehicles
CGU	Census geographic unit
CMA	Census metropolitan area
CT	Census tract
CTAM	Car technology acceptance model
DOI	Theory of Diffusion of Innovations
Eq	Equation
GGH	Greater Golden Horseshoe
GTHA	Greater Toronto and Hamilton Area
h	hour
HOV	human-operated vehicle
Hwy	Highway
IT	Information technology
km	kilometer
Max	Maximum
Min	Minimum
min	minute
NOC	National Occupation Classification
PAV	Private autonomous vehicle
PPSC	The Policy and Planning Support Committee
PUDO	pick up and drop off / pick-up-and-drop-off
PV	private vehicle
SAV	Shared autonomous vehicle
SD	Standard deviation
St	Street
TAM	Technology Acceptance Model
UTAUT	Unified theory of acceptance and use of technology
UTAUT2	Expanded unified theory of acceptance and use of technology
VMT	vehicle miles traveled
WTP	Willingness to pay

Chapter 1: Introduction

1.1 Brief Introduction to Autonomous Vehicles

Major automobile companies such as Mercedes-Benz, BMW, and Toyota have started selling private vehicles with certain automated functions, such as automatic lane positioning, automatic braking, and adaptive cruise control. According to the six levels of vehicle automation proposed by SAE International (2017), most of the cars available for sale on the market today have a level-1 or level-2 automation.

Table 1.1 Levels of Vehicle Automation

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Source: SAE International (2017), p. 2.

Talking of vehicle automation, it is necessary to distinguish two terms: automated vehicles, and autonomous vehicles (AVs). Automated vehicles would require human efforts during operation despite some autonomous functions (Woudsma & Braun, 2017). Thus, the levels of automation of automated vehicles are at levels 1 to 4. Autonomous vehicles, strictly speaking, have a level-5 automation, whereas many articles and reports include level-4 automated vehicles in their concepts of autonomous vehicles due to their very high level of automation (see Table 3.1). This common inclusion would be used in this thesis.

1.2 Government Preparation for Autonomous Vehicles

With the development of autonomous vehicle (AV) technology, we anticipate seeing more vehicles of higher levels (3 to 5) of automation in the near future. Thus, Canadian governments of all levels are starting to prepare themselves for an AV-dominant future. On behalf of the Canadian federal government and several Canadian provincial governments (Ontario, New Brunswick, Quebec, Alberta, and British Columbia), the Policy and Planning Support Committee Working Group on Connected and Automated Vehicles (2018) – also known as the PPSC Working Group on Connected and Automated Vehicles – has published a report named *The Future of Automated Vehicles in Canada*. This report provides guidance for the federal and provincial governments to prepare for AV adoption. Particularly, it provides many suggestions on what the federal and provincial governments should consider in terms of legislation and policy making.

Before the publication of the report, Ontario had already been the first Canadian province to permit AV on-road testing in 2016 (Ontario Centres of Excellence, 2018). In the same year, Ontario also became the first Canadian province to create a pilot regulation for AVs: Autonomous Vehicle Pilot Regulation 306/15 (Parks, 2018; The Government of Ontario, 2015a). Under the influence of this regulation, the Municipal Alliance for Connected and Autonomous Vehicles in Ontario (2018) was initiated by the Ontario Good Roads Association. It has goals of creating the world's first province-wide AV testing corridor and road network, facilitating the learning and cooperation of all Ontario municipalities in AV programs, attracting auto companies and AV technology developers to Ontario, and making Ontario a world leader in AV innovation and adoption. Although there has been no legislation to boost these purposes, the Ontario government has shown support and enthusiasm for AV adoption.

Efforts to prepare for AV adoption at the local municipal level in the Greater Toronto and Hamilton Area (the GTHA) are limited. Nonetheless, some preliminary works have been done by the City of Toronto, the Region of Peel, the City of Hamilton, York Region, and the City of Brampton (Sample works see Transit Council of Chairs Committee of the Council of the Corporation of the City of Brampton, 2018; Werner, 2018; The City of Toronto, 2018a; The City of Toronto, 2018b; Region of Peel, 2017; York Region, 2016). These preliminary works are the first steps for the local governments in the GTHA to plan for an AV-dominant future.

There are two government actions in the GTHA worth highlighting for this thesis. First, the City of Toronto's Transportation Services Division and Metrolinx cooperated with Ryerson University, and completed an AV consumer survey (Olsen et al., 2018; Laidlaw et al., 2018). After the original survey, their subsequent analyses focus on:

- scenarios under which consumers would adopt private autonomous vehicles (PAVs) and shared autonomous vehicles (SAVs),
- changes of people's travel behaviors after their adoptions of PAVs and SAVs,
- factors that influence people's decision making on PAV and SAV adoptions, and
- the roles of planners and policy makers in PAV and SAV adoptions.

Second, enlightened by the survey results, the Division and Metrolinx cooperated with Leah Birnbaum Consulting and Ryerson University, and hosted 5 focus group workshops (Birnbaum et al., 2018). Almost all of the workshop participants were interested in AVs. Later, the Division and Metrolinx funded Leah Birnbaum Consulting and Ryerson University to write a report on the workshops, so as to understand the following:

- reasons why many people are interested in PAVs and SAVs,
- public reaction to PAVs and SAVs as two types of future common transportation options, and
- expectations of the public on the policies for AV adoption and operation.

As a public transit agency of the Government of Ontario, Metrolinx also has an interest in understanding the impacts of AVs on public transit, especially its regional transit services. In addition, Metrolinx would like to know how the adoption of AVs would change the parking demand at its GO stations. Moreover, Metrolinx wants to know the feasibility of using SAVs to increase its ridership. Furthermore, Metrolinx hopes to find where locate the people who would be more willing to use PAVs, and where locate the people who would be more willing to use SAVs. Therefore, Metrolinx has realized the necessity of knowing more about AVs before coming up with some strategies to adapt its transit services to the future general adoption of AVs.

1.3 Goals and Objectives

Now that the governments and planners in the GTHA have developed a sense of the factors influencing the adoption of PAVs and SAVs, one next step is utilizing these insights to find the spatial characteristics of PAV or SAV adoption potential. This would help the planners choose areas for future pilot projects on AVs as an example. In addition, it would allow planners to know the areas where PAVs or SAVs would likely be first adopted, helping them as well as AV developers predict the market penetration of PAVs and SAVs in the GTHA. Moreover, planners can use this answer to assess the characteristics of the areas where the PAV or SAV adoption potential is high. Lastly, transit planners could use this adoption potential to predict changes in public transit ridership, and demand for current and future infrastructures as a result of AV influence.

This thesis is the first work indexing the potential adoption of AVs, and a work providing the spatial aspects of the adoption for planners and policy makers. In particular, by using the GTHA as the study area, the thesis will answer the following research questions.

1. What are the factors that influence the potential adoptions of Private and Shared Autonomous Vehicles?
2. How can we assess this potential in the urban context?
3. How can the assessment be utilized to inform planning and policy development?

To answer these questions, several steps are to be followed. In Chapter 2, the thesis will identify the discernible factors that would affect AV adoption through an exploration of adoption theories. This would indicate some significance of looking at the impacts of socioeconomic and travel characteristics of individuals and land use on AV, PAV and SAV adoptions. In Chapter 3, the focus would be on selecting the factors for indexing PAV and SAV adoption potential, and assigning weights to them through review of relevant studies on AV adoption in particular. In Chapter 4, the methodology will be outlined where the adoption index will be established. The chapter will also discuss the GIS tools and spatial data sources that would be used to map the potential. In addition, the chapter will brief the use of some statistical tools and one online tool in exploring the planning implications of PAV and SAV adoptions. Chapter 5 will present the results and detail the implications as generated from Chapter 4. Chapter 6 will summarize the thesis, present research limitations, and discuss directions of further studies.

Chapter 2: Constructs behind the Intention to Adopt AVs

There are many theories and models on technology adoption, which could help explain why people would or would not like to adopt AVs. This section would introduce the relevant ones on AV adoption.

2.1 Technology Acceptance Model (TAM)

2.1.1 TAM

Davis (1989)'s TAM is a famous model explaining why people would adopt an information technology in their work. He believes that two theoretical constructs can explain it. One is perceived usefulness, which is the extent to which a person believes that the technology would improve his or her work productivity. The other is perceived ease of use, which is related to the complexity of and difficulty in utilizing a technology to increase one's work productivity. By reviewing 7 studies on testing the validity of TAM, Pikkarainen et al. (2004) found that TAM consistently explains roughly 40% of people's variances in their intentions and decisions on a technology adoption.

The validity of TAM is further supported by Ittersum and Feinberg (2010)'s use of their cumulative timed intent measure. They found that the more practical functions that a technology would bring to people, the more likely the technology would be adopted more quickly. In addition, the more complex a technology, the longer it takes for people to adopt it. Obviously, these two findings demonstrate that a more useful technology is easier to be accepted, while a technology that is more difficult to learn and use is less attractive.

2.1.2 Two Extensions of TAM

Through their exploration of the impacts of experiencing riding a level 3 automated vehicle on people's intention to ride in a level 5 AV, Xu et al. (2018) extended TAM by adding a construct: trust. They define trust as one's "belief that permits the public and potential consumers to willingly become vulnerable to AVs" (Xu et al., 2018, p. 323). By analyzing and comparing the survey results from 300 undergraduate students from Chang'an University, who did one questionnaire before and another after trying a ride of a level 3 automated vehicle, they found that the relationships between trust and perceived usefulness, between trust and perceived ease of use, between trust and the behavioral intention to ride level 5 AVs, and between perceived usefulness and the behavioral intention to ride level 5 AVs are all positively significant before and after a ride of a level 3 automated vehicle. However, the relationship between perceived ease of use and the intention to ride a level 5 AV becomes positively significant only after people try the riding of a level 3 automated vehicle. In addition, riding a level 3 automated vehicle would significantly enhance the positive significance between perceived usefulness and perceived ease of use, between trust and perceived ease of use, between perceived usefulness and the behavioral intention to ride a level 5 AV, and between trust and the behavioral intention to ride a level 5 AV. These enhancements are mainly due to that riding a level 3 automated vehicle would significantly increase one's perceived usefulness of, perceived ease of use of, and trust in level 5 AVs. Riding a level 3 automated vehicle would not have a significant impact on the relationship between trust and perceived usefulness though this relationship is already positively significant before the ride (Xu et al., 2018).

Similar to Xu et al. (2018), Panagiotopoulos and Dimitrakopoulos (2018) added perceived trust as a construct to TAM for intended AV adoption. However, their meaning of perceived trust is more concrete. It refers to people's confidence in the operational safety and data security of AVs. In addition to perceived trust, they added social influence as a construct. It refers to the peer pressure from one's relatives and friends to persuade him or her to appreciate and use AVs.

Through their analysis of 483 complete survey responses on intended AV adoption from Europeans, Panagiotopoulos and Dimitrakopoulos (2018) found that perceived trust and social influence have a negatively significant correlation. In terms of the two constructs of TAM – perceived usefulness and perceived ease to use, they are positively correlated. They also found that perceived ease of use indirectly affects one's intention to use AVs through perceived usefulness. For all the four constructs, they are positively significantly correlated with an intention to use AVs. Their extended ATM model can explain 43.7% of the reasons why people intend to use AVs, with perceived usefulness being the most important construct (explanatory power: 21.3%).

Talking of the remaining 56.3% of the reasons why people would or would not intend to use AVs, Panagiotopoulos and Dimitrakopoulos (2018) proposed two major types of factors. One is the performance of AVs, such as their "productivity, efficiency, [and] environmental impact[s]" (p. 783). Another is the socioeconomic characteristics of individuals, such as "gender, education level, occupation, household income, driving experience, [and] involvement into accidents" (p. 783).

2.2 The Unified Theory of Acceptance and Use of technology (UTAUT), and Its Extension (UTAUT2)

2.2.1 UTAUT

By extensively reviewing literature, Venkatesh et al. (2003) developed unified theory of acceptance and use of technology (UTAUT). This theory argues that there are three constructs explaining people's intention to adopt an information technology (IT). The first and the most influential construct is performance expectancy. It refers to the extent to which a consumer believes that an IT would bring the benefits that he or she has been waiting for. The second construct is effort expectancy. It tells the degree to which a consumer trusts that an IT would be easy to learn, and handy to use. The third construct is social influence. It is the impact that the perceptions of one's families and friends have on the person. Clearly, performance expectancy is similar to perceived usefulness, and effort expectancy is merely the same as perceived ease of use. It is social influence that makes UTAUT stand out of the shade of TAM.

According to UTAUT, after one's intention to adopt an IT is formed, it would be this intention and the IT's facilitating conditions that would determine whether the person would adopt the IT (Venkatesh et al., 2003). Facilitating condition means the usefulness of an IT to help realize one's behavioral goal. There is no doubt that the meanings of facilitating condition and performance expectancy overlap, but facilitating condition emphasizes the ability of an IT to help a person *physically* do something, and this thing is what the person has been wanting to do.

Venkatesh et al. (2003) found out four factors helping explain people's differences in the constructs: gender, age, personal experience (only helping explain the effort expectancy and social influence), and voluntariness (only helping explain social influence). In addition, age and personal experience also influence people's perceptions of the facilitating conditions of an IT.

No more than 2 years after UTAUT was theorized, voluntariness was removed from the explanatory factors because whether a person would voluntarily or be forced to adopt an IT is decided by the remaining three factors – gender, age, and personal experience – and the construct: social influence (Venkatesh et al., 2012; Morris et al., 2005).

2.2.2 UTAUT2

Through a comprehensive review of the studies referencing UTAUT, and a self-critique on UTAUT, Venkatesh et al. (2012) expanded UTAUT into UTAUT2. Except dropping voluntariness from UTAUT, UTAUT2 identifies gender as a factor contributing to one's understanding of an IT's facilitating conditions. It also includes facilitating conditions as a construct of behavioral intention. Other than these, UTAUT2 keeps the theoretical structure of UTAUT, and adds complementary elements.

The first set of added complementary elements includes three constructs influencing the formation of one's behavioral intention. They are hedonic motivation, price value, and habit (Venkatesh et al., 2012). Hedonic motivation refers to one's intrinsic intention to enjoy life. It enhances performance expectancy – the extrinsic stimulus triggering a person's intention to enjoy life by using an IT – as the most influential construct of behavioral intention. Price value is one's judgment of whether the price of an IT is worth the benefits it provides. A habit is a routine way in which a person does something. It is formed through and changes with a person's experience.

Gender, age, and personal experience are still used to explain people's differences in different constructs (Venkatesh et al., 2012). In regard to the three new constructs added by UTAUT2, gender and age help explain all of the three constructs, while experience helps explain hedonic motivation and habit.

In terms of the determinants of people's final decision to adopt an IT, UTAUT2 adds habit to UTAUT's behavioral intention, and facilitating conditions (Venkatesh et al., 2012).

One key identity of UTAUT and UTAUT2 is that they do not use gender, age, and personal experience to directly explain why people choose to adopt an IT or not, but as influential factors contributing to the quality or quantity of more direct factors influencing people's IT adoption decisions. In addition, some constructs (facilitating conditions, and habit) can directly influence both behavioral intention and user behavior, but others only indirectly influence user behavior through behavioral intention.

2.3 Car Technology Acceptance Model (CTAM)

Osswald et al. (2012) adapted Venkatesh et al. (2003)'s UTAUT, and developed their Car Technology Acceptance Model (CTAM). They kept all the constructs of UTAUT, and added four constructs to better explain why people would or would not intend to adopt an in-car technology for their cars of automation levels 0 to 2. They are anxiety, perceived safety, self-efficacy, and attitude towards using technology.

Anxiety has two components. One is one's discomfort and dis-confidence in interpreting surrounding driving environment, and executing driving tasks (Osswald et al., 2012). The other is one's worry of the unreliability or malfunction of the technologies in his or her car. If a person believes that a new technology would reduce his or her worries of these kinds, he or she would be more inclined to adopt the technology.

Perceived safety is one's perception that incorporating a technology would reduce his or her likelihood of getting trouble or encountering a danger (Osswald et al., 2012). It is partially shaped by one's personality, which is related to UTAUT2's two constructs: hedonic motivation and habit.

Self-efficacy is one's belief that he or she can master how to use a technology. It is partially shaped by one's personality, emotion, and affection, while affection is more or less related to the next construct (Osswald et al., 2012). Again, personality, emotion, and affection are related to UTAUT2's hedonic motivation and habit. In addition, the meanings of self-efficacy and TAM's perceived ease of use highly overlap (if not being the same).

Attitude towards using technology specifically refers to one's feeling of using a technology (Osswald et al., 2012). This feeling would reinforce or diminish all other constructs.

Through designing and conducting a survey, and analyzing the survey responses of 21 participants, Osswald et al. (2012) validated their model. However, they remind that their model would not explain all but the majority of the reasons why people would or would not adopt an in-car technology.

2.4 Zmud and Sener (2017)'s AV Acceptance Model

Building upon Osswald et al. (2012)'s CTAM, Zmud and Sener (2017) developed an AV acceptance model. They first dropped facilitating condition as a construct not because it is unimportant, but because they are uncertain about the future infrastructural support for AVs. Then, they added three constructs: desire for control, technology use, and technology acceptance.

Desire for control refers to how much a person feels that he or she would only accept a total control of his or her vehicle (Zmud and Sener, 2017). This construct is a very weak yet un-negligible construct of people's inclination to use AVs. Its explanatory power is no more than 2% in Austin, Texas. Bazilinskyy et al. (2015) agree that desire for control cannot be neglected. From 494 text survey responses from tens of countries, they found that favoring manual driving over hands-free driving is the most prominent reason, and unwilling to lose the joy of manual driving is the third most prominent reason why some people do not want to adopt AVs.

Technology use is not directly explained, but its meaning is implied. It refers to people's knowledge of commonly used technologies, such as smartphone, Facebook, online shopping, email, text messaging, and transportation apps (Zmud and Sener, 2017). It also refers to the frequency at which people use them. Through a quantitative and a qualitative study, Zmud and Sener (2017) found that social media technologies have significant impacts on people's AV adoption, while other technologies do not.

Technology acceptance is not explained. Implied from the meaning of technology use, it may refer to the overall extent to which a person likes commonly used technologies, such as smartphone, Facebook, online shopping, email, text messaging, and transportation apps (Zmud and Sener, 2017). It is also implied that only the acceptance of social media technologies is significant.

Through scrutinizing Zmud and Sener (2017)'s quantitative and qualitative studies in Austin, Texas, it is better to describe their three constructs as desire for control, social media technology use, and social media technology acceptance. Their studies also cover the verification of the constructs in UTAUT and CTAM, and they are verified true. In addition, their studies also indicate that having a physical impairment or disability, or owning a level 1 or 2 automated vehicle would contribute to a stronger inclination to adopt AVs. They are proofs that people's socioeconomic characteristics play roles in shaping their intentions to adopt AVs.

2.5 Technology Adoption as a Function of the Characteristics of a Technology

Rogers (2003) believes that the characteristics of a technology are sufficient for the prediction of whether and when most people would adopt it. The characteristics consist of relative advantage, compatibility, complexity, trialability, and observability.

Relative advantage refers to the net benefits compared to the current technology that the new technology is to replace (Rogers, 2003). This construct not only supports TAM's perceived usefulness, UTAUT's performance expectancy and facilitating condition, and UTAUT2's price value, but also reminds that the characteristics of the technology that is to be replaced also play some roles.

Compatibility refers to the degree at which the new technology meets the needs and values of potential consumers (Rogers, 2003). This construct more directly supports TAM's perceived usefulness, UTAUT's performance expectancy and facilitating condition, and UTAUT2's price value.

Complexity refers to the difficulty of being understood and learnt (Rogers, 2003). It backs up TAM's perceived ease of use, and UTAUT's effort expectancy.

Trialability refers to the possible maximum population scale at which the new technology can be tried out, and how easy it can be tried out. This construct reminds us to be careful of Xu et al. (2018)'s conclusions because their survey participants did not try a ride of a level 5 AV, but a level 3 automated vehicle, though it was an inevitable research limitation.

Observability refers to the level at which the benefits of the new technology can be seen. Again, this construct reminds of Xu et al. (2018)'s inevitable research limitation, and a need to test relevant technology acceptance theories after AVs emerge. It also hints that information dissemination may have an influence on people's decision making about AVs.

2.6 Technology Adoption Rate as a Complicated Function of Market Demand and Supply

Hall and Khan (2003) consider the acceptance of a technology is a process of technology diffusion. The speed of the diffusion is a complex function of market demand and supply. What particularly interest this thesis are the influence of market demand and two proposed explanations on an S-shaped curve, which is to be mentioned soon.

On the demand side, customers make decisions on technology adoptions by weighing the benefits of using a new technology (echoes TAM's perceived usefulness), and a series of costs and risks associated with the adoption (Hall & Khan, 2003). Examples of the costs include those from purchasing the new technological product, using and maintaining it, and recycling and replacing it when the product is out of date or no longer usable. Sample risks include the uncertainties of the speed of technology upgrade, the quality and benefits of future newer technological product compared to the current new product of the same kind, and the attitude of policies. It should be noted that customers do not weigh the factors once, but over time. Through ongoing weighing, customers may advance or postpone the time when they would adopt the technology.

By reviewing the adoption of some major technologies – electric service, refrigerator, telephone, washing machine, videocassette recorder, and personal computer in household – in the twentieth century America, and plotting the proportion of customers who have adopted a new technology against time, Hall and Khan (2013) found that their plots always show an S-shaped curve. Similar S-shaped curves were also found by Ittersum and Feinberg (2010) when they were plotting people's likelihood of adopting three technologies – an advanced golf course mower, an auto-guidance farm system, and cell phones with GPS technology – at a 3-month interval. The S-shaped curve shows that a technology adoption goes through three stages (Hall & Khan, 2003; Ittersum & Feinberg, 2010). First, a few people purchase and use the technology.

Second, the majority of the public purchase and use the technology. Third, as the market is approaching saturation, some late adopters start purchasing and using the technology.

Hall and Khan (2003) introduce there are two theories explaining the S-shaped curve: adopter heterogeneity, and adopter learning. Adopter heterogeneity proposes that people have different values on a new technology, and the values are normally distributed. More people choose to adopt it as the cost constantly reduces, and becomes less than their values. Thus, the normally distributed values and constantly reducing cost result in the S-shaped curve. Adopter learning argues that people give the same value to a new technology. When they would adopt it depends on when they would know its existence. Thus, it is the nature of how information is disseminated from one person to all the society that gives rise to the S-shaped curve. These two theories remind people of the importance of cost and information dissemination in people's decision making about AVs.

2.7 A Loose Diffusion-of-Innovation-Based Model

Talebian and Mishra (2018) forecast that connected autonomous vehicle (CAV) adoption would happen between 2025 and 2050, by means of using the theory of Diffusion of Innovations (DOI), the concept of resistance, agent-based modeling, and model validation through a survey of the students and employees at the University of Memphis. Although not systematically summarized and visually presented, Talebian and Mishra (2018) actually have a loose DOI-based model explaining why people would or would not adopt CAVs. By scrutinizing the authors' discussion and findings, the factors deciding people's decision on CAV adoption can be summarized as follows.

- Cost. A lower purchase cost, and a faster annual reduction of CAV purchase cost both contribute to a quicker CAV adoption. It is a premise of CAV adoption that the purchase cost is lower than one's willingness to pay (WTP).
- Policy. Policies providing incentives to subsidize consumers' purchase cost and vehicle registration fee, and manufacturers' production cost would speed up CAV adoption.
- Readiness of the infrastructure. Lack of infrastructures supporting the operation of CAVs would discourage people's adoption of CAVs.

- Traditions and social norms. For example, people who have been used to using a steering wheel, and who consider using a steering wheel is a part of a definition of vehicle would not be likely to adopt CAVs. For another example, if owning CAVs is considered a good indication of a high social status in a society, people in the society are more willing to purchase CAVs.
- Adopters' physical conditions. People with mobility-relevant disabilities or impairments are more favorable of CAVs.
- Peer influence. The authors point out, "individuals heavily rely on the information they receive from their peers when assessing adoption of a radical innovation such as connected autonomous vehicles" (p. 376). This construct is highly similar to Panagiotopoulos and Dimitrakopoulos (2018)'s social influence.
- Media advertisement. It encourages people to adopt CAVs.

This theory reminds that policy, readiness of infrastructure, traditions, and social norms are influential factors in terms of the decision making on CAVs. Adding to the importance of policy, Shabanpour et al. (2018) noticed that policy can be a strong agent boosting people's desire to adopt AVs. They found that more than 70% Chicagoans consider driver liability is a major concern discouraging them to adopt AVs. Thus, Shabanpour et al. (2018) argue that a policy change that allows drivers to be free of liability in traffic violation and accident would be a vital policy incentive persuading people to adopt AVs. Similar to Talebian and Mishra (2018), Nieuwenhuijsen et al. (2018) consider that mass media is a critical factor that should be considered in forecasting the market penetration and fleet size of AVs in the Netherlands.

2.8 Influence of Geographic Difference

By "using data on the diffusion of 15 technologies ['on transportation, telecommunication, information technology, health care, steel production, and electricity' (p. 2032)] in 166 countries over the last two centuries" (p. 2031), Comin and Hobijn (2010) found that in average, a country takes 45 years to adopt a technology after its invention, while the standard deviation is outstanding: 39 years. Although the large standard deviation is mainly caused by the differences across technologies (explanatory power: 59%), the contributions of the differences across countries (explanatory power: 18%) and the co-effect of the two differences (explanatory power: 11%) cannot be ignored.

2.9 Some Specific Factors Encouraging or Discouraging AV adoption

Different researchers find different specific factors encouraging or discouraging AV adoption. Previous sections have mentioned some of them, and they are summarized in Table 2.1 and Table 2.2, along with many other factors not mentioned so far. It is common to find that multiple sources realize the importance of the same factor. The column "Sources" lists the academic works that support the significance of a factor. By comparing the meanings of the factors in relevant works with the meanings of the constructs as mentioned in sections 2.1 to 2.8, noticeable relevant constructs for each factor are listed in the "Key relevant constructs" column.

It should be reminded that the Tables do not contain socioeconomic and travel characteristics of individuals, and land use. Excluding them is because they will be comprehensively discussed in Chapter 3.

Table 2.1 Some Specific Factors Encouraging AV Adoption

Type	Factor	Key relevant constructs	Sources
Safety	Make driving safer	Perceived safety; performance expectancy; perceived usefulness	Panagiotopoulos and Dimitrakopoulos (2018); Shabanpour et al. (2018); Howard and Dai (2013)
Safety	Make vehicles safer for other road users	Perceived safety; performance expectancy; perceived usefulness	Panagiotopoulos and Dimitrakopoulos (2018); Shabanpour et al. (2018); Howard and Dai (2013)
Mobility	Increase the mobility of disabled people	Facilitating condition; net benefits with respect to current technology; perceived usefulness	Talebian and Mishra (2018); Konig and Neumayr (2017)
Mobility	Increase the mobility of seniors	Facilitating condition; net benefits with respect to current technology; perceived usefulness	Konig and Neumayr (2017)
Mobility	Transport people when they are unconscious, drowsy, or after medical treatment	Performance expectancy; facilitating condition; perceived usefulness	Konig and Neumayr (2017)
Use of time	Allow a more efficient use of time	Performance expectancy; facilitating condition; perceived usefulness; characteristics of a technology	Panagiotopoulos and Dimitrakopoulos (2018); Howard and Dai (2013); Konig and Neumayr (2017)
Use of time	Mitigate traffic congestion	Performance expectancy; perceived usefulness; characteristics of a technology	Shabanpour et al. (2018)
Use of time	Reduce travel time	Performance expectancy; perceived usefulness; characteristics of a technology	Shabanpour et al. (2018)
Operation	Make driving more interesting	Hedonic motivation; performance expectancy; perceived usefulness	Panagiotopoulos and Dimitrakopoulos (2018)
Operation	Believe it is easy to learn	Effort expectancy; self-efficacy; attitude towards using technology; information technology use; information technology acceptance; perceived ease of use; anxiety	Panagiotopoulos and Dimitrakopoulos (2018)
Operation	Full human takeover is allowed	Anxiety; performance expectancy; habit; trust; desire for control; perceived safety; characteristics of a technology	Konig and Neumayr (2017)
Infrastructur e	No need to park	Performance expectancy; effort expectancy; facilitating condition; perceived usefulness; perceived ease of use; characteristics of a technology	Howard and Dai (2013); Konig and Neumayr (2017)
Regulation	Provision of education campaigns	Policy	Martinez-Diaz and Soriguera (2018)
Regulation	Government incentives	Policy	Martinez-Diaz and Soriguera (2018); Konig and Neumayr (2017)
Regulation	Remove driver liability of traffic violation and accidents	Policy; perceived usefulness; anxiety	Konig and Neumayr (2017)
Culture	Represent a high social status	Social influence; hedonic motivation; traditions and social norms; social influence; peer influence	Panagiotopoulos and Dimitrakopoulos (2018); Talebian and Mishra (2018)
Information disseminatio n	Positive feedback from relatives and friends	Social influence; traditions and social norms; social influence; peer influence; media; information technology use; information technology acceptance; desire to wait for more reliable technology	Panagiotopoulos and Dimitrakopoulos (2018); Talebian and Mishra (2018); Nieuwenhuijsen et al. (2018); Konig and Neumayr (2017)
Information disseminat-ion	Advertisement	Media; social influence; traditions and social norms; information technology use; information technology acceptance	Nieuwenhuijsen et al. (2018)
Fuel	Have a higher fuel efficiency	Performance expectancy; price value; perceived usefulness	Shabanpour et al. (2018)

Table 2.1 Continued

Type	Factor	Key relevant constructs	Sources
Personal traits	Tech-savvy	Hedonic motivation	Martinez-Diaz and Soriguera (2018)
Personal traits	favorable of high-tech applications in vehicles	Hedonic motivation	Martinez-Diaz and Soriguera (2018)
Personal traits	passionate for environmental protection	Hedonic motivation	Martinez-Diaz and Soriguera (2018)
Experience	Tried levels 1-3 automated vehicles	facilitating condition; anxiety; perceived safety; self-efficacy; attitude towards using technology; experience; perceived trust; characteristics of a technology	Xu et al. (2018)

Table 2.2 Some Specific Factors Discouraging AV Adoption

Type	Factor	Key Relevant constructs	Sources
Safety	Uncertain cyber security and data privacy	Perceived safety; trust; performance expectancy; information technology use; anxiety; characteristics of a technology	Panagiotopoulos and Dimitrakopoulos (2018); Bazilinskyy et al. (2015); Shabanpour et al. (2018); Martinez-Diaz and Soriguera (2018); Konig and Neumayr (2017)
Safety	Uncertain reliability of the automation system	Perceived safety; trust; performance expectancy; perceived usefulness; anxiety; desire for control; desire to wait for more reliable technology; readiness of infrastructure; characteristics of a technology	Bazilinskyy et al. (2015); Shabanpour et al. (2018); Martinez-Diaz and Soriguera (2018); Konig and Neumayr (2017)
Operation	Lose control of the vehicle	Desire for control; hedonic motivation; habit; traditions and social norms; performance expectancy; perceived usefulness; effort expectancy; facilitating condition; trust	Bazilinskyy et al. (2015); Talebian and Mishra (2018); Howard and Dai (2013); Konig and Neumayr (2017)
Infrastruc-ture	Uncertain infrastructural support	Readiness of infrastructure; trust; performance expectancy; facilitating condition; perceived safety; anxiety	Bazilinskyy et al. (2015); Shabanpour et al. (2018); Talebian and Mishra (2018)
Cost	Potentially pricy	Cost; price value; net benefits with respect to current technology; policy	Shabanpour et al. (2018); Talebian and Mishra (2018); Howard and Dai (2013); Nieuwenhuijsen et al. (2018)
Cost	Recently purchased a non-AV	Cost; price value; net benefits with respect to current technology	Mueller et al. (2007)
Regulation	Uncertain liability	Policy; perceived usefulness; anxiety	Shabanpour et al. (2018); Howard and Dai (2013); Konig and Neumayr (2017)
Regulation	Lack of purchase subsidy	Policy; cost; price value; net benefits with respect to current technology	Talebian and Mishra (2018)
Regulation	Lack of discount for vehicle registration fee	Policy; cost; price value; net benefits with respect to current technology	Talebian and Mishra (2018)
Information disseminat-ion	Negative feedback from relatives and friends	Social influence; traditions and social norms; social influence; peer influence; media; information technology use; information technology acceptance; desire to wait for more reliable technology	Panagiotopoulos and Dimitrakopoulos (2018); Talebian and Mishra (2018); Nieuwenhuijsen et al. (2018); Konig and Neumayr (2017)

Chapter 3: Impacts of Individual Characteristics and Land Use on AV Adoption

As known from Chapter 2, Panagiotopoulos and Dimitrakopoulos (2018)'s discussion of the limitation of their extended TAM reminds, and Zmud and Sener (2017)'s AV acceptance model reveal that the socioeconomic characteristics of individuals are influential in shaping their intentions to adopt AVs. This chapter will not only discuss the influences, but also the influences of individual travel characteristics and land use. Discussing the influences of these factors is important because the factors are often surveyed in a census, which would provide important data for realizing the indexing of the PAV and SAV adoption potential of a geographic location, and for mapping out these potential. In addition, the discussion will provide important implications on which variables are relatively more important for the indexing as well as mapping.

The thesis tries to find as many studies as possible that use a solid quantitative or qualitative approach to demonstrate the existence of a relationship between a studied variable and the intended adoption of AVs, PAVs, or SAVs (see a list of studied variables in Table 4.1). However, as AVs had not become a popular topic among transportation researchers until the mid-2010s, the described studies are not substantial in quantity, and they were mostly published after 2014 (clearly indicated from Table 3.1). Eventually, 24 articles were found for an exploration of the relationships between the studied variables and intended adoption of AVs, PAVs, or SAVs (see Table 3.1). The 24 articles represent most (if not all) of the articles (1) that have explored some of the relationships through a solid research approach, (2) that are accessible by the end of 2018, (3) that are recognized as academic works, (4) that were written in English, and (5) that were published by a well-known and well-accredited journal or presented at a professional or academic conference of a decent reputation. Therefore, these studies should represent a maximum extent to which we know about the impacts of the studied variables on the AV adoptions.

Table 3.1 Summary of Articles Referenced in This Chapter

Source	Eventual sample size (n)	Geographies	Survey time	Quantitative method, qualitative method, or literature review	Meaning of SAVs (on-demand, carpooling, or unspecified)	Level of vehicle autom-ation
Schoettle and Sivak (2014)	1,533	America (n = 501), UK (n = 527), and Australia (n = 505)	Unknown	Quantitative method	Unspecified	3, 4 (discussed together)
Bansal and Kockelman (2018)	1,088	Texas	Unknown	Quantitative method	On-demand SAVs	2, 3, 4 (discussed separately)
Bansal et al. (2016)	347	Austin, Texas	Late 2014	Quantitative method	On-demand SAVs	3, 4 (discussed separately)
Liljamo et al. (2018)	2,036	Finland	May 2017 – Aug 2017	Quantitative method	On-demand SAVs	4, 5 (discussed together)
Zmud et al. (2016)	556; 44	Austin, Texas	May 2015	Quantitative method (n = 556), and qualitative method (n = 44)	On-demand SAVs, and carpooling SAVs	5
Georgieva and Kolodge (2018)	Unknown	Unknown	Unknown	Quantitative method (from 2 secondary sources)	Unspecified	5
Shabanpour et al. (2018)	1,013	Chicago, Illinois	Dec 2016	Quantitative method	On-demand SAVs	5
Hohenberger et al. (2016)	1,300	Germany	Feb 2014 – Nov 2014	Quantitative method	Unspecified	2 to 5 (discussed together)
Lavieri et al. (2017)	Unknown	Puget Sound, Washington	2014 – 2015	Quantitative method (from a portion of the data for the 2014-2015 Puget Sound Regional Travel Study)	On-demand SAVs, and carpooling SAVs	5
Hulse et al. (2018)	916	UK	Started in Apr 2016	Quantitative method	Unspecified	5
Krueger et al. (2016)	435	Major metropolitan areas in Australia	Unknown	Quantitative method	On-demand SAVs with or without dynamic ride-sharing	Unknown, implied 5

Table 3.1 Continued

Source	Sample size (n)	Geographies	Survey time	Quantitative method, qualitative method, or literature review	Meaning of SAVs (on-demand, carpooling, or unspecified)	Level of vehicle auto-mation
Kyriakidis et al. (2015)	4,886	109 countries	Unknown	Quantitative method	Unspecified	1 to 5 (discussed together)
Pettigrew et al. (2018)	1,624; 43	Primarily Australia	Unknown	Quantitative method (n = 1,624), and qualitative method (n = 43)	On-demand SAVs	Un-known, implied 5
Souders and Charness (2014)				Literature review	Unspecified	Un-known
Haboucha et al. (2017)	682	Israel (n = 357), and North America (n = 325)	Sep 2014 – Nov 2014	Quantitative method	On-demand SAVs	5
Panagiotopoulos and Dimitrakopoulos (2018)	483	Unknown	Unknown	Quantitative method	Unspecified	3, 4, 5 (discussed together)
Konig and Neumayr (2017)	489	Austria (n = 366), and other 32 countries (n = 123)	Jul 2015	Quantitative method	Unspecified	5
Bazilinskyy et al. (2015)	494	No more than 112 countries	Unknown	Qualitative method (309 positive and 185 negative comments on AVs)	Unspecified	5
Laidlaw & Sweet (2017)	3,201	The GTHA	2016	Quantitative method	On-demand SAVs	5
Laidlaw et al. (2018)	3,201	The GTHA	2016	Quantitative method	On-demand SAVs	5
Heinrichs (2016)		General cities	No survey conducted	Literature review	On-demand SAVs	5
Meyer et al. (2017)		Switzerland	No survey conducted	Quantitative method	On-demand SAVs	5
Soteropoulous et al. (2019)				Literature review (international study)	On-demand SAVs, and carpooling SAVs	Un-known, implied 4

Table 3.1 Continued

Source	Sample size (n)	Geographies	Survey time	Quantitative method, qualitative method, or literature review	Meaning of SAVs (on-demand, carpooling, or unspecified)	Level of vehicle autom-ation
Zhang (2017)		Atlanta, Georgia	No survey conducted	Quantitative method	On-demand SAVs, and carpooling SAVs	5

Note: Bansal and Kockelman (2018), and Bansal et al. (2016) use practical significance – a stricter significance than statistical significance.

Before the discussion of the studied variables, three things should be clarified. First, all relationships relevant to SAVs should be considered as the ones relevant to on-demand SAVs because most of the 24 studies refer SAVs as on-demand SAVs (see Table 3.1). Second, some articles not only discuss AVs of level 4 or 5, but also discuss automated vehicles of level 3 or lower. The thesis only considers their conclusions on AVs of level 4 or 5. Third, intended SAV adoption is sometimes discussed in different price scenarios. With reference to Appendix A, if the price of SAVs falls in the range of $0.37/km to $0.85/km, the price is considered comparable to the cost of private vehicles (PVs) (hereafter, referenced as "the price is fair"). If the price is in the range of $0.86/km to $2.00/km, the price is considered high. Choosing $2.00/km as the upper limit is because the three studies that modeled intended SAV adoption at different prices – Laidlaw and Sweet (2017), Bansal and Kockelman (2018), and Bansal et al. (2016) – did not discuss a price beyond $2.00/km.

3.1 Impacts of the Socioeconomic Characteristics of Individuals

Among the 24 studies listed in Table 3.1, the first 19 studies will contribute to the content of Section 3.1. Most of them adopted a modeling approach, while a few of them made their discussions around a comprehensive literature review.

3.1.1 Age

Many researchers found that age is closely related to people's intention to adopt AVs. Through percentage comparison, Panagiotopoulos and Dimitrakopoulos (2018) found that Europeans aged less than 40 have a much stronger intention to adopt AVs. In addition, Liljamo, Liimatainen, and Pollanen (2018) found that the 25-to-34-year-old Finns have significantly higher positive attitudes towards AVs, while other age groups do not differ significantly in terms of their overall attitudes towards AVs. In another study, Schoettle & Sivak (2014) found that younger Americans and Australians have more passion for AV adoption. They suppose this passion is due to their enthusiasm for new technologies as they show obviously less concerns about congestion and travel time, compared to older people. Shabanpour et al. (2018) suppose that technology being more important in the life of young people causes their higher enthusiasm for new technologies. They reached their supposition after finding that Chicagoan Millennials (born in 1979-1994, and aged 24 to 39 in 2018) are most interested in adopting AVs, and that their life is more involved in technology use compared to older generations. Adding to the previous suppositions on why young people are more interested in AVs, Bansal and Kockelman (2018) found from their study in Texas that age is a practically significant covariate for the subjectivity to peer pressure to adopt AVs as well as the timing of AV adoption. In specific, younger Texans would be more subject to peer pressure, and adopt AVs quicker than older people under the pressure.

Talking of the timing of adopting AVs, Lavieri, Garikapati, Bhat, Pendyala, Astroza, and Dias (2017) found that the aged 18-44 years old Puget Sound residents in the Washington State would be early AV adopters. In addition, Zmud et al. (2016) noticed that age is an indicative variable of Austinites' timing of AV adoption. Among the early AV adopters, the less-than-30-year-old comprises the largest proportion. Among the late AV adopters, the over-65-year-old is the majority.

It should be clarified that people who are passionate about AVs are not necessarily early AV adopters. Zmud et al. (2016) found that there are a number of AV enthusiasts less than 30 years old or more than 65 years old who would like to adopt AVs late. That is because they do not think they would be capable of affording AVs. Thus, cost and income are mediators of the relationship between age and intended AV adoption.

From their qualitative data, Zmud et al. (2016) found that age is related to different reasons for AV adoptions. For senior Austinites, improving their mobility is a key reason, while for the 30-45 years old Austinites, working while travelling is a more valued merit. However, in Georgieva and Kolodge (2018)'s presentation, people of different ages do not appear to be different in terms of their perceived top 3 benefits of and top 3 concerns on AVs from 7 choices. Considering there are only 7 choices for interviewees, this study may not provide a valid proof that people of different ages have few difference in their perceived most important reasons for adopting or not adopting AVs. Although the participants could write their own reasons, they may have chosen to save some time by quickly picking up 3 out of 7 provided reasons, without carefully thinking about what other reasons are more important for their AV choice. On the contrary, Zmud et al. (2016)'s findings were derived from their participants' written answers. Thus, these participants were forced to think over why they would or would not adopt AVs.

Evident from the discussion on age up to here, seniors are likely to be late AV adopters, and are not passionate about adopting AVs. These two findings do not mean there are no ways to increase the attractiveness of AVs to seniors. Souders & Charness (2014) did a literature review of seniors' perceptions of AVs. They observed that seniors of 65 years old and over quite appreciate the mobility benefits of AVs: AVs would help them keep their mobility independence, maintain their self-esteem and sense of social inclusion. This appreciation is due to the fact that seniors have a declining health – their sense, cognition, stamina, hearing, vision, and mobility are weakening. These declines will result in their driving cessation sooner or later. This cessation will take away their mobility independence, hurt their self-esteem, and damage their sense of social inclusion.

In addition to the mobility benefits, there are other factors influencing seniors' preference to AVs. Two of them are cost, and confidence in learning and using (Souders & Charness, 2014). Souders and Charness (2014) infer that seniors would be a major group to adopt AVs – especially purchasing PAVs – if the cost is acceptable, and if they are educated to learn the possibly easy-to-operate AVs. Therefore, it is the uncertainty of cost and easiness of use that may prevent seniors from being equally favorable of AVs as the younger generations. These two factors may reflect that the senior generation is more prudent in making shopping choices, while the younger generations are more confident in the efficiency of AVs (Konig & Neumayr, 2017; Hulse et al., 2018).

Some researchers have been interested in studying whether age would still be an important factor in terms of different road users. In Hulse et al. (2018)'s study, participants were asked to imagine themselves as an HOV car driver, a motorcyclist, and then a cyclist before answering a series of questions. It turned out that younger and older UK residents have no significant difference in their risk-perceptions of driving or riding AVs, but older UKs perceive AVs as significantly unsafer for pedestrians. In addition, the authors found that younger UK residents overall are substantially more positive towards AVs. Therefore, when discussing AVs with respect to its danger to different road users, differences between age groups blur, though seniors are more concerned about safety.

The road users that Haboucha et al. (2017) examined were the drivers in Israel, America, and Canada. Using the 25-to-44-year-old drivers as the base group, the 45-to-64-year-old drivers are significantly more reluctant to replace their current cars by either a PAV or an SAV. This reluctance is doubled among those aged 65 and over. These significant relationships are quite indicative of people's attitudes towards AVs. No significant difference is found between the base group and the 17-to-24-year-old, which implies that the drivers aged 44 and below have a similar preference to AV.

Not all researchers found a significant relationship between age and AV adoption. For example, Kyriakidis et al. (2015) cannot find it. There are two likely reasons. First, as their survey participants come from 40 countries, the authors could not weigh their data due to the nature of cross-country data collection. Second, their data are overrepresented by people no more than 30 years old – they comprise half of the survey participants.

Regarding PAVs, Bansal and Kockelman (2018) found that age is a practically significant and moderately influential covariate for willingness to pay (WTP) for a level 4 PAV in Texas. They are negatively correlated. This relationship is also found consistent for WTP for a level 3 and a level 2 private automated vehicles, though they did not study level 5 AVs. Thus, it is fair to conclude that younger Texans are more likely to pay more for a PAV.

Narrowing down to the population of a Texas city: Austin, Bansal et al. (2016) found that age has a practically significant relationship with Austinites' WTP for adding level 4 automation to one's vehicle. Among their 13 studied covariates of WTP for level 4 automation, age is the most practically significant (with a positive correlation) if adding the automation costs less than $2,000. In addition, age is the second most practically significant covariate (with a negative correlation) if adding the automation costs more than $10,000. Thus, senior Austinites have the most interest in adding level 4 automation to their vehicles if the addition is cheap, while the millennials are the generation that is most willing to pay a lot for level 4 automation. This study implies that the relationship between age and PAV purchase is not a simple correlation. Its positive or negative being depends on the vehicle cost with respect to people's WTP.

Bansal et al. (2016) shows that younger people are more willing to pay a higher price for PAVs, but this may not be true in all geographies. In Puget Sound, residents aged 18-24 show practically significantly less intention to buy PAVs, possibly due to their relatively lower incomes and savings (Lavieri et al., 2017).

In the GTHA, the relationship between age and PAV adoption is similar to that in Austin. Using the 35-to-55-year-old GTHA residents as the reference group, the 18-34 years old are significantly more willing to pay for a PAV, while the 56-75 years old are significantly more reluctant to pay for a PAV (Laidlaw & Sweet, 2017). Although the three age groups are distinct in terms of WTP for PAVs, the distinction is obviously less between the 18-34 years old and the 35-55 years old. Overall, age is a strong influencer in the PAV adoption in the GTHA.

Regarding SAVs, the millennials in Austin are practically significantly more likely to use SAVs at least once a month if the cost of SAVs is $2/mile ($1.24/km) (Bansal et al., 2016). The significance is not found at $1/mile ($0.62/km) and $3/mile ($1.86/km). Thus, in Austin, the robustness of the relationship between age and SAV adoption is subject to the change of cost. Nonetheless, the millennials is a group favorable of SAVs.

Not considering the variation of SAV cost, Lavieri et al. (2017) does not find a significant relationship between age and SAV adoption, though adults aged 24 or below have an insignificantly stronger intention to use SAVs, compared to those aged 25 or more. If Lavieri et al. (2017) were able to design their questionnaire with the consideration of different SAV costs, some significant findings may have occurred.

Not like Bansal et al. (2016) discussing SAVs by 3 costs, Krueger, Kashidi, and Rose (2016) discuss SAVs by 2 types: SAVs with and without dynamic ride-sharing. In their study, the authors classified age into 5 groups: 18-23, 24-29, 30-49, 50-64, and 65-84. Using 30-49 as the base group, the authors found that the 24-to-29-year-old metropolitan Australians have significantly more preference to change their current major modes of travel to using SAVs with dynamic ride-sharing. However, there is no such discernible difference if the SAVs do not have dynamic ride-sharing. Thus, equipping SAVs with dynamic ride-sharing tools would significantly increase SAV ridership from the 24-29 years old.

In the GTHA, the relationship between age and SAV adoption is quite different from the relationship between age and PAV adoption. First, the 35-55 years old and the 56-75 years old would use SAVs at similarly low frequencies if the price is $0.50/km (Laidlaw & Sweet, 2017). This small difference is significant only if the travel characteristics of individuals are not considered. Second, compared to the relatively more linear decay of the attractiveness of PAVs with respect to age, the decay of the attractiveness of SAVs is more exponential. This curvature becomes more prominent as the price increases to $1.00/km, and then $1.50/km. It is necessary to restrict the truth of this trend in the domain because Bansal et al. (2016) did not find a practically significant difference between their five age groups when the SAV cost is $1.86/km in Austin, Texas. Hence, the significant difference between the age groups in the GTHA may be lost if the price increases from $1.50/km to $1.86/km.

3.1.2 Gender

Males and females are first distinct in their confidence in AVs. Through a survey, Schoettle and Sivak (2014) reveals that males are overall very confident that AVs would reduce crash accidents, the severity of the accidents, traffic congestion, travel time, vehicle emission, and fuel usage. However, females overall hesitate that the benefits would be realized. In addition, females are more worried about the safety of AVs, such as cyber security and data privacy, though males have a similar concern, and safety is what they most care about. (Schoettle & Sivak, 2014; Liljamo et al., 2018). Moreover, males tend to be more concerned about the price of AVs (Lijamo et al., 2018).

In terms of whether they would adopt AVs, males are more passionate about the adoption, and would like to adopt them earlier (Liljamo et al., 2018; Hulse et al., 2018; Zmud et al., 2016; Konig & Neumayr, 2017; Hohenberger, Sporrle, & Welpe, 2016; Bansal et al., 2016; Kyriakidis et al., 2015). Some researchers found some reasons for it. First, males are more risk-taking (Hulse et al., 2018). Second, males and females have different “affective reactions” (p. 378) to using AVs (Hohenberger et al., 2016): males generally expect using AVs to be a pleasant experience, whereas females are generally more or less anxious about using AVs. This gender difference decreases as people’s age increases.

From a planning perspective, Hohenberger et al. (2016) suggest that to boost AV adoption, the government does not need to focus on narrowing the gender differences. Rather, the government should accentuate and propogate the benefits of AVs because doing so would not only enhance men’s appreciation of AVs, but also relief women’s anxiety of using AVs. As a result, both men and women would adopt AVs quicker.

Not all researchers find or always find that gender differentiates AV adoption. Bansal and Kockelman (2018) did not find a practically significant relationship between gender and AV adoption in Texas, whereas both researchers found it in their co-authored article: Bansal et al. (2016), which is a study in Austin, Texas. The difference may lie in the choice of different geographic scale. Recalling from Chapter 2, traditions and social norms, and habits are important constructs of people’s intentions to adopt AVs, so it may also be the socioeconomic differences, and differences in lifestyle and world view between Austinites and the suburban and rural residents of Texas that contribute to the opposite findings.

Panagiotopoulos and Dimitrakopoulos (2018) surprisingly found that females are 32% more likely to purchase or use AVs, and thus concluded that there is a huge gender difference in intention to adopt AVs in Europe. However, the validity of their finding is doubtable because males comprise about seven tenths of their samples, while they did not weigh their data before analysis. In addition, their sample size (n = 483) may be too small to represent all Europeans.

When distinguishing PAVs and SAVs from each other, males and females are often not significantly different. As introduced before shortly, Bansal et al. (2016) found gender is a practically significant factor explaining Austinites' difference in their intentions to adopt AVs, but they noticed that gender difference is not prominent if PAVs and SAVs are discussed separately. Lavieri et al. (2017) also noticed the same phenomenon. However, in this study, a specific group of males has significantly more interest in using SAVs for car sharing (but not for ride sourcing). This group is males with at least one car-sharing experience. This significance is probably because in Puget Sound, a higher proportion of males than that of females have tried car sharing (Lavieri et al., 2017). In Australian metropolitan areas, males and females are similar in their preference to using SAVs either with or without dynamic ride-sharing (Krueger, Rashidi, & Rose, 2016). In the GTHA, gender is not found significant for both PAV and SAV adoptions (Laidlaw & Sweet, 2017).

It is not at all places that gender is not significant for PAV and SAV adoptions. In Haboucha et al. (2017)'s study, Israeli male drivers are noticeably more favorable of SAVs than Israeli female drivers, though this significance is not found in America and Canada. As the data from all the three countries were analyzed using the same statistical models, Haboucha et al. (2017) is a strong proof that geography as well as culture, religion, and social norms play roles in shaping males' and females' intentions to adopt PAVs and SAVs.

3.1.3 Ethnicity, Citizenship, and Country of Residence

There is no significant difference between countries in people's WTP for PAVs, but people from more developed countries, which overall have "lower accident rates, higher education, and higher income" (Kyriakidis et al., p. 138), are obviously more worried about the security of AV data transmission (Kyriakidis et al., 2015; Bazilinskyy et al., 2015). Kyriakidis et al. (2015) provided one reason for this difference: as people from more developed countries have more deposits and more valuable properties and belongings, the unpleasant outcomes of data misuse may be severer accordingly. People from less developed countries value more on life safety than property safety. One key reason is that less developed countries have more fatalities from car accidents.

Although there is a lack of studies talking about the differences of less developed countries in AV adoption, differences between some more developed countries can be found. Compared to UK people and Australians, Americans are more likely to be "'very concerned' about legal liability, data privacy (location and destination tracking), interacting with non-self-driving vehicles, system performance in poor weather, and self-driving vehicles not driving as well as human drivers" (Schoettle & Sivak, 2004, p. 23). UK people are often "moderately concerned" (Schoettle & Sivak, 2004, p. 23) about these items, while Australians are often "slightly concerned" (Schoettle & Sivak, 2004, p. 23) about them. Despite these differences, Schoettle and Sivak (2004) specify that the people of the three countries overall are quite similar in terms of their preferences to AVs. Haboucha et al. (2017) indicate that Israeli and North American drivers have drastic differences in their attitudes towards AVs. First of all, North American drivers are over 2 times more reluctant to replace their current vehicles with PAVs or SAVs (32.7% in North America, and 13.8% in Israel). This difference contributes to Israeli drivers' 66% more willingness to abandon their current vehicles, and use both PAVs and SAVs (10.5% in North America, 17.4% in Israel). In addition, Israeli drivers are 43% more prone to comprehensively use their current cars and two types of AVs (PAVs, and SAVs) (16.5% in North America, and 23.6% in Israel), and 50% more preferred to use SAVs only (5.4% in North America, and 8.1% in Israel). In terms of cost, North American drivers care more about purchasing cost, while Israeli drivers pay more attention to subscription cost. Overall, Israelis are more acceptant of AVs, PAVs, and SAVs.

There is a couple of studies discussing the relationship between ethnicity and AV adoption. Pettigrew, Fritschi, and Norman (2018) point out that in Australia, AVs have a potential to increase the job accessibility of indigenous people as most of them do not have a driver's license, while driver's license occupancy is mandatory for many jobs. Thus, AVs would help the indigenous people acquire a higher job accessibility. Bansal & Kockelman (2018) reveal that in Texas, White, European White, or Caucasian Texans overall have almost no intention to use SAVs even if the price is fair, whereas other ethnicities do not have such a low intention.

3.1.4 Education

There is an intense debate on the relationship between education and intended AV adoption. Schoettle and Sivak (2014), Liljamo et al., (2018), and Shabanpour et al. (2018) argue that the relationship is significant, and that people with a higher highest completed education more welcome AVs, more appreciate the benefits of AVs, and are more likely to adopt them first. On the country, Bansal and Kockelman (2018), Zmud et al. (2016), and Lavieri et al. (2017) argue the opposite.

By analyzing the surveys of the studiess, there exist some clues explaining their difference. First of all, the three studies arguing the absence of the relationship between education and intended AV adoption all studied places in US. The three studies arguing the existence of the relationship cover a much broader geographic area (see Table 3.1). It is implied that the absence of the significant relationship happens at some places in America, but not the whole America. In addition, the significance may commonly exist in the developed countries except America. Possibly, the significance between education and intended AV adoption may often fluctuates around the significance threshold across geographies. This guess is inferred from two sources. Haboucha et al. (2017) admit that their found significance is weak, whereas Lavieri et al. (2018) reminds that education has a latent effect on people's AV adoption choice despite that they do not find the significance. The latent effect is that higher education would make people less averse to accepting AVs.

Regarding PAVs particularly, Kyriakidis et al. (2015) found that people with a higher education level are willing to pay more for both level 4 and level 5 PAVs. It is partially because they are more confident in driving a vehicle without a steering wheel. Using the GTHA residents without a professional degree or without a graduate degree as a reference group, Laidlaw and Sweet (2017) found that the GTHA residents with a professional degree are more willing to pay more for PAVs, and this relationship is outstandingly strong. As medicine, dentistry, veterinary medicine, and optometry are the considered majors of a professional degree, workers doing medical science jobs may particularly value some characteristics of PAVs, which may include allowing them to rest or read patients' cases, and having no interruption from other people when they rest or work in a vehicle. On the contrary, Laidlaw and Sweet (2017) did not find a significant relationship between holding a general graduate degree and having a higher intention to purchase PAVs. Probably it is because they used the people with a bachelor's degree or a lower level of diploma or certificate as a reference group, which is usually not a way in which other researchers study the impact of education. Usually, researchers separate people with a diploma or certificate lower than a bachelor's degree from people with a bachelor's degree when forming a reference group. By separating them, Shabanpour et al. (2018) reveal that people with a graduate or professional degree would be early adopters of PAVs. In a similar way, Haboucha et al. (2018) demonstrate that people with at least a college certificate are more willing to buy PAVs. Therefore, it is fair to judge that people with a bachelor's degree or a higher degree are more likely to be early consumers of PAVs.

Talking of SAVs, the medical science graduates, and the general master's degree and PhD degree holders in the GTHA are major groups intending to use SAVs now and then (Laidlaw & Sweet, 2017). Comparing the two groups, the former is willing to pay more for SAVs for getting access to transit stations, whereas the latter is more willing to use SAVs for general use. Similarly, Lavieri et al. (2017) found that the Puget Sound residents with an undergraduate or a graduate degree appear to have more passion for SAV use. In addition, Haboucha et al. (2018) observed that people with at least a college certificate are more willing to use SAVs. Therefore, the attitudes of well educated people towards PAVs and SAVs are similarly high.

3.1.5 Student status

Students aged 18 or over are a major group favoring AVs. Haboucha et al. (2017) argues that drivers who have a student status would likely become early AV adopters in North America and Israel. Zmud et al. (2016) found that home-based Austin students particularly intent to drive PAVs. Hence, PAVs have a potential to increase the mobility of home-based students. There is a lack of study discussing the relationship between student status and intended SAV adoption.

3.1.6 Employment status

Regarding AVs, in America, UK, and Australia, full-time employees would be a major group to adopt AVs when they become market available (Schoettle & Sivak, 2014). It is because they are more confident in AV safety, and more believe that AVs would contribute to a lower insurance rate.

Regarding PAVs, Zmud et al. (2016) found that home-based Austin workers particularly intent to drive more in an AV-dominant future. This is an evidence that the availability of AVs would encourage more people to drive PAVs, and therefore increase the density of vehicles on road. Laidlaw and Sweet (2017) also looked at home-based workers. They found that in the GTHA, these people are significantly more willing to pay a higher price for PAVs. This significance is also true for those who work more than 60 hours per week probably because they want to have a good rest on their way to and from their workplaces.

Regarding SAVs, Bansal and Kockelman (2018) did not find a practically significant relationship between employment status and SAV adoption in Texas, though unemployed Texans are noticed more likely to use SAVs as the price is reduced. This finding suggests that the unemployed may become a major group to use SAVs if the price is fair. Narrowing the geographic scale down to Austin, full-time workers are likely to use SAVs at least once a month (Bansal et al., 2016). Nevertheless, this frequency is low. In the GTHA, four of five studied employment statuses have close relationships with SAV adoption (Laidlaw & Sweet, 2017). Working at home, and working full time or part time are the top 2 socio-economic variables strongly related to intended SAV adoption. In addition, people without a job or not in the labour force, and those working more than 60 hours per week are other two groups likely to use SAVs frequently. As people of all major employment status are associated with a higher likelihood of using SAVs, employment status is not a good indicator of one’s likelihood of using SAVs. The retired GTHA residents do not have a significantly more or less interest in using SAVs. This is consistent with their finding that in the GTHA, people more than 55 years old are much less interested in adopting SAVs.

3.1.7 Occupation

As mentioned in Chapter 2, reluctance to lose the control of the steering wheel is a reason why some people would not want to adopt AVs. Thus, it is anticipated that professional drivers would be hostile to AVs, which is what Pettigrew, Fritschi, and Norman (2018) suppose. They believe that the intensity of the hositility depends on whether they would find satisfying alternative jobs after AVs replace their socioeconomic functions, which is associated with how much efforts that their current employers and the government would put to help them.

Laidlaw and Sweet (2017) studied the impacts of three groups of occupations. They are (1) manufacturing, construction, and trades; (2) professional, management, and technical; and (3) sales and service. None of them are significantly associated with PAV adoption, but the first two groups are more or less significantly associated with SAV adoption. In specific, the GTHA residents working in the first occupation group significantly more favor SAVs. On the contrary, the GTHA residents working in the second occupation group are significantly less favorable of SAVs under certain price and trip purpose. However, reminded by section 3.1.4, medical science labourers should be excluded from this group as they favor SAVs.

3.1.8 Household income

Bansal and Kockelman (2018) did not find a practically significant relationship between household income and intended AV adoption in Texas. The absence of this significance may be due to the research's ignorance of peer influence. Bansal et al. (2016) found that in Austin, Texas, people with lower annual household incomes would like to adopt AVs when 50% of their friends have adopted them, whereas the majority of people with higher annual household incomes are inclined to adopt AVs once 10% of their friends have adopted them. Therefore, people with higher household incomes are much less subjective to peer influence. Moreover, annual household income is an indicator of how soon different people would adopt AVs.

In terms of people's preference to purchase PAVs, Shabanpour et al. (2018) observed that Chicagoans with a household income of more than $100,000 are resistant to the changes of purchase price and fuel cost. On the contrary, people with less incomes would be more reluctant to buy PAVs if the purchase cost or the fuel cost goes higher. Bansal and Kockelman (2018) and Bansal et al. (2016) have similar findings. Bansal et al. (2016) also found that median household income is an indicator of whether the households of a neighbourhood are overall favorable of PAVs. The three studies demonstrate the importance of cost as a construct, and this importance is more prominent as the cost goes up.

Despite the consistency of the above two findings, the relationship between household income and intended PAV adoption is not consistent across geographies. For example, in the GTHA, most income ranges are not significant for PAV adoption, except for the $0 to $15,000 range (Laidlaw & Sweet, 2018). Similar to Bansal and Kockelman (2018)'s study in Texas, Laidlaw and Sweet (2018) do not include peer review as a mediator of the relationship between household income and intended PAV adoption, which may hide some importance of household income.

Contrary to their findings about PAVs, Laidlaw and Sweet (2017) observed that some household income groups have a significant relationship with intended SAV adoption under certain costs and trip purpose. Similarly, Bansal and Kockelman (2018) found in Texas that people with a household income of less than $30,000 are more in favor of using SAVs only if the price is fair.

3.1.9 Personal income

Studies focusing on different geographic scales have different findings on the relationship between personal income and intended AV adoption. Lavieri et al. (2017), and Krueger (2016), whose samples were from metropolitan areas, did not find the relationship significant. Kyriakidis et al. (2015), and Haboucha et al. (2017), who collect samples at a national scale, found that the relationship is implied significant and positive.

Focusing on a subgroup of the population, Haboucha et al. (2017) found that drivers of low incomes would not like to replace their current cars with a PAV, while drivers of high incomes are overall in favor of the replacement if the purchase cost is less than that of conventional vehicles. However, if the purchase cost is higher than that of conventional vehicles, the high-income drivers would be significantly discouraged to arrange the replacement. Thus, cost is a mediator of the relationship between personal income and PAV adoption.

3.1.10 Household Size

Bansal and Kockelman (2018), and Bansal et al. (2016) do not find a practically significant relationship between household size and intended AV adoption. It is noticed that practical significance is a stricter significance than statistical significance (Bansal & Kockelman, 2018; Bansal et al., 2016). Thus, a statistical significance may exist between household size and intended AV adoption.

Regarding PAVs, Shabanpour et al. (2018) point out that households with more members – especially those with at least 3 household members – are more prone to buy PAVs in Chicago, Illinois. They think one reason is that parents would like to use PAVs to pick up and drop off their children without their presence, which would spare more time to them. They backed up their thought by their finding that large households that share vehicles among their members are more likely to buy PAVs. However, this thought is suspicious because households with 3 or more members do not have to have young dependents. In the GTHA, household size is not a significant factor for PAV adoption (Laidlaw & Sweet, 2017). This different finding may be caused by three reasons. First, the significance may vary across geographies. Second, they designed their surveys in different ways. Shabanpour et al. (2018) asked their survey participants lots of scenario questions, and then asked them whether they would buy the PAV as described. On the contrary, the survey that Laidlaw and Sweet (2017) used did not ask people's willingness to buy PAVs of different traits. Hence, a large household in the GTHA may have a stronger preference to buy PAVs of certain traits. Third, Shabanpour et al. (2018) treat households with at least 3 members as a group, while Laidlaw and Sweet (2017) do not indicate they do so.

In the GTHA, household size is a significant factor for SAV adoption: households with more members are likely to use SAVs more frequently only when the price is fair (Laidlaw & Sweet, 2017). In addition, using SAVs for accessing transit would obviously reduce the significance of household size for SAV adoption. Different from Laidlaw and Sweet, Bansal and Kockelman (2018) and Bansal et al. (2016) can only find a significant impact of household size on SAV adoption when the price is high, though the significance is not consistent in their studied high price range. Synthesizing the three studies, it seems that the significance of household size for SAV adoption do exist, but only at certain prices. Meanwhile, the significance varies at different geographies.

3.1.11 Household children

Some evidence shows that the number of children in a household has insignificant impacts on intended AV and PAV adoptions (Bansal & Kockelman, 2018; Zmud et al., 2018; Laidlaw & Sweet, 2017). However, its impact on intended SAV adoption is under debate. Krueger et al. (2016) did not find the impact significant in the metropolitan areas in Australia. Haboucha et al. (2017) found that in North America and Israel, drivers' households (not general households) with at least 1 child is moderately yet significantly associated with a higher favor of SAVs. In the GTHA, however, households with at least one member aged 15 or below are significantly less inclined to use SAVs if the SAVs are not used for accessing transit stations (Laidlaw & Sweet, 2017). On the contrary, these households are significantly more prone to use SAVs if SAVs are used for accessing transit stations.

There are some factors that may explain the differences. First is geography, which was clearly indicated above. Second is approach of data analysis. Haboucha et al. (2017) did not discuss presence of children in household in terms of different prices of SAVs and trip purposes, while Laidlaw and Sweet (2017) did. Thus, Haboucha et al. (2017) found one significant correlation, whereas Laidlaw and Sweet (2017) found the impact of household children is quite sensitive to trip purpose.

3.1.12 Driver's License Occupancy and Driving Experience

The impact of possession of a driver's license on people's intended PAV adoption is mediated by some agents. Specifically, people holding a driver's license but having a low WTP for PAVs typically do not want to buy PAVs (Bansal & Kockelman, 2018). This relationship is even stronger if they are older and more experienced in driving. These people are also substantially less interested in adding connectivity to AVs. Thus, CAVs do not make PAVs more acceptable to senior experienced drivers.

Some people with a driver's license as well as drivers are averse to PAVs not because they worry about cyber security and data privacy, and lack confidence in the reliability of the vehicle automation system. Kyriakidis et al. (2015) studied the correlations between 18 population features and confidence in AV-associated data transmission. They found that the number of years holding a driver's license has the highest absolute as well as positive impact on this confidence.

They also found that more experienced drivers are generally more confident in the safety of AVs without a steering wheel. Recalling Chapter 2, the thesis realizes that more experienced drivers are more reluctant to drive vehicles without a steering wheel because of a combined effect of desire for control, hedonic motivation, habit, traditions and social norms, performance expectancy, perceived usefulness, effort expectancy, facilitating condition, and trust. Thus, despite a strong trust in the reliability of PAVs, experienced drivers as well as people holding a driver's license for more years do not want to lose their control of their vehicles because they have been used to using the steering wheel, maneuvering their vehicles, and living with their developed driving habit.

Possession of a driver's license often discourages people to use SAVs (Bansal & Kockelman, 2018; Bansal et al., 2016). However, the discouragement is mediated by the purpose of using SAVs. In Puget Sound, people owning a driver's license are willing to use SAVs for car sharing, but not for on-demand vehicle services (Lavieri et al., 2017). The authors think one possible reason is that a driver's license would still be a necessity in car sharing, but would not in ride sourcing. Relating to the last paragraph, a more concrete explanation is that many people who have a driver's license have been used to using their license to drive, and have developed a habit of using a steering wheel when traveling; thus, they can accept an alternative travel mode still coping with their current travel behaviors, but cannot accept a travel mode that would cause the loss of their travel habits.

Like its impact on intended PAV adoption, the influence of possessing a driver's license on intended SAV adoption is mediated by some agents. In Texas, licensed people have a limited passion for SAV adoption (Bansal & Kockelman, 2018). This passion is even less if a Texan driver is a Caucasian, experienced, or live far away from a transit station. For another instance, experienced Austin drivers as well as senior Austin drivers typically show few interest in using SAVs (Bansal et al., 2016). Bansal et al. (2016) propose a few reasons. First, experienced drivers consider that learning using SAVs is a burden. Second, driving is enjoyable for them, so they do not want to lose the joy. The first reason reveals that perceived ease of use shapes senior drivers' intention to use SAVs. The second reason emphasizes that desire for control is a key construct of experienced drivers' reluctance to use SAVs. There may be other reasons. Liljamo et al. (2018)

reminds that possession of a driver's license is closely related to a limited use of public transit, while Laidlaw and Sweet (2017) consider SAVs would have an important function: improving people's accessibility to transit stations. Hence, the other reasons may include (1) being unwilling to share travel space with too many people, (2) suspecting that SAVs would be primarily used for accessing transit stations, and (3) believing that using SAVs would not be as time-saving as PAVs.

3.1.13 Personal Vehicle Ownership

Generally, there is a lack of significant relationship between personal vehicle ownership and intended AV adoption (Bansal & Kockelman, 2018;). However, people owning vehicles of some level of automation are more acceptable of AVs (Zmud et al., 2016; Konig & Neumayr, 2017).

3.1.14 Household Vehicle Ownership

The relationship between household vehicle ownership and intended AV adoption varies at different places. In Finland, households without a car, which usually rely on public transit, are significantly more enthusiastic about adopting AVs (Liljamo et al., 2018). On the contrary, households with at least 4 cars typically do not welcome AVs. In Puget Sound, the number of vehicles in a household has no significant relationship with intended AV and PAV adoptions (Lavieri et al., 2017). Similarly in the GTHA, households with 3 or more private vehicles do not appear significantly different from other households in terms of WTP for PAVs (Laidlaw & Sweet, 2017). However, two subgroups should get an attention. First, households owning a vehicle costing $30,000 or more are significantly more willing to pay more for PAVs. This point shows again that income is positively correlated with the intention to adopt PAVs. Second, households owning a hybrid vehicle strongly resist PAVs. Similarly in Puget Sound, experience of using car sharing would boost the likelihood that a household without or with only 1 vehicle would use AVs for car sharing (Lavieri et al., 2017). This point reflects again that technology use is an important construct of people's intention to adopt AVs.

Regarding SAVs, Laidlaw and Sweet (2017) draws more attention to the households with more private vehicles. They found that in the GTHA, households with 3 or more private vehicles would be significantly more averse to using SAVs if SAVs are not used to access transit stations at a fair prize. This aversion is actually outstandingly strong. This finding suggests that the significant negative correlation between household vehicle ownership and intended SAV adoption only exists under certain price and trip purpose. Looking at some subgroups is important as well. In the GTHA, households owning a vehicle costing $30,000 or more, and households owning a hybrid vehicle have significantly less favor of SAVs if using SAVs is not for accessing transit station at a fair price (Laidlaw & Sweet, 2017). Thus, the households may use SAVs more frequently if they are used to access public transit.

3.1.15 Vehicle Accident Experience

People who experienced at least one vehicle accident (not necessarily incurred an injury) are usually found to have better attitudes towards AVs, have a higher WTP, and would be future early AV adopters (Bansal & Kockelman, 2018; Bansal et al., 2016; Shabanpour et al., 2018; Kyriakidis et al., 2015). They usually significantly more appreciate the safety benefits of AVs (Bansal & Kockelman, 2018; Shabanpour et al., 2018). People with more experiences of vehicle accidents usually more value the safety benefits of AVs, and more want to adopt AVs (Bansal & Kockelman, 2018). Moreover, removing PAV drivers' liability in an accident, or drawing dedicated lanes for AVs would boost these people's passion for adopting AVs (Shabanpour et al., 2018).

Not directly contradicting with the above findings, experiencing one or more vehicle crashes significantly reduces people's WTP for PAVs in the GTHA (Laidlaw & Sweet, 2017). It is unknown whether the lower WTP implies a lower probability that they would eventually buy PAVs. Hence, the GTHA residents with at least one crash history may still be willing to purchase PAVs only if the purchase cost is low.

The relationship between vehicle accident experience and intended SAV adoption is not stable. In Texas, More than one fatal or serious crashes experienced in past 15 years is significantly related to a stronger wish to use SAVs as their primary or sole transportation mode even if the price is to be high (Bansal & Kockelman, 2018). Similarly in Austin, Texas, the number of experienced vehicle crashes is practically significantly and positively associated with the inclination to use SAVs at least once a week even if the price is to be high (Bansal et al., 2016). Thus, Bansal & Kockelman (2018) and Bansal et al. (2016) both reveal that people with at least 2 fatal or serious crashes would quite rely on SAVs, and their loyalty to SAV is resistant to price change. Probably, that is because these people highly doubt their driving skills, and have little trust in the safety of manually operated vehicles.

Different from the above two studies, Laidlaw and Sweet (2017) did not find a significant relationship between crash experience and intended SAV adoption in the GTHA. Probably it is because they discuss one and more crashes altogether, whereas one crash and more than one crash are discussed separately in the two case studies in Texas. It could also because the number of people having experienced more than one severe crash is much less in the GTHA.

3.1.16 Disability or Low Mobility

There are some observational evidence that people with a disability or low mobility may be more willing to adopt AVs, but the truth of the statement is yet to be further assessed. In Texas, this significance is indicated absent (Bansal & Kockelman, 2018). However, in Austin, Texas, Zmud et al. (2016) interviewed 11 people with a travel-restrictive disability. They were all highly enthusiastic about AVs because they commonly anticipated that AVs would fundamentally improve their mobility. If the 11 people perfectly represent the people with travel-restrictive mobility, then it would be true that travel-restrictive disability would ensure a high favor of adopting an AV. Adding to Zmud et al. (2016)'s qualitative finding, Shabanpour et al. (2018) quantified that Chicagoans with a disability are willing to pay 27% more for AVs.

As the study area of Zmud et al. (2016) is contained in the study area of Bansal and Kockelman (2018), it is necessary to figure out why the two sources suggest opposite relationships. The reason may be that Zmud et al. (2016) particularly interviewed people with a travel-restrictive disability, whereas Bansal and Kockelman (2018) studied the whole disabled population. As not all disabilities cause a decrease in travel mobility, the answers of people with a non-travel-restrictive disability may have diluted the effect of travel-restrictive disability on AV adoption. The difference of the two sources may also suggest there are lots of disabled people without a reduced travel mobility in Texas as well as its city: Austin.

There are some observational evidence that people with a disability or low mobility may be more willing to purchase PAVs. From an assessment of the textual responses to their international survey from people with a definite physical impairment or disability, Bazilinskyy et al. (2015) observed that people with mobility issues are quite looking forward to the market availability of AVs. For them, AVs would likely help them get a driver's license, and be a driver. They highly value this potential because they want to gain more mobility, and travel around independently. Laidlaw and Sweet (2017) noticed that the GTHA residents with a physical disability seem more willing to pay more for PAVs, though this tendency is insignificant.

In the GTHA, people with a disability are significantly more reluctant to use SAVs if the price is to be high (Laidlaw & Sweet, 2017). Thus, to increase their favor of SAVs, the price should be controlled at a fair level. In addition, SAVs should not be exclusively used for accessing transit because this exclusion would make them dramatically less favorable of SAVs. Nevertheless, even if the price is to be fair, the attractiveness of SAVs to these people would not be significantly high.

Krueger et al. (2016) studied a subgroup of people with declining mobility in Australia. They first hypothesized that either seniors aged 65 or over, or seniors aged 75 or over would be a major age group more favoring using SAVs because many seniors aged 75 or more lost their legal right to drive due to their declined health, while SAVs do not require users to have a driver's license. However, their hypothesis was rejected by their data analysis. This finding supports the finding from Section 3.1.1 that seniors have a much lower interest in SAVs.

3.1.17 Two Insufficiently Studied Variables

Bansal and Kockelman (2018) do not find that the number of workers in a household, and marital status have a practically significant relationship with AV adoption. Future AV researchers can verify this relationship, and also check whether the two variables have a significant relationship with intended PAV or SAV adoption.

3.2 Impacts of the Travel Characteristics of Individuals

8 of the 19 sources used in Section 3.1 also comprehensively modeled the relationship between the travel characteristics of individuals and people's intended adoption of AVs (Bansal & Kockelman, 2018; Bansal et al., 2016; Zmud et al., 2016; Shabanpour et al., 2018; Krueger et al., 2016; Haboucha et al., 2017; Konig & Neumayr, 2017; Laidlaw & Sweet, 2017). They will be

used for this section. As most of the studies discuss PAVs and SAVs separately, the section would put more efforts in discussing the impacts of the travel characteristics on the adoptions.

3.2.1 Trip purpose

Regarding PAV adoption, Bansal et al. (2016) found that Austinites who drive to work alone are likely to pay more than $10,000 to add level 4 automaton. It is unsure whether it is true at other places.

Regarding SAV adoption, Bansal and Kockelman (2018) found in Texas that a larger number of recreational trips is associated with a higher likelihood of using SAVs, and the tendency persists even if the price is high. Krueger et al. (2016) used trips for an educational purpose, or for going back home as bases, and found that two trip purposes – shopping, and medical or dental appointment – significantly decrease metropolitan Australians' likelihood of using SAVs without dynamic ride-sharing. In addition, no studied trip purpose (work, shopping, leisure, and medical or dental appointment) is significantly related to the Australians' likelihood of using SAVs with dynamic ride-sharing. Thus, leisure as well as casual trips is not significant in the SAV adoption in the metropolitan areas in Australia. Moreover, trips for work or school seem more involve SAVs there. Therefore, Bansal and Kockelman (2018), and Krueger et al. (2016) infer that trip purpose may be significantly related to intended SAV adoption at some places. Even if the significance exists, the influential trip purposes would vary from one place to another.

3.2.2 Transportation mode

Frequency of driving is not significantly associated with intended AV adoption (Konig & Neumayr, 2017).

Regarding PAVs, the GTHA residents who often drive are likely to become early adopters of PAVs (Laidlaw & Sweet, 2017). Other primary travel modes are not indicators of the GTHA residents' likelihood of adopting PAVs. Also found in Bansal and Kockelman (2018), Bansal et al. (2016), and Kyriakidis et al. (2015), people who drive more frequently are more likely to be early adopters of PAVs.

Regarding SAVs, primary travel mode is an indicator of the GTHA residents' likelihood of adopting SAVs (Laidlaw & Sweet, 2017). When SAVs are not for accessing transit, people who often drive would not use SAVs. However, when SAVs are for accessing transit, people of all primary transportation modes would be very passionate about using SAVs. Thus, the general public in the GTHA would be acceptable of using SAVs for increasing transit accessibility. Despite so, the passion of frequent drivers is obviously lower, which Bansal et al. (2016) also noticed.

Although not varying SAV price, Krueger et al. (2016) have similar findings as Laidlaw and Sweet (2017). They found that compared to those whose primary transportation modes are cycling and walking, Australians whose primary transportation modes are driving, taking public transit, or using both modes are more willing to use SAVs without dynamic ride-sharing, and transit users are more passionate about SAVs than drivers regardless of SAV types. They also found that people often comprehensively using multiple transportation modes prefer to use SAVs. Moreover, they noticed that frequent car-sharing users quite prefer to adopt SAVs with dynamic ride-sharing.

3.2.3 Travel frequency

Number of driving errands is an indicator of people's AV adoption (Zmud et al., 2016; Haboucha et al., 2017). Specifically, people who rarely drive or who do not drive express more enthusiasm towards AVs, while people with more daily driving errands would be more likely to keep their current vehicle, without a replacement by an AV. The second half of the relationship is consistent with a prior finding that more experienced drivers tend not to adopt AVs.

Regarding PAVs, in the GTHA, the residents who use on-demand driving services no more than once a week have a substantial passion to buy PAVs, with a higher WTP (Laidlaw & Sweet, 2017). Furthermore, the less they use on-demand driver services, the more passionate they are for PAV purchase. Thus, the attitudes of on-demand driving services users towards PAVs are differentiated by their frequencies of using the services. These findings are harmonious with a previous finding that frequent drivers are more likely to adopt PAVs.

Haboucha et al. (2017) found that in North America and Israel, the number of "errands on the way to work or in the middle of the day" (p. 45) has no significant relationship with the people's intended PAV adoption (Haboucha et al., 2017). Thus, their finding is different from that of Laidlaw and Sweet (2017). It is noticed that Haboucha et al. (2017) implemented analysis at a national scale, while Laidlaw and Sweet (2017) did it at a metropolitan scale. Hence, the difference in geographic scale may be a source of their difference.

Regarding SAVs, in the GTHA, the frequency of using on-demand driving services is significantly and positively related to intended SAV adoption (Laidlaw & Sweet, 2017). Therefore, frequent on-demand driving services users have drastically different attitudes towards PAVs and SAVs. Recalling that people who frequently drive, people who have a high household income, and people whose households have more private vehicles also have different attitudes towards PAVs and SAVs, it is necessary to discuss and model PAV and SAV adoptions separately.

Haboucha et al. (2017) found that in North America and Israel, the number of "errands on the way to work or in the middle of the day" (p. 45) has no significant relationship with the people's intended SAV adoption. However, in these regions, if people need to transport more items in a trip, they would be more reluctant to use SAVs.

3.2.4 Trip Distance / Travel Time

Regarding PAVs, a longer travel distance and a longer travel time both contribute to a stronger desire to purchase PAVs. Bansal and Kockelman (2018) mentioned that distance from workplace to home is positively and significantly correlated to WTP for level 4 automation, though this correlation is not practically significant (Bansal & Kockelman, 2018). In addition, Shabanpour et al. (2018) revealed that a longer annual vehicle miles traveled (VMT), and a longer travel time contribute to a higher demand for PAVs. Similarly, Kyriakidis et al. (2015) demonstrated that people who travel a longer distance usually are keener to purchase PAVs.

Trip distance is also an important factor for intended SAV adoption. Practically significantly, as the distance from one's home to his or her nearest transit station decreases, an Austinite is more likely to become one of the first to adopt SAVs as his or her primary or sole transportation mode, and vice versa (Bansal & Kockelman, 2018). The likelihood is higher if the price is lower. Thus, in Austin, people would be in favor of using SAVs for a short run to a transit station, especially if the price is to be fair. In terms of the trip distance to one's workplace, Bansal et al. (2016) identified that the relationship between the distance and intended SAV adoption is practically significant and positive when the price is fair. As the price rises over the fair range, the significance quickly weakens, and finally disappear. Thus, a fair SAV price may trigger people to live far away from their workplaces. Although not considering the variation of SAV price, Haboucha et al. (2017) also argue that people who needs to spend a longer time for commuting are more favorable of SAVs.

3.3 Impacts of Land Use

It is challenging to find studies discussing the impacts of land use on AV adoption. This challenge was also mentioned by Schelecter (2018). Only one paper has been found to exclusively model the impacts: Nodjomian and Kockelman (2018). A summary of some of their important findings is in Appendix B.

Some papers also model the impacts, though not exclusively (Laidlaw & Sweet, 2017; Bansal & Kockelman, 2018; Bansal et al., 2016; Liljamo et al., 2018). These papers will be used for the discussion in this section. In addition, Laidlaw et al. (2018) have some brief discussions on the impacts. Thus, it will also be used.

Contrary to the few amount of articles discussing the impacts of land use on AV adoption, there are many articles discussing the impacts of AV adoption on land use. Some of them include Bansal and Kockelman (2018), Bansal et al. (2018), Zmud et al. (2016), Heinrichs (2016), Meyer et al. (2017), Rice and Tomer (2017), Schlecter (2018), Soteropoulous et al. (2019), Henaghan (2018), Larson and Zhao (2017), Zhang (2017), Bertoncello and Wee (2015), and Hawkins and Habib (2019).

The importance of these articles have been carefully evaluated. First, it is aware that the impacts of AV adoption on land use do not necessarily provide implications on the impacts of land use on AV adoption. For example, Heinrichs (2016), Rice and Tomer (2017), Soteropoulous et al. (2019), Henaghan (2018), Zhang (2017), Bertoncello and Wee (2015), and Hawkins and Habib unanimously support that AVs, PAVs, and SAVs would all cause a reduction in parking spaces, with a loss of approximately 15% of current parking spaces in a PAV-only world, and approximately 90% of current parking spaces in an SAV-only world. However, it is not reasonable to say that the places with more parking spaces would be more harmonious to AV, PAV, and SAV adoptions. That is because it would be the built environment resulting from a conversion from parking spaces that would have some influences, while it is uncertain how many parking spaces would be lost in the future, where the loss would eventually happen, what exact built environment would be produced, and how many of the spaces would be converted into AV drop-off areas instead of a built environment (Heinrichs, 2016; Rice & Tomer, 2017; Soteropoulous et al., 2019; Zhang, 2017).

Understanding how AVs would change land uses has limited implications on understanding how land uses would affect AV adoptions also because the change of land uses is a very slow process – even slower than the slow change of the workplace locations and the residential locations of the population (Wegener, 2004).

3.3.1 Population Relocation

Although land use change is a very slow process, a large population relocation due to the general availability of AVs would still shape the future land uses, and would question the logic of using the current socioeconomic and travel characteristics of population, and land uses to model the PAV and SAV adoption potential of a place. Thus, it is necessary to examine whether the relocation would be in a large scale.

Many researchers have found that the relocation would be in a small scale. In Texas, it is expected that approximately 8 in 10 people would not make the relocation (Bansal & Kockelman, 2018; Bansal et al., 2016). Among those who would like to relocate themselves, roughly half of them would move farther away from a central city, while the remaining would move in the opposite direction. Typically, those who would like to move away from a central city have already lived in the suburb, while those who would like to move into the central city have already lived close to the central city. Thus, the distance of most Texans to their central cities would not radically change.

Zmud et al. (2016) used a qualitative approach to explore why some Austinites would like to relocate due to AV availability. Some would like to move away from the central city because they think the houses farther away from the central city may be more attractive. Thus, it is AVs' facilitating condition of realizing their goal of living in a better house that makes them wish to move towards the suburb. Some seniors wish to move closer to the central city because they are losing their confidence in driving, and thus need to use alternative travel modes, while using SAVs is considered a good alternative for them. They also explain that they anticipate SAVs to be concentrated in the more populated central city. These explanations remind that although seniors in general have much less favor of AVs, PAVs, and SAVs (see Section 3.1.1), transportation planners may not ignore the attraction of SAVs to some seniors as well as the economies of scale of using SAVs in denser areas.

The proportion of the population in other geographic areas who would like to relocate due to AVs is typically much lower than that in Texas. Soteropoulos et al. (2019) noticed from a review of more than 30 studies that this proportion is usually forecasted at no more than 5%. In addition, seniors are a major group intending to move to the suburb, while young people are a major group intending to move to the central city.

Meyer et al. (2017) used road capacity and accessibility to model the population relocation due to AV availability. They argue that both PAVs and SAVs would encourage people to use a vehicle for commuting. Thus, the already crowded roads in the central city would be more crowded and less accessible, while the suburban and rural roads would have an ample space to accommodate the increasing vehicle volume. As PAVs and SAVs would support long-distance commutes, many people would move further away from their central cities so as to enjoy a better traffic and accessibility. Therefore, both PAVs and SAVs would contribute to urban sprawl. The logic of Meyer et al. (2017) is that accessibility can efficiently predict where people would relocate, but this logic is likely problematic. This is because more than 30 studies argue that SAVs would contribute to an increase of inner city population, rather than inner city decay (Soteropoulos et al., 2019). Zhang (2017) supplements that SAVs would indeed contribute to a longer commuting distance, but this contribution does not guarantee a longer commuting distance from one’s home to one’s central city. In fact, this distance would not change much. In addition, Zhang (2017) pointed out some concrete reasons why people would not move away from the central city due to the availability of SAVs. First, the waiting time of SAVs would be shorter in denser areas, so the best efficient use of SAVs would not be in suburbs or rural areas.

Second, better educational institutions and resources are usually not in rural areas but in city or town centers. They will attract people to stay closer to them. Third, there would be much less job opportunities in rural and suburban areas.

Urban morphology is a mediator of the impacts of AVs, PAVs, and SAVs on population migration. Herinrichs (2016) believe that the land use impacts of AVs, PAVs, and SAVs would be different at different types of cities. He classified cities into three categories: (1) regenerative city, which is characterized by a development focus on energy-sector-related technologies, intense competition with other cities to attract population, and a relatively compact urban landscape; (2) hypermobile city, which is characterized by a development focus on lifestyle-and-commercial-benefit-oriented technology, cooperation between the public and the private sectors, and a continuous and sprawled urban landscape; and (3) endless city, which is characterized by limited and passive technological development, weakly powered government, and a fragmented urban landscape with a low population density. In an AV-dominant world, a current regenerative city would develop into a large region with a central business district and multiple local urban centers, and would have SAVs more commonly used than PAVs. A hypermobile city would have young people moving to and staying in the central business district. It would also have high-income people moving to the suburb and even the nearby rural areas. It is implied that SAVs would be more important in the central business district, while PAVs would be more important in the suburb and rural areas. An endless city would be sprawling, and its central business district will be decaying. PAVs would dominant there.

3.3.2 Distance from the Central City

Section 3.3.1 seemingly implies that distance from the central city is an indicator of where would locate the people who would more prefer AVs, PAVs or, SAVs when AVs become market available. However, this implication is verified not true in Texas (Bansal & Kockelman, 2018). More verifications need to be done in other places before deciding the general truth of this implication.

Distance from the central city may be an indicator of SAV adoption. Bansal and Kockelman (2018) found that the Texans living more than 10 miles (16 km) from downtown are willing to use

SAVs, though whether it is practically significant is not directly mentioned. This finding contrasts the argument that SAVs are only important in the central city. However, the importance of SAVs in the suburb needs more research to be confirmed and explained. Bansal and Kockelman (2018) also found that the Texans living in proximity to and in urban centers are anticipated to be more favorable of SAVs if the price is to be fair. This finding is consistent with the relevant finding of Soteropoulos et al. (2019) (see Section 3.3.1).

3.3.3 Population Density

There is a significant relationship between population density and intended AV adoption. In Texas, it is practically significant that the less the population density, the higher the proportion of people who are in favor of adopting AVs (Bansal & Kockelman, 2018). Liljamo et al. (2018) have an opposite finding. They classified Finland into (1) densely populated area, (2) sparsely populated urban area, and (3) sparsely populated area. Then, they found that the proportion of Finns favoring AVs is the highest in the first area, and the lowest in the third area. In addition, the proportions are obviously different in the three areas. Thus, in Finland, a higher population density is associated with a higher likelihood of AV adoption. There are two possible explanations on the difference of the two studies. First, the relationship between population density and intended AV adoption may vary across geographies. Second, the default meaning of AVs may vary across geographies, while as shown by previous sub-sections and sections in this Chapter, the impact of a factor is often different for PAVs and SAVs.

Regarding PAVs, there is no practical significance between population density and intended PAV adoption in Texas (Bansal & Kockelman, 2018). This insignificance should be checked in other geographies.

Regarding SAVs, there is no practical significance between population density and intended SAV adoption in Texas (Bansal & Kockelman, 2018). However, when the geographic scale is downscaled to the capital city of Texas, a practical significance emerges: SAVs are more adaptable in the census blocks with a higher population density (Bansal et al., 2016). This difference suggests that discussing SAVs as well as PAVs and AVs at a scale larger than a metropolitan scale may dissipate the significance of population density. Inferred from Laidlaw and Sweet (2017), the GTHA residents living in and near densely populated areas, such as urban and suburban centers, are more favorable of using SAVs.

3.3.4 Job Density / Employment density

There is no practical significance between employment density and intended AV adoption in Austin, Texas (Bansal et al., 2016). However, it does not mean it is absent in other cities and metropolitan areas. By measuring job density by the number of jobs within ten kilometers of one's living neighbourhoods, a higher job density is significantly associated with a higher passion for PAV adoption (Laidlaw & Sweet, 2017). The significance presents for SAV adoption as well only if SAVs are not exclusively for accessing transit at a fair price. Interestingly, in the range of $0.50/km to $1.50/km, the higher the price, the stronger the significance. Thus, the significance of job density is resistant to price change.

3.3.5 Housing Type

Housing type is not significant for intended PAV adoption in the GTHA (Laidlaw and Sweet, 2017). There is a mere significant and positive relationship between living in an apartment and intending to use SAVs when the price is fair and when they are not for accessing transit. Laidlaw and Sweet (2017) consider the mere significance as an important evidence that people living in and near densely populated areas are more likely to use SAVs.

3.3.6 Household density

The impacts of household density may vary across geographies. In Puget Sound, people living in the census blocks with a household density of at least 3,000 households per square mile (1,158 households per square km) are significantly more willing to adopt both PAVs and SAVs (Lavieri et al., 2017). However, an interesting phenomenon exists in Austin, Texas: practical significance with intended SAV adoption is lost when population density is replaced by household density (Bansal et al., 2016). The loss may reflect that population density is a better measure to consider for planning SAV as well as AV and PAV adoptions. There is one evidence to support this reflection: population density directly reveals how many people – the consumers of PAVs and SAVs – live in a unit area, whereas household density does not.

3.4 Summary of Chapter 3

This chapter provides a profile of the impacts of (1) the socioeconomic characteristics of individuals, (2) the travel characteristics of individuals, and (3) land use on intended AV, PAV, and SAV adoptions. Table 3.2 summarizes what are expected to be generally true about the impacts, from the reviewed 24 studies. This table would be a good resource for the planners and policy makers around the world, especially those in developed countries.

Table 3.2 Impacts of Studied Variables on Intended AV, PAV, and SAV Adoptions

Variable	AVs	PAVs	SAVs
Impacts of the Socioeconomic Characteristics of Individuals			
Age	–	–	– (price sensitive)
Gender	Male: + Female: –	x	x
Citizenship	Varies from country to country	Varies from country to country	Varies from country to country
Ethnicity	Indigenous people (Australia): – Whites / European Whites / Caucasians: ?	Indigenous people (Australia): – Whites / European Whites / Caucasians: ?	Indigenous people (Australia): – Whites / European Whites / Caucasians (Texas): –
Education	Some places: +	+	+ (price sensitive)
Student status	+	Home-based students: + All students: ?	?
Employment status	Full-time: +	Full-time: + Home-based: + Work > 60 h: +	Jobless: + Not in the labour force: + Home-based: + Full time/part time: + Work > 60 h: + (price sensitive) Retired: x
Occupation	Professional driver: –	Professional driver: – Manufacturing, construction, and trades: x Professional, management, and technical (excluding medical science labourers): x Sales and service: x Medical science: +	Professional driver: – Manufacturing, construction, and trades: + Professional, management, and technical (excluding medical science labourers): – (price sensitive) Sales and service: – Medical science: + (price sensitive)
Number of workers in household	x	?	?
Household income	+ (place sensitive)	+ (place sensitive)	No observable linear correlation. Some household income ranges may be significant under certain prices or trip purposes
Personal income	Generally: + (geographic-scale sensitive) driver: +	Generally: ? Driver: +	?
Household size	?	Relationship depends on vehicle traits	+ (price sensitive)
Household children	x	x	Relationship depends on price and trip purpose

Table 3.2 Continued

Variable	AVs	PAVs	SAVs
Marital status	x	?	?
Driver's license occupancy / driving experience	?	–	On-demand SAVs: – As carpooling SAV driver: +
Private vehicle (PV) ownership	Generally: x Not owning an automated vehicle: ? Owning an automated vehicle: +	Generally: x Own > 1 vehicle: + Own an automated vehicle: +	To use on-demand SAV: – To be carpooling SAV driver: +
Household vehicle ownership	In Finland: – In Puget Sound: x	Generally: x Own a relatively more expensive PV: + Own a hybrid vehicle: –	– (price sensitive and trip purpose sensitive)
Vehicle accident experience	?	In general: +	< 2 severe crash experience: x > 1 severe crash experience: +
Disability / low mobility	Travel-restrictive disability: + General: x	Positive (insignificant)	– (price sensitive)
Impacts of the Travel Characteristics of Individuals			
Trip purpose	?	?	Vary from place to place
Transportation mode	Impact is different between PAVs and SAVs	Primary travel mode = driving: +	Primary travel mode: vary from place to place, but often driving: – Ride-sharing users: + Multi-mode travelers: +
Travel frequency	# daily driving errands: –	# On-demand driving services use per month: – # errands on the way to work or in the middle of the day: x	# On-demand driving services use per month: + # errands on the way to work or in the middle of the day: x Often transport lots of items on a trip: –
Trip distance / travel time	?	Distance from workplace: +	Distance from workplace: (1) fair price: + (2) high price: x
Impacts of Land Use			
Population Relocation	Impacts depend on type of AVs	Encourage a small portion of the population to move farther away from the central city and local urban centers	Encourage a small portion of the population to move closer to the central city and local urban centers
Distance from the central city	x	x	In and near the central city or local urban centers: + In the suburb: ?

Table 3.2 Continued

Variable	AVs	PAVs	SAVs
Population density	Varies over geographies	?	At a metropolitan scale: + At a provincial/state scale: x
Job density / Employment density	# jobs within 10 km of one's home: +	# jobs within 10 km of one's home: +	# jobs within 10 km of one's home: +
Housing type	?	x	Apartment: + (price sensitive and subject to trip purpose) Townhouse: x House: x
Household density	?	≥ 1,158 households/km^2: +	≥ 1,158 households/km^2: +

Notes:
+ Significant positive correlation
– Significant negative correlation
x No significant correlation
? Unknown or unclear correlation

Chapter 4: Methodology

This thesis has used Chapter 2 and Chapter 3 to find out many factors that influences one's decision making on AVs, PAVs, and SAVs. The two chapters are the efforts of answering the first research question. They reveal that talking PAVs and SAVs together as AVs is problematic as the impacts of a variable on them are often different. Thus, there is no necessity to model AV adoption potential. Hence, this chapter would only model the PAV and SAV adoption potential in the urban context.

As Table 3.1 reflects, many AV researchers develop a survey to assess what variables are significantly related to the people's intentions to adopt PAVs and SAVs, how significant the relationships are, and what variables are relatively more influential in the people's intentions in a geographic area. If the samples of a survey well represent the whole population of the area, the survey results can be formulated into mathematical equations, which provide scores representing the PAV and SAV adoption potential in the area. As Chapter 3 indicates that some variables significant in one location are not significant in another, this approach accurately finds the variables that have a significant impact in a particular area, and thus accurately models the potential in the area. However, not all urban areas have sufficient resources, funding, and time to design and conduct a survey, and analyze and formulate the survey results. Therefore, the planners of some municipalities would prefer to find and use a commonly true model to decently model the PAV and SAV adoption potential in their municipalities, though the model may not generate the most accurate results.

Chapter 3 also indicates that multiple studies find the same relationship between a variable and one's intention to adopt PAVs or SAVs at multiple geographic locations. This indication justifies that there exist commonly true models that yield the PAV and SAV adoption potential of most (if not all) municipalities. Therefore, this thesis comprehensively reviewed other AV researchers' findings, and would soon select the variables that usually influence one's intention to adopt PAVs or SAVs. Later, the thesis would assess the studies that assign a weight to each of their studied variables. Through the selection and assessment processes, the thesis would eventually formulate a few mathematical equations that can be commonly used in evaluating the PAV and SAV adoption potential in a municipality, or an urban area. As no AV researchers have formulated the equations, this thesis is the first effort to create the indices.

The thesis is aware that the socioeconomic profile and land uses of an urban area vary internally. Thus, the PAV and SAV adoption potential varies internally in the area. Hence, to also model the variation, an urban area would be divided into the census geographic units (CGUs) of the same hierarchy, such as the census tracts (CTs) in Canada, and the census blocks in America. Hence, it is the PAV and SAV adoption potential in each CGU that would be modeled.

In addition to creating the models, the thesis would introduce some methods of using the modeling results to analyze the PAV and SAV adoption potential in the urban area. This introduction would build a methodological foundation for the next chapter, which would be a case study of the potential in the GTHA.

4.1 Modeling the PAV and SAV Adoption Potential in a CGU

4.1.1 The Scoring Model

Social scientists often use a linear regression, or a linear model to simulate the relationship between a response variable and its explanatory variables. Sample works include the studies listed in Table 3.1 that use a quantitative method with a definite sample size. Thus, the thesis chooses to formulate PAV and SAV adoption potential into linear equations, and the thesis calls them scoring models. The general form of a scoring model is

$$y = a_1x_1 + a_2x_2 + \cdots + a_nx_n \tag{1}$$

where y is an adoption potential score; $x_1, \ldots, x_n$ are the normalized quantified importance of the explanatory variables for y; and $a_1, \ldots, a_n$ indicate the weights of their corresponding explanatory variables in the generation of the score. Particularly, $a_1 + a_2 + \cdots + a_n = 1, a \in (0,1)$, and $x \in [0,1]$.

4.1.2 The Database for the Modeling

Census data is a common type of data to which planners and researchers have access. However, different countries may differ somewhat in terms of the specific data for collection. To make sure the eventually built models are usable in the GTHA as well as other municipalities and metropolitans in Canada, the variables not collected by the 2016 Canadian census data (hereafter, referenced as "the census data") will not be qualified as a modeling variable. In addition, how a modeling variable is measured will be tailored to how the data of the variable is collected by the census.

4.1.3 Three Scenarios for the Modeling

As mentioned in Chapter 3, PAV and SAV adoptions should be discussed separately. In addition, a variable may affect one's intention to adopt SAVs differently at different prices. Therefore, the thesis will create three scenarios for modeling: (1) adopting PAVs, (2) adopting SAVs with a fair price, and (3) adopting SAVs with a high price. Adopting PAVs is not differentiated by different price levels because no reviewed study has modeled intended PAV adoption at different costs. Due to a similar reason, there would be no scenario for adopting SAVs with a low price because no reviewed study has modeled this price scenario.

It is aware that Laidlaw and Sweet (2017) demonstrate the importance of discussing intended SAV adoption in terms of SAVs' function to public transit. However, in addition to Laidlaw and Sweet (2017), no other studies have this discussion. Therefore, SAVs as a means of accessing public transit is not fully explored, so no scenarios will be created due to this means.

4.1.4 The Variables Chosen for the Modeling

For the simplicity of the scoring models, for each adoption scenario, 6 variables will be chosen as the explanatory variables for modeling (hereafter, referenced as "modeling variables"). To select the variables, the following steps will be followed. First, the variables without a 2016 Canadian census data are disqualified. Second, the variables identified as not significant and not sufficiently studied in Chapter 3 are disqualified. Third, the abstracts and conclusions of all reviewed studies in chapters 3 will be re-examined. If the importance of a variable for an adoption scenario is mentioned in the abstract or the conclusion of a study, it will be considered emphasized by the study for that scenario. Particularly for the last two scenarios, it is noticed that only three studies discuss intended SAV adoption by different prices. Thus, the thesis

Table 4.1 Qualification of Reviewed Variables from Chapter 3

Variable	Intended PAV adoption in the GTHA	Intended SAV adoption (fair price) in the GTHA	Intended SAV adoption (high price) in the GTHA
Socioeconomic Characteristics of Individuals			
Age	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016); Shabanpour et al. (2018); Haboucha et al. (2017)	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016); Lavieri et al. (2017); Krueger et al. (2016); Haboucha et al. (2017)	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016)
Gender	Disqualified by Chapter 3 (no significant impact)	Disqualified by Chapter 3 (no significant impact)	Disqualified by Chapter 3 (no significant impact)
Citizenship	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not sufficiently studied)
Ethnicity	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not sufficiently studied)
Education	Importance emphasized by Laidlaw and Sweet (2017); Haboucha et al. (2017)	Importance emphasized by Laidlaw and Sweet (2017); Lavieri et al. (2017); Haboucha et al. (2017)	Importance emphasized by Laidlaw and Sweet (2017)
Student status	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)
Employment status	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Occupation	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Number of workers in household	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)
Household income	Importance emphasized by Bansal and Kockelman (2018); Bansal et al. (2016); Shabanpour et al. (2018)	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Personal income	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)
Household size	Disqualified by Chapter 3 (no generally true impact)	Importance not emphasized by any reviewed studies	Disqualified by Chapter 3 (no significant impact)
Household children	Disqualified by Chapter 3 (no significant impact)	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Marital status	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)	Disqualified by Chapter 3 (not studied)
Driver’s license/driving experience	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified for lack of census data

Table 4.1 Continued

Variable	Intended PAV adoption in the GTHA	Intended SAV adoption (fair price) in the GTHA	Intended SAV adoption (high price) in the GTHA
PV ownership	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified for lack of census data
Household vehicle ownership	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified by Chapter 3 (no significant impact)
Vehicle accident experience	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified for lack of census data
Disability / low mobility	Disqualified for lack of census data	Disqualified by Chapter 3 (no significant impact)	Disqualified for lack of census data
Travel Characteristics of Individuals			
Trip purpose	Disqualified by Chapter 3 (not sufficiently studied)	Disqualified by Chapter 3 (lack of generally true findings)	Disqualified by Chapter 3 (lack of generally true findings)
Transportation mode	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016); Kyriakidis et al. (2015)	Importance emphasized by Laidlaw and Sweet (2017); Bansal et al. (2016); Lavieri et al. (2017); Krueger et al. (2016)	Importance supported by Laidlaw and Sweet (2017); Bansal et al. (2016)
Travel frequency	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified for lack of census data
Trip distance / travel time	Importance supported by Shabanpour et al. (2018); Kyriakidis et al. (2015); Haboucha et al. (2017)	Importance supported by Haboucha et al. (2017)	Disqualified by Chapter 3 (no significant impact)
Land Use			
Population relocation	Disqualified for lack of census data	Disqualified for lack of census data	Disqualified for lack of census data
Distance from the central city	Disqualified by Chapter 3 (not sufficiently studied)	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016)	Importance emphasized by Laidlaw and Sweet (2017); Bansal and Kockelman (2018); Bansal et al. (2016)
Population density	Disqualified by Chapter 3 (not sufficiently studied)	Importance emphasized by Bansal et al. (2016)	Importance emphasized by Bansal et al. (2016)
Job density / employment density	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Housing type	Disqualified by Chapter 3 (no significant impact)	Importance not emphasized by any reviewed studies	Importance not emphasized by any reviewed studies
Household density	Importance not emphasized by any reviewed studies	Importance emphasized by Lavieri et al. (2017)	Importance not emphasized by any reviewed studies

assumes that when survey participants are asked about their intention to use SAVs without being provided with an assumed price, they would assume the price to be fair. Therefore, the conclusions from the studies not discussing SAVs by price scenarios will be used for the scenario that the price of SAVs would be fair. Table 4.1 summarizes the works done through the first three steps. Fourth, the variables not emphasized by any reviewed studies will be discussed because the importance of some of them may have been ignored by AV researchers from a planning perspective. Thus, this step tries to identify one or a few variables that have been ignored by the scholars, and that must be included in the scoring modeling for an adoption scenario. Fifth, through a further discussion, the thesis will decide the final chosen variables for the modeling.

4.1.4.1 Two Scoring Models for Intended PAV Adoption

Table 4.2 indicates that there are five primary candidates for the scoring modeling for the PAV adoption in the GTHA beca use their importance is emphasized by at least one study. Three of them belong to the socioeconomic characteristics of individuals: age, education, and household income. Two of them belong to the travel characteristics of individuals: transportation mode, and trip distance. As the meanings of the five variables are relatively independent, and as the number of primary candidates is less than 6, all of the five primary variables will be used for the scoring modeling for the intended PAV adoption in the GTHA.

There is a need to find one more candidate to reflect the impacts of land use on intended PAV adoption. There are two such candidates. One is job density. The other is household density. Job density is chosen because of its uniqueness. It reflects the number of people going to a census tract, so it is associated with people's as well as their vehicles' destinations. Thus, places with a higher job density are likely to have a higher traffic volume of PAVs and also SAVs. It should be emphasized that job density is the only variable that directly reflects people's destinations, and that is not disqualified by Table 4.1 in any of the three scenarios. Therefore, job density will join the scoring modeling for all three scenarios.

The thesis decides to create two scoring models for each scenario because of a challenge. All reviewed studies use different approaches to study the impacts of some variables on intended PAV or SAV adoptions, and the variables and the number of variables that they discuss are usually different. Thus, it is impossible to check whether the relative importance of one variable is consistent among a fixed set of variables. Hence, it is challenging to assign an exact weight to a variable. One way to circumvent the challenge is to assume that all modeling variables are equally important. Another way is to give an overall assessment of the ranks of the importance of the variables in each relevant study, and use a set of weights to demonstrate the result of the assessment. The two ways will yield two models for each scenario.

Despite that two models are created for each scenario, the thesis would give the models produced by the second way more emphasis. There are two reasons for it. First, the first way assumes that all modeling variables are equally important, but in reality, the importance of modeling variables are not necessarily the same. This reality does not mean that creating a model assuming all modeling variables being equally important is meaningless because it would be used to compare with the model assuming all modeling variables not necessarily being equally important. Particularly, the thesis would examine whether the latter model would produce a different result from the former model, and how much the difference would be.

Table 4.2 shows the ranks of the importance of the six variables as demonstrated by the modeling results of selected studies. They have at least 5 modeled variables that the thesis also studies. To illustrate how to read the Table, the cell with "6th out of 9" means 9 of the variables that Laidlaw and Sweet (2017) modeled are what the thesis also studies. Meanwhile, they are found significantly associated with intended PAV adoption in Laidlaw and Sweet (2017). Among the 9 variables, the importance of age is ranked the sixth in Laidlaw and Sweet (2017) in terms of intended PAV adoption. The rank is then converted to a percentile (6 ÷ 9 = 67% = 67th percentile). Through this conversion, the importance and rank of each modeling variable from all the studies become comparable.

Assuming the average percentiles of rank in Table 4.2 well indicate the relative importance of the six variables for the intended PAV adoption, the first scoring model is

$$y = \frac{1}{6}x_1 + \frac{1}{6}x_2 + \frac{1}{6}x_3 + \frac{1}{6}x_4 + \frac{1}{6}x_5 + \frac{1}{6}x_6 \quad (2)$$

where, as adopted to the 2016 Canadian census data,

x_1 is the normalized percentage of people who have a university certificate, diploma or degree at bachelor level or above, in a CGU, which measures education;

Table 4.2 The Importance of 6 Variables for Intended PAV Adoption

Variable	Age	Education	Household income	Transportation mode	Trip distance / travel time	Job density
Laidlaw and Sweet (2017)	6th out of 9 (67th percentile)	2nd out of 9 (22nd percentile)	1st out of 9 (11th percentile)	7th out of 9 (78th percentile)		9th out of 9 (100th percentile)
Bansal and Kockelman (2018)	2nd out of 6 (33rd percentile)		6th out of 6 (100th percentile)		5th out of 6 (83rd percentile)	
Bansal et al. (2016)	7th out of 8 (88th percentile)		8th out of 8 (100th percentile)	1st out of 8 (13th percentile)	5th out of 8 (63rd percentile)	
Shabanpour et al. (2018)	5th out of 7 (71st percentile)		4th out of 7 (57th percentile)	1st out of 7 (14th percentile)	7th out of 7 (100th percentile)	
Average percentile of rank	**65th**	**22nd**	**67th**	**35th**	**82nd**	**100th**
Percentile of importance	**35th**	**78th**	**33rd**	**65th**	**18th**	**10th** [1]
Normalized importance	**0.15**	**0.33**	**0.14**	**0.27**	**0.07**	**0.04**

1 The percentile of importance is actually 0th, but it is adjusted to 10th for the recognition of the importance of job density.

x_2 is the normalized percentage of people whose main mode of commuting is driving a car, a truck , or a van, among the people who are at least 15 years old, who live in a private household, and who are employed, in a CGU, which measures transportation mode;

x_3 is the normalized percentage of people who are 15 to 34 years old in a CGU, which measures age;

x_4 is the normalized percentage of private households in a CGU whose annual total income are at least \$100,000, which measures household income;

x_5 is the normalized percentage of people who spend at least 30 minutes for the commute from their homes to their workplaces, among the people who report their commuting time from their homes to their workplaces, who are at least 15 years old, who live in a private household, and who are employed, in a CGU, which measures trip distance;

x_6 is the normalized number of jobs per square kilometer in a CGU, which measures job density; and

y is the PAV adoption potential score of the CGU, generated from its values of x_1, x_2, x_3, x_4, x_5, and x_6.

This model assumes that the importance of household income, education, age, transportation mode, trip distance, and job density for intended PAV adoption is the same.

The second scoring model is

$$y = 0.33x_1 + 0.27x_2 + 0.15x_3 + 0.14x_4 + 0.07x_5 + 0.04x_6 \tag{3}$$

where the meanings of x_1, x_2, x_3, x_4, x_5, x_6, and y are the same as those of Equation (2). This model assumes that the importance of household income, education, age, transportation mode, trip distance, and job density for intended PAV adoption is not necessarily the same.

4.1.4.2 Two Scoring Models for the Intended SAV Adoption at a Fair Price

This sub-section is to create two scoring models for the SAV adoption assuming the price of SAVs would be fair. By Section 4.1.4.1, job density is a modeling variable for this scenario. Now, 5 more modeling variables need to be chosen.

Table 4.1 indicates that there are 7 variables whose importance for the adoption scenario has been emphasized by at least one study. 2 of them belong to the socioeconomic characteristics of individuals: age, and education. 2 of them belong to the travel characteristics of individuals: transportation mode, and trip distance. 3 of them belong to land use: distance from the central city, population density, and household density.

Although not disqualified by Table 4.1, the qualifications of three of the seven variables are arguable. First, section 3.2.4 points out that the conclusion of Haboucha et al. (2017) on the impact of trip distance on intended SAV adoption is likely unsuitable for an urban area, whereas Haboucha et al. (2017) is the only study emphasizing the significance of the impact. Therefore, trip distance is removed from the candidates. Second, Sections 3.3.1 and 3.3.2 reveal that the impact of distance from the central city is not linear. Rather, it is in the central city and in the narrow belt adjacent to the central city that SAVs are most favored. However, no study mentions how wide the belt is. Thus, it is challenging to develop a strategy to measure the distance from the central city. Therefore, it is removed from the candidates. In spite of this challenge, the studies emphasizing the importance of distance from the central city remind that this importance can be partially covered by the importance of population density and job density. This is because the central city and the adjacent belt have a high density.

As the meanings of household density and population density highly overlap, it may not be ideal to include both in the modeling. As section 3.3.6 points out that population density is a better choice, compared to household density, population density becomes the second chosen modeling variable for the scenario.

After age, education, and transportation mode join population density and job density, there needs to find one more variable to join the modeling process. There are five variables whose importance for the scenario is not emphasized by any studies. They are employment status, occupation, household income, household size, and housing type. Among them, Laidlaw and Sweet (2017) identify employment status as the most statistically influential variable, followed by household income, and occupation. Section 3.1.6 reminds that employment status is not a practical indicator of intended SAV adoption because no particular social group stands for this variable. In terms of household income, Laidlaw and Sweet (2017) do not find any income groups significantly more favoring SAV adoption at a fair price, though they found many income groups have substantially less passion for SAVs. As Laidlaw and Sweet (2017) found people doing a few types of occupations particularly more favor SAVs, occupation is chosen to join the modeling.

Like section 4.1.4.1, two equations will be generated. Assuming the average percentiles of rank well indicate the relative importance of the six variables for the intended SAV adoption scenario, the third scoring model is

$$y = \frac{1}{6}x_1 + \frac{1}{6}x_2 + \frac{1}{6}x_3 + \frac{1}{6}x_4 + \frac{1}{6}x_5 + \frac{1}{6}x_6 \quad (4)$$

where, as adopted to the 2016 Canadian census data,

x_1 is the normalized percentage of people whose main mode of commuting is riding (but not driving) a car, a truck , or a van; using public transit; walking; or cycling, among the people who are at least 15 years old, who live in a private household, and who are employed, in a CGU, which measures transportation mode;

x_2 is the normalized percentage of people aged 15 or over in the labour force whose National Occupation Classification (NOC) occupations are one of the following: (1) trades, transport and equipment operators and related occupations; and (2) occupations in manufacturing and utilities, in a CGU, which measures occupation;

x_3 is the normalized percentage of people who have a university certificate, diploma or degree at bachelor level or above in a CGU, which measures education;

x_4 is the normalized percentage of people who were 15 to 34 years old in a CGU, which measures age;

x_5 is the normalized number of jobs per square kilometer in a CGU, which measures job density;

x_6 is the normalized number of people per square kilometer in a CGU, which measures population density; and

y is the SAV adoption potential score of the CGU generated from its values of x_1, x_2, x_3, x_4, x_5, and x_6. This score refers to the case that the price of SAVs would be fair. This model assumes that the importance of transportation mode, occupation, education, age, job density, and population density for intended SAV adoption at a fair price is the same.

Table 4.3 The Importance of 6 Variables for Intended SAV Adoption at a Fair Price

Variable	**Age**	**Education**	**Occupation**	**Transportation mode**	**Population density**	**Job density**
Laidlaw and Sweet (2017)	10th out of 13 (77th percentile)	7th out of 13 (54th percentile)	6 out of 13 (46th percentile)	1st out of 13 (8th percentile)		11th out of 13 (85th percentile)
Bansal and Kockelman (2018)						
Bansal et al. (2016)					6th out of 6 (100th percentile)	
Average percentile of rank	**77th**	**54th**	**46th**	**8th**	**100th**	**85th**
Percentile of importance	**23rd**	**46th**	**54th**	**92th**	**10th** [1]	**15th**
Normalized importance	**0.10**	**0.19**	**0.23**	**0.38**	**0.04**	**0.06**

1 The percentile of importance is actually 0th, but it is adjusted to 10th for the recognition of the importance of population density.

The fourth scoring model is

$$y = 0.38x_1 + 0.23x_2 + 0.19x_3 + 0.10x_4 + 0.06x_5 + 0.04x_6 \quad (5)$$

where the meanings of x_1, x_2, x_3, x_4, x_5, x_6, and y are the same as those of Equation (4). The weights of each variable are assigned through a similar process as the one producing Equation (3) (see Table 4.3). This model assumes that the importance of transportation mode, occupation, education, age, job density, and population density for intended SAV adoption at a fair price is not necessarily the same.

4.1.4.3 Two Scoring Models for the Intended SAV Adoption at a High Price

This sub-section is to create two scoring models for the intended SAV adoption assuming the price of SAVs would be high. By section 4.1.4.1, job density is a modeling variable for this scenario. Now, 5 more modeling variables need to be chosen.

Table 4.1 indicates that there are 5 variables whose importance for the adoption scenario has been emphasized by at least one study. 2 of them belong to the socioeconomic characteristics of individuals: age, and education. 1 of them belong to the travel characteristics of individuals: transportation mode. 2 of them belong to land use: distance from the central city, and population density. As discussed in section 4.1.4.2, distance from the central city will not participate in the modeling, while the other four variables will participate in the modeling.

Now, there needs to find one more variable to join the modeling process. There are six variables whose importance for the scenario is not emphasized by any studies. They are employment status, occupation, household income, household children, housing type, and household density. Among them, Laidlaw and Sweet (2017) identifies employment status as the most statistically influential variable, followed by household income and occupation. Due to the same reasons as mentioned in section 4.1.4.2, occupation is chosen to join the modeling.

It is noticed that the modeling variables in section 4.1.4.2 and this section are the same. Therefore, assuming the importance of the six variables is the same for the high-price scenario, the scoring model is

$$y = \frac{1}{6}x_1 + \frac{1}{6}x_2 + \frac{1}{6}x_3 + \frac{1}{6}x_4 + \frac{1}{6}x_5 + \frac{1}{6}x_6 \tag{6}$$

where the meanings of x_1, x_2, x_3, x_4, x_5, x_6, and y are the same as those in Equation (4). This score refers to the case that the price of SAVs would be high. As Equation (4) and Equation (6) are the same, assuming modeling variables having the same importance would not result in different SAV adoption potential scores.

Equation (7) models the high-price SAV adoption potential score assuming the modeling variables do not necessarily have the same importance. This equation is

$$y = 0.35x_1 + 0.16x_2 + 0.24x_3 + 0.16x_4 + 0.05x_5 + 0.04x_6 \quad (7)$$

where the meanings of x_1, x_2, x_3, x_4, x_5, x_6, and y are the same as those of Equation (4). The weights of each variable are assigned through a similar process as the one producing Equation (3) (see Table 4.4). Through a comparison between Equation (5) and Equation (7), the fair price and the high price scenarios both have the same modeling variables, though they often differ in their weights. This difference gives a meaning to discussing intended SAV adoption at different prices.

Table 4.4 Importance of 6 Variables for Intended SAV Adoption at a High Price

Variable	Age	Education	Occupation	Transportation mode	Population density	Job density
Laidlaw and Sweet (2017)	9th out of 14 (64th percentile)	5th out of 14 (36th percentile)	8th out of 14 (57th percentile)	1st out of 14 (7th percentile)		12th out of 14 (86th percentile)
Bansal and Kockelman (2018)	2nd out of 9 (22nd percentile)					
Bansal et al. (2016)	8th out of 9 (89th percentile)				9th out of 9 (100th percentile)	
Average percentile of rank	**58th**	**36th**	**57th**	**7th**	**100th**	**86th**
Percentile of importance	**42nd**	**64th**	**43rd**	**93rd**	**10th [1]**	**14th**
Normalized importance	**0.16**	**0.24**	**0.16**	**0.35**	**0.04**	**0.05**

1 The percentile of importance is actually 0%, but it is adjusted to 10% for the recognition of the importance of population density.

Comparing Equations (2) to (7), some differences exist between the equations for intended PAV adoption and those for intended SAV adoption. First, they differ in how transportation mode is measured. The equations modeling intended PAV adoption model driving, whereas the equations modeling intended SAV adoption model the transportation modes excluding driving. Second, the equations modeling intended PAV adoption use household income and trip distance as two modeling variables, while the equations modeling intended SAV adoption use occupation and population density as two modeling variables. Their commonality is that they use three same modeling variables: education, age, and job density, though their weights often differ. Therefore, it would be interesting to see whether the two types of equations with many similarities would generate drastically different PAV and SAV adoption potential scores in a CGU.

4.2 Mapping the AV Adoption Potential in the GTHA

No study has been found to have mapped the PAV or SAV adoption potential in a geographic area. Thus, no researchers have been found to have visualized the PAV or SAV adoption potential of a geographic area, and analyze the visualized patterns. Thus, this thesis would like to put the first effort to implement the visualization and the adoption potential patterns analysis. Section 4.1 provides the tools to find the PAV and SAV adoption potential scores of a CGU. Now, Section 4.2 would discuss how the scores can be mapped and analyzed in a case study of the GTHA.

ArcMap is a commonly used tool for mapping. One of its recent versions ArcMap 10.5.1 will be used. 7 shapefiles were acquired to help visualize and analyze the PAV and SAV adoption potential variations in the GTHA (see Table 4.5 for a brief description of each shapefile). Table 4.5 indicates that mapping and analysis will be done at the census tract level. This is because it is a CGU level at which Canadian planners often map and analyze data.

Table 4.5 Sources of the Shapefiles used in All Maps

Description of the shapefile	Source
Boundaries of the census tracts in Toronto CMA, Hamilton CMA, and Oshawa CMA	Statistics Canada (2018b)
Boundaries of the regional (upper-tier) municipalities in the GTHA	Ontario Ministry of Natural Resources (2012)
Boundaries of the local (lower-tier) municipalities in the GTHA	Ontario Ministry of Natural Resources (2012)
Highways	The Government of Ontario (2015b)
GO train stations	The Government of Ontario (2016)
GO train railways	DMTI Spatial (2014a)
Water bodies	DMTI Spatial (2014b)

The specific mapping procedures are as follows. After one of Equations (2) to (7) generates scores for all the census tracts in the GTHA, these scores will be classified into 5 groups, using the classification method: natural breaks (Jenks). This classification method is unique from other classification methods in that it classifies data “based on natural groups inherent in the data” (Law & Collins, 2015, p. 264), and that the boundaries of the groups are usually located “where there are relatively large gaps between values” (Law & Collins, 2015, p. 264). Thus, natural breaks (Jenks) allows the census tracts in the GTHA to be naturally grouped based on their scores. This grouping would show the locations and clusters of the census tracts that have a relatively higher or lower PAV or SAV adoption potential.

It should be reminded that as mentioned before, Equation (2) is based on a less robust assumption than that of Eqaution (3); hence, the result from Equation (2) would be primarily used for a comparison with the result from Equation (3). Thus, the thesis would primarily the maps and results produced by Equation (3) for discussion and analysis. People being interested in seeing the cartographic result from Equation (2) can read Map D1 in Appendix D. Due to a similar reason, the result from Equation (4) would be primarily used for a comparison with the results from Equation (5) and Equation (7), and its cartographic result would be placed in Appendix D as a supplementary information.

In addition to making maps by Equations (2) to (7), four other maps will be produced. One map would show the areas that have high scores in both PAV and SAV adoption potential if the SAV price is to be fair. The second map would be a similar one, but the SAV price is assumed to be high. The third and fourth maps would show the areas that have low scores in both PAV and SAV adoption potential at the two price scenarios. Chapter 5 will provide a clearer definition on what scores are considered high or low (with reference to Table 5.3).

4.3 Tools and Methods for Finding the Planning Implications from the Maps

The maps produced from Equation (3), Equation (5), and Equation (7) would provide important information on where locate the areas where either PAVs or SAVs would be more or less likely to be adopted. To find the exact locations of the areas, the ArcMap base map: Imagery with Labels will be added for reference. Google Maps (2019) will be another important reference when examining the land uses in the areas. This examination will reveal some characteristics of the areas.

In addition to the qualitative examination, two Excel statistical tools are useful in identifying whether a quantity is significantly different between inside and outside the areas. One tool is the F-test function. The other is the t-test function. The F-test function reports “the two-tailed probability that the variances in Array1 and Array2 are not significantly different” (Microsoft Excel, 2013, para. 1). Thus, at a confidence level of 95%, if an F-test result is less than or equal to 0.05, the variances of two arrays of data are considered significantly different in a t-test. On the contrary, if an F-test result is larger than 0.05, the variances of the corresponding two arrays of data can be reasonably assumed the same in a t-test. The t-test function reports the probability that the means of two arrays of data are not significantly different. That is to say, at a confidence level of 95%, if a t-test result is less than or equal to 0.05, the means of the corresponding two arrays of data are significantly different. Therefore, the F-test and the t-test provide statistical evidence on whether a quantity in an area differs so significantly from that outside the area that the difference is an identity or characteristic of the area.

As the shapefiles of GO train stations and GO train railways are available, and as the GO train service is an important regional public transit service for the residents in the GTHA, the thesis would do some further analyses for the sake of the transportation planners in the GTHA to find some public-transit-planning implications of the PAV and SAV adoption potential in the GTHA. Particularly, the thesis would use the F-test function and the t-test function to check whether the service areas of the GO train stations in the GTHA have higher or lower overall PAV or SAV adoption potential than those outside the areas. In addition, the thesis would use the same functions to check whether the GO train lines differ significantly in their overall PAV or SAV adoption potential. Moreover, the thesis would calculate the overall PAV and SAV adoption potential scores of each GO train station in the GTHA, and check whether the service area of some stations has a particularly high or low PAV or SAV adoption potential.

To answer the two questions, there is a need to define the station service area in terms of park-and-ride (driving a vehicle to a GO train station and then take the train) and kiss-and-ride (riding a vehicle as a passenger to a GO train station and then take the train). However, Metrolinx, which is responsible for GO train services, does not have a clear definition on it, though it has a clear definition in terms of walk-and-ride (walking to a GO train station and then take the train). According to Metrolinx (2008)'s definition of major transit station areas, a GO train station area is "the area within an approximate 500 metre radius of a transit station, representing about a 10-minute walk" (p. 88). Thus, 10 minutes is implied the temporal service distance of a GO station.

Now, it is time to figure out how long a person can travel in 10 minutes from a GO train station by driving a vehicle (i.e. park and ride), or riding a vehicle as a passenger (i.e. kiss and ride).

Metrolinx (2008) defines “arterial road” as “[a] high-volume urban road with at least four lanes, having a typical speed limit of 50 to 60 km/hour and typical spacing between traffic signals of 200 to 400 metres. The typical volume of an arterial road is less than 20,000 vehicles/day and it connects to collector roads, other arterial roads and expressways” (p. 85). Accordingly, the thesis assumes that all park-and-ride and kiss-and-ride passengers travel primarily on arterial roads to a GO train station, and always need to wait for one or a few red lights. Thus, the average speed of their vehicles is assumed 42km/h. Therefore, the service radius of a GO train station is assumed 7km.

Through a test-drawing of the 7km service buffer of all the GO train stations in the GTHA, it is found that many census tracts are served by multiple GO train stations. However, the residents in the census tracts would only use the station closest to them. Therefore, the actual service area of a GO train station is often a portion of its 7km buffer, and only covers the census tracts whose closest station is itself.

It is common that a portion of a census tract is closest to one station, while the other portion is closest to another. To keep the definition simple, the park-and-ride and kiss-and-ride service area of a GO train station consists of the census tracts whose closest GO train station is the station, as measured from the centroids of the census tracts; and whose distances from their centroids to the station is no more than 7 kilometers. By using the “feature to point” tool of ArcMap 10.5.1, all the census tracts (polygon features) are converted to points (point features), and these points are the centroids of the census tracts. Then, by using the “near” tool, the GO train station closest to each centroid is found, along with the distance between them. Then, by using the Select By Attributes function of ArcMap 10.5.1 to limit the distance at no more than 7km, the service area of a GO train station is identified. The average PAV and SAV adoption potential scores of the census tracts in the service area are the overall PAV and SAV adoption potential scores of the station. It should be clarified that the different geographic sizes of the census tracts would not cause an unacceptable bias or error because all census tracts have a similar number of residents (Statistics Canada, 2018c).

To get a sense of the internal variance of the scores in the service area, scores will be calculated at 3 buffers: 1km buffer, 4km buffer, and 7km buffer. To test whether the score of selected service areas significantly differ from that of another selected area, the F-test function and the t-test function will be utilized.

In order to get more accurate findings on the GO train system, the shapefiles of GO train stations and GO train railways are edited. Through a scrutiny of the locations of the point features representing the GO train stations against the ArcMap base map: Imagery with Labels, it was surprisingly found that the point features are often offset from the actual locations of their corresponding stations. Some features even have an offset of 100 meters to 700 meters from their true station locations. Therefore, the features representing the GO train stations are manually moved to the true locations with reference to the base map. Then, York University GO train station is removed because it is soon to be decommissioned. Later, two missing stations are added, again with reference to the base map. They are Downsview Park, and Gormley. As there is no line feature representing the railway from Richmond Hill GO train station to Gormly GO train station, such line features are manually added with reference to the base map. Last but not least, the features representing GO train stations outside the GTHA are removed, except the one representing Bradford GO train station. This exception is due to the fact that Bradford is the home station for some GTHA residents.

Chapter 5: Findings

This chapter presents the findings from the works as described in Chapter 4. The findings will be organized in the following ways. Section 5.1 will present the numeric and cartographic findings from Section 4.1 and Section 4.2, except for those on GO train stations. The findings will demonstrate some phenomena that are often found in areas with high or low PAV or SAV adoption potential score. Section 5.2 will particularly present the findings relevant to GO train stations.

5.1 Areas in the GTHA with a High or Low PAV or SAV adoption Potential Score

5.1.1 Numeric summary

There are 1,426 census tracts in Toronto CMA, Hamilton CMA, and Oshawa CMA. Their geographic spans highly overlap with the geographic span of the GTHA. As the data of Statistics Canada are retrieved by CMAs, the data from the three CMAs are used to model the PAV and SAV adoption in the GTHA.

It is observed that 9 census tracts do not have data for all the modeling variables, though their existing data contribute to the normalization of all modeling variables. Despite their contributions, Excel does not generate *y* values for them due to their data flaws. This problem further causes the relevant Excel sheet to be unable to be joined with the relevant attribute table of the census tracts in ArcMap 10.5.1. Thus, to make Microsoft Excel 2013 and ArcMap 10.5.1 function smoothly, mapping and data analysis exclude the 9 census tracts. In addition, the 9 census tracts have no or few residents, so the planning significance of assigning a score to them is not high. As there are only 9 out of 1,426 (0.6%) census tracts excluded, the validity of the findings in the chapter persists.

Table 5.2 numerically summarizes the modeling results at the GTHA scale. The full meanings of variables in Table 5.2 are explained in Table 5.1. Evident from the statistical summary under "Before normalization" in Table 5.2, the census tracts in the GTHA differ obviously in the compositions of highly educated people, the high income, people who primarily drive, people who primarily do not drive, and long commuters. Although the census tracts overall do not differ a lot in the compositions of the younger generation, and the people whose occupations belong to the NOC 07 and NOC 09 classifications, some of them have a quite higher or lower proportion of one of the two types of people. In addition, the majority of the jobs and the residents in the GTHA are located in some census tracts. Moreover, there are two major characteristics of the population in the GTHA. First, vehicles play a critical role in their life because most census tracts have more than half of their residents dependent on driving for commuting. Second, in addition to driving, most GTHA residents do not have an often used alternative transportation mode.

Table 5.1 The Meanings of Some Variable Names in the Tables of Chapter 5

Variable	Meaning
Age (15 to 34 years old)	The proportion (out of 1.000) of people who were 15 to 34 years old in 2016
Education (≥ bachelor)	The proportion (out of 1.000) of people who had a university certificate, diploma or degree at bachelor level or above in 2016
Household income (≥ $100,000)	The proportion (out of 1.000) of private households in a GTHA census tract whose total income in 2015 were at least $100,000
Job density	The number of jobs per square kilometer in 2016
Occupation (NOC = 07 or 09)	The proportion (out of 1.000) of people aged 15 or over in the labour force whose National Occupation Classification (NOC) occupations were one of the following in 2016: (1) trades, transport and equipment operators and related occupations (NOC = 07); and (2) occupations in manufacturing and utilities (NOC = 09)
Population density	The number of people per square kilometer in 2016
Driving	The proportion (out of 1.000) of people whose main mode of commuting was driving a car, a truck , or a van, among the people who were at least 15 years old, who lived in a private household, and who were employed in 2016
Not Driving	The proportion (out of 1.000) of people whose main mode of commuting was riding (but not driving) a car, a truck , or a van; using public transit; walking; or cycling, among the people who were at least 15 years old, who lived in a private household, and who were employed in 2016
Trip distance (≥ 30 min)	The proportion (out of 1.000) of people who spent at least 30 minutes for the commute from their homes to their workplaces, among the people who reported their commuting time from their homes to their workplaces, who were at least 15 years old, who lived in a private household, and who were employed in 2016

With reference to the weights of the modeling variables, the statistical summary under "After normalization" in Table 13 allows researchers to know the typical values of the modeling variables (mean ± SD) before being weighed.

In terms of the scores, the assessed 1,417 census tracts all get scores of more than 14%. Thus, all the census tracts have some potential for both PAV and SAV adoptions, though their potential varies. In addition, the maximum scores never surpass 73%. It reflects that no census tract has high values in all the relevant modeling variables. Overall, the census tracts have much less potential for SAV adoption (p = 0.0000), which indicates that the GTHA residents are generally more favorable of PAVs. When the price of SAVs rises, the overall SAV adoption potential does not change much in the census tracts (p = 0.1387). It suggests that SAV pricing is not a critical factor influencing the overall attitudes of the GTHA residents towards SAVs.

Table 5.2 Statistical Summary of the Modeling Results for the Census Tracts in the GTHA

Variable	Before normalization					After normalization				
	Max	Min	Median	Mean	SD	Max	Min	Median	Mean	SD
Age (15 to 34 years old)	0.660	0.000	0.258	0.265	0.061	1.000	0.000	0.391	0.403	0.090
Education (≥ bachelor)	0.742	0.023	0.278	0.305	0.142	1.000	0.000	0.353	0.390	0.197
Household income (≥ $100,000)	0.797	0.022	0.388	0.389	0.162	1.000	0.000	0.476	0.477	0.210
Job density	251,427	0	529	1,891	8,779	1.000	0.000	0.002	0.008	0.035
Occupation (NOC = 07 or 09)	0.405	0.000	0.164	0.165	0.085	1.000	0.000	0.404	0.407	0.209
Population density	82,434	0	3,533	4,997	5,951	1.000	0.000	0.043	0.061	0.072
Driving	0.931	0.066	0.701	0.645	0.180	1.000	0.000	0.734	0.669	0.208
Not driving	0.911	0.068	0.290	0.345	0.179	1.000	0.000	0.264	0.329	0.212
Trip distance (≥ 30 min)	0.801	0.000	0.550	0.542	0.102	1.000	0.000	0.686	0.677	0.127
y of Equation (2)						0.610	0.250	0.440	0.437	0.066
y of Equation (3)						0.717	0.256	0.490	0.484	0.089
y of Equation (4) or (6)						0.583	0.142	0.256	0.266	0.061
y of Equation (5)						0.652	0.174	0.320	0.336	0.091
y of Equaiton (7)						0.729	0.155	0.324	0.341	0.096

Note: the maximums and minimums of the response variables are not 1.000 and 0.000 because the response variables are the summations of the normalized modeling variables. As the summing process happens after the modeling variables are normalized, the statistical summary of the response variables is put under "After normalization."

Table 5.2 also shows there are obvious differences between assuming the modeling variables have an equal weight and assuming them not necessarily having an equal weight in generating the scores. By comparing the maximums, medians, and means of the results from Equation (2) and Equation (3); and then comparing the alike from Equation (4) and Equations (5) and (7), the latter assumption generally results in higher scores. This is an evidence that Equations (3), (5), and (7) are more accurate models as they better differentiate the census tracts with high PAV or SAV adoption potential from those not.

Appendix C shows the statistical distributions of the modeling variables and the modeling results. It graphically reflects the above findings from Table 5.2. It more clearly demonstrates that most jobs and population cluster in a small number of census tracts. The appendix also shows that more highly educated people tend to locate in certain census tracts. Moreover, the distributions of PAV adoption potential scores are pretty normal, whereas those of SAV adoption potential scores are slightly skewed to the right. It means that more census tracts have a relatively lower SAV adoption potential score.

5.1.2 Notes on the Maps and Some Descriptions

This chapter has a total of 11 maps. To help readers better understand the last 8 maps, the first 3 maps provide some basic information on the GTHA. Map 5.1 presents the boundaries and names of the upper-tier municipalities in the GTHA. Map 5.2 shows the boundaries and names of the lower-tier municipalities in the GTHA. It is noted that Toronto and Hamilton are single-tier municipalities. Map 5.3 introduces the names of the GO train stations serving the GTHA residents.

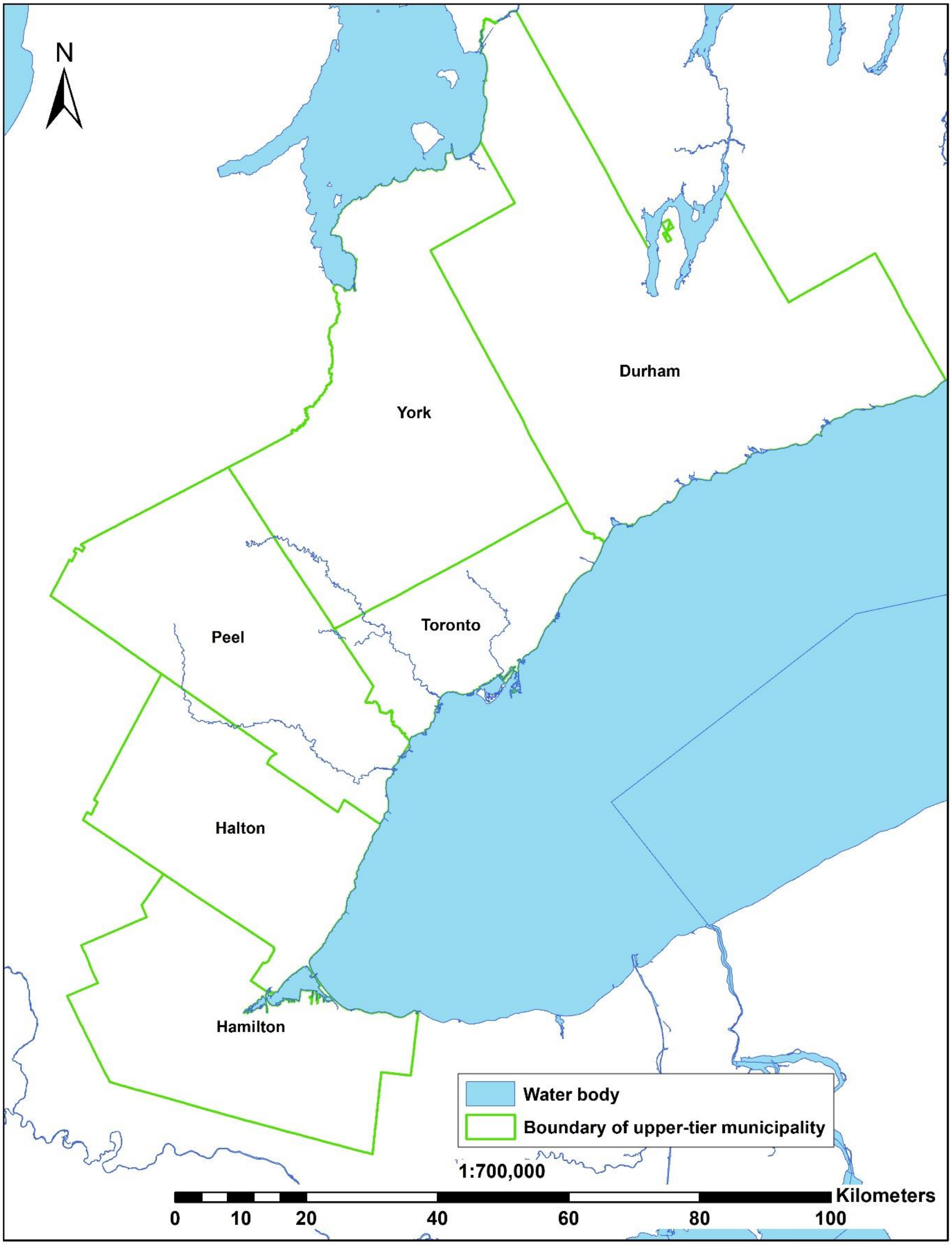
Table 5.3 shows the meanings of some descriptions on the results from the indices. The classification of the ranges is based on the 5 classes as generated from the natural breaks (Jenks) classification method.

Table 5.3 The Meanings of Some Descriptions on the PAV and SAV Adoption Potential Scores

Description	Range		
	PAV adoption potential score	SAV adoption potential score (fair price)	SAV adoption potential score (high price)
Low	0.256 to 0.377	0.174 to 0.267	0.155 to 0.275
Below average	0.378 to 0.452	0.268 to 0.329	0.276 to 0.344
Average	0.453 to 0.518	0.330 to 0.400	0.345 to 0.421
Above average	0.519 to 0.584	0.401 to 0.493	0.422 to 0.529
High	0.585 to 0.717	0.494 to 0.652	0.530 to 0.729

The highways in Ontario are classified into a few categories, such as King's highways, secondary highways, tertiary highways, and the Trans-Canada Highway. King's highways are commonly known as the major provincial highways, and all the highways in the maps are King's highways. The Trans-Canada Highway is not shown because it is away from the GTHA. Although other levels of highways are not shown in the maps for a better visual presentation of the indices results, their presence is considered when analyzing the importance of highways for intended PAV and SAV adoptions.

Map 5.1 The Upper-Tier Municipalities in the GTHA



Map 5.2 The Lower-Tier Municipalities in the GTHA

Map 5.3 The GO Train Stations Serving the GTHA Residents

5.1.3 The PAV Adoption Potential in the GTHA

Map 5.4 shows the variation of the PAV adoption potential in the GTHA. Assessing its indicated patterns, there is an obscure trend that the PAV adoption potential increases as the geographic location moves from Toronto to the inner suburb of the GTHA, and then gently decreases as the location moves from the inner suburb to the outer suburb. Without doubt, the reliability of the trend is questionable because there are areas with a high PAV adoption potential in Toronto and the outer suburb, and there are areas with a low PAV adoption potential in the inner suburb.

Table 5.4 provides some explanations on why some areas have a high PAV adoption potential. These areas typically have much more highly educated people, high-income households, and people heavily depending on driving for commuting. In terms of their predictabilities in the geographic locations of the areas with high PAV adoption potential, education, household income, and dependency on driving are essentially the same, and quite high.

It is noticed that the areas with a high PAV adoption potential have less young people, and their job densities are relatively lower. It does not mean that the two modeling variables: age, and job density are wrong choices for Equation (3). It just shows that the geographic locations with more young people and higher job densities do not highly overlap with the areas with high PAV adoption potential.

Table 5.5 provides some explanations on why some areas have a low PAV adoption potential score. These areas typically have much less highly educated people, high-income households, and people heavily depending on driving for commuting. In addition, they have a bit more young people. These characteristics are contrary to those of the areas with high PAV adoption potential. Therefore, these characteristics are efficient in distinguishing the areas with high PAV adoption potential from those having low PAV adoption potential. It is also observed that in the areas with low PAV adoption potential, there are a bit more long commuters. In terms of their predictability in the locations of the areas with low PAV adoption potential, education, dependency in driving, and household income are essentially the same, and quite high.

Map 5.4 The PAV Adoption Potential in the GTHA

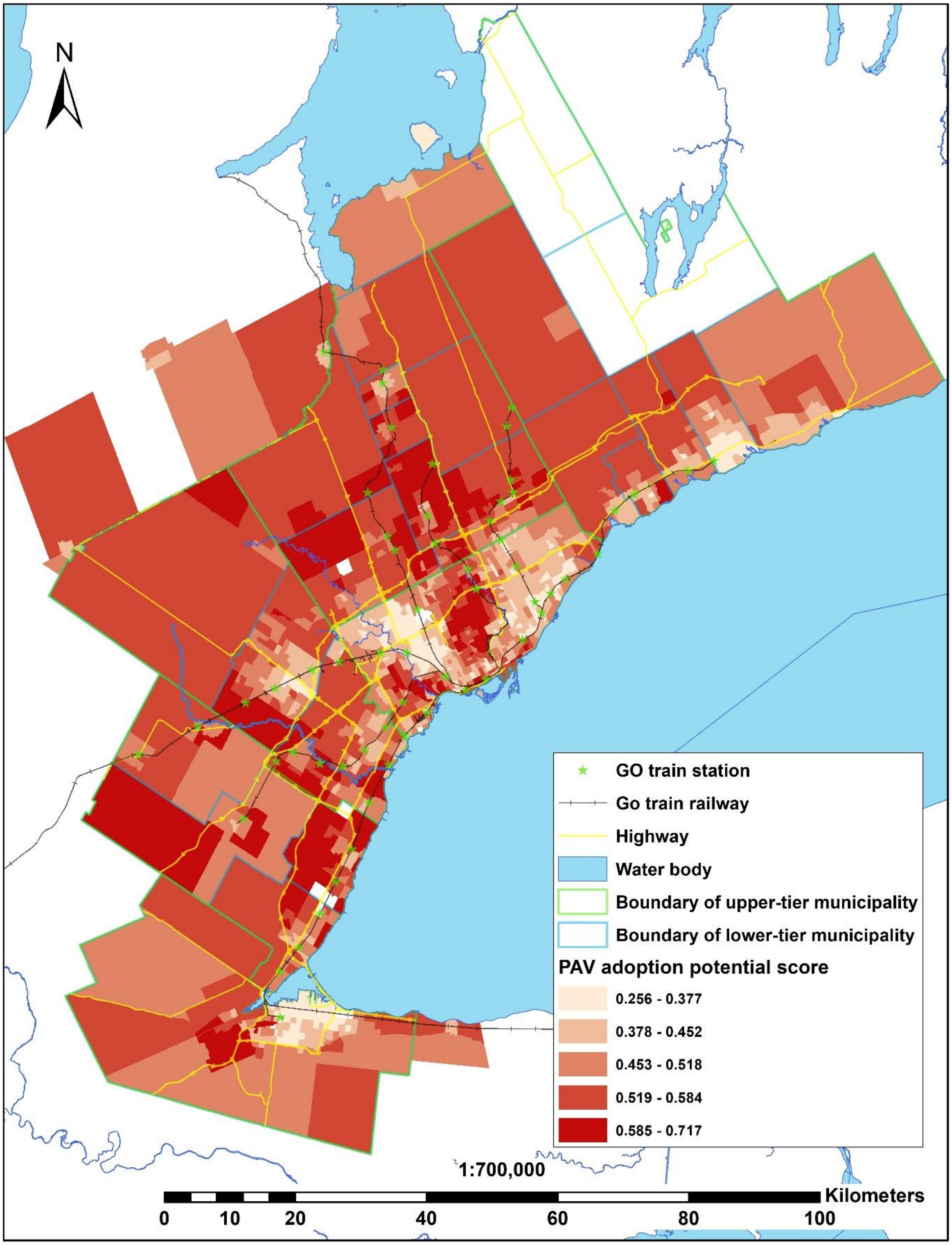


Table 5.4 Comparison between the Areas with High PAV Adoption Potential and Those Not

Variable	Weight	CTs with a high PAV adoption potential score		CTs without a high PAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Education (≥ bachelor)	0.33	0.468	0.099	0.278	0.129	0.190	0.0000	0.0000
Driving	0.27	0.726	0.120	0.631	0.186	0.095	0.0000	0.0000
Age (15 to 34 years old)	0.15	0.244	0.060	0.269	0.059	-0.025	0.5299	0.0000
Household income (≥ $100,000)	0.14	0.605	0.086	0.354	0.142	0.251	0.0000	0.0000
Trip distance (≥ 30 min)	0.07	0.552	0.087	0.541	0.104	0.011	0.0026	0.0976
Job density	0.04	1,061	4,696	2,033	9,299	-972	0.0000	0.0228
PAV adoption potential score	1.00	0.619	0.029	0.462	0.075	0.157	0.0000	0.0000

Table 5.5 Comparison between the Areas with Low PAV Adoption Potential and Those Not

Variable	Weight	CTs with a low PAV adoption potential score		CTs without a low PAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Education (≥ bachelor)	0.33	0.156	0.082	0.327	0.135	-0.171	0.0000	0.0000
Driving	0.27	0.506	0.155	0.665	0.175	-0.159	0.0194	0.0000
Age (15 to 34 years old)	0.15	0.274	0.052	0.264	0.061	0.010	0.0002	0.0083
Household income (≥ $100,000)	0.14	0.164	0.068	0.423	0.144	-0.259	0.0000	0.0000
Trip distance (≥ 30 min)	0.07	0.563	0.128	0.540	0.096	0.023	0.0000	0.0347
Job density	0.04	1,714	2,977	1,923	9,368	-209	0.0000	0.5270
PAV adoption potential score	1.00	0.337	0.030	0.507	0.073	-0.170	0.0000	0.0000

Scrutinizing the land uses in the areas with high PAV adoption potential with reference to Google Maps (2019), some land uses often present in the areas. First, the neighbourhoods in the areas primarily consist of single detached houses, usually with lots of green spaces. Second, golf course is a common landmark in these neighbourhoods. However, it should be reminded that the presence of some or all of the land use characters does not guarantee that a neighbourhood has high PAV adoption potential. Nonetheless, the presence of these land use characters is a good indicator of whether a neighbourhood likely has high PAV adoption potential. In terms of transportation facilities, most of the neighbourhoods have at least one highway either crossing or near them. However, it is not true that the presence of a highway is always related to the presence of a neighbourhood high in PAV adoption potential because of two reasons. First, some neighbourhoods with a high PAV adoption potential score are far from a highway. Second, the highways also cross areas with a low or below-average PAV adoption potential score. It should be clarified that lack of public transit services is not a reason why some neighbourhoods have a high PAV adoption potential score. It is because many of them are decently or well served by public transit.

Scrutinizing the land uses in the areas with low PAV adoption potential with reference to Google Maps (2019), some land uses often present in the areas. They can be coarsely classified into two categories. The first category is a mixture of industrial, business, and commercial uses, with no or a few households. The second category is the residential use mixed with on-street businesses, or adjacent to a local or town center. The zones for residential use often have multiple housing types, though single detached house is usually the dominant type. For both categories, there is often a GO train station or a subway station inside or nearby.

Comparing the land uses in the areas with high PAV adoption potential with those in the areas with low PAV adoption potential, some differences are evident. First, the former areas often have a very low density, while the latter areas usually have a concentration of jobs. Second, the infrastructure for vehicle driving is much more important in the former areas, while the infrastructure for high-capacity public transportation is much more important in the latter areas.

Whether assuming the modeling variables have the same importance does yield different patterns, but they are only discernible – not drastic at all. When assuming the modeling variables have the same importance, there are 205 census tracts having high PAV adoption potential, and 183 census tracts having low PAV adoption potential. When assuming the opposite, there are 202 (3 less) census tracts having high PAV adoption potential, and 186 (3 more) census tracts having low PAV adoption potential. The differences are obviously quite small, considering there are 1,417 studied census tracts. Both assumptions indicate that there are slightly more census tracts having high PAV adoption potential than those having low potential in the GTHA. Comparing Map 5.4 with Map D1, the patterns of the PAV adoption potential in the GTHA produced by both assumptions highly overlap, and Map D1 supports the findings generated from Map 5.4. Last but not least, through a scrutiny of Map 5.4 and Map D1, it is further found that a census tract scoring high from Equation (3) often score high from Equation (2), and always score at least above-average from Equation (2); and vice versa. Moreover, a census tract scoring low from Equation (3) often score low from Equation (2), and always score at most below-average from Equation (2); and vice versa.

5.1.4 The SAV Adoption Potential in the GTHA

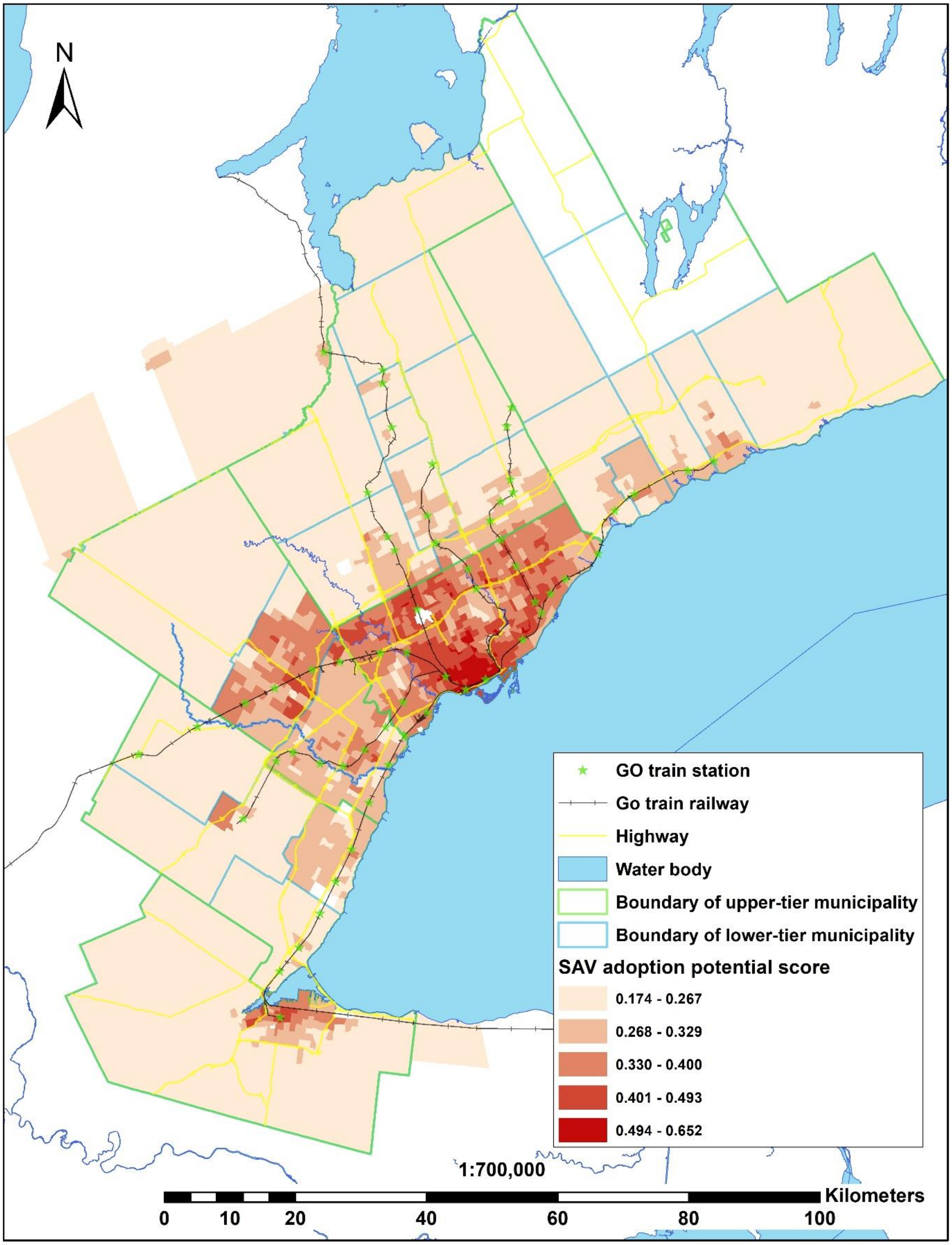
Map 5.5 shows the variation of the SAV adoption potential in the GTHA assuming the price of SAVs would be fair. Map 5.6 shows the same type of variation assuming the price would be high. Assessing their similarly indicated patterns, there is a trend that the SAV adoption potential decreases with fluctuations as one moves from Downtown Toronto (an area around Union GO train station), to the rest of Toronto, then to the inner suburb of the GTHA, and finally to the outer suburb of the GTHA. The largest fluctuation occurs around Hamilton GO train station: as one approaches the station, the potential increases quickly from a low level to an above-average level. Although it does not reach a high level, this fluctuation reminds that an area in the outer suburb of another metropolitan area may have high SAV adoption potential. Nonetheless, in the GTHA, all the areas with high SAV adoption potential are in Toronto.

Table 5.6 and Table 5.7 provide some explanations on why some areas have a high SAV adoption potential. No matter whether the price would be fair or high, the areas with high SAV adoption potential overall have quite a lot more people not dependent on driving for commuting, and substantially more highly educated and young people. The areas also overall have a higher job density and population density. In terms of their predictabilities in the geographic locations of the areas with high SAV adoption potential, independence from driving, education, age, job density, and population density are essentially the same, and quite high.

It is noticed that the areas with high SAV adoption potential has less people whose NOC occupations are either trades, transport and equipment operators and related occupations (NOC = 07); or occupations in manufacturing and utilities (NOC = 09). It does not mean that choosing occupation as a modeling variable is wrong for Equation (5) and Equation (7). It just shows that the geographic locations with more people having the two types of occupations do not overlap much with the areas with a high SAV adoption potential.

Table 5.8 and Table 5.9 provide some explanations on why some areas have a low SAV adoption potential. No matter whether the price would be fair or high, the areas with a low SAV

Map 5.5 The SAV Adoption Potential in the GTHA (Fair Price)



Map 5.6 The SAV Adoption Potential in the GTHA (High Price)

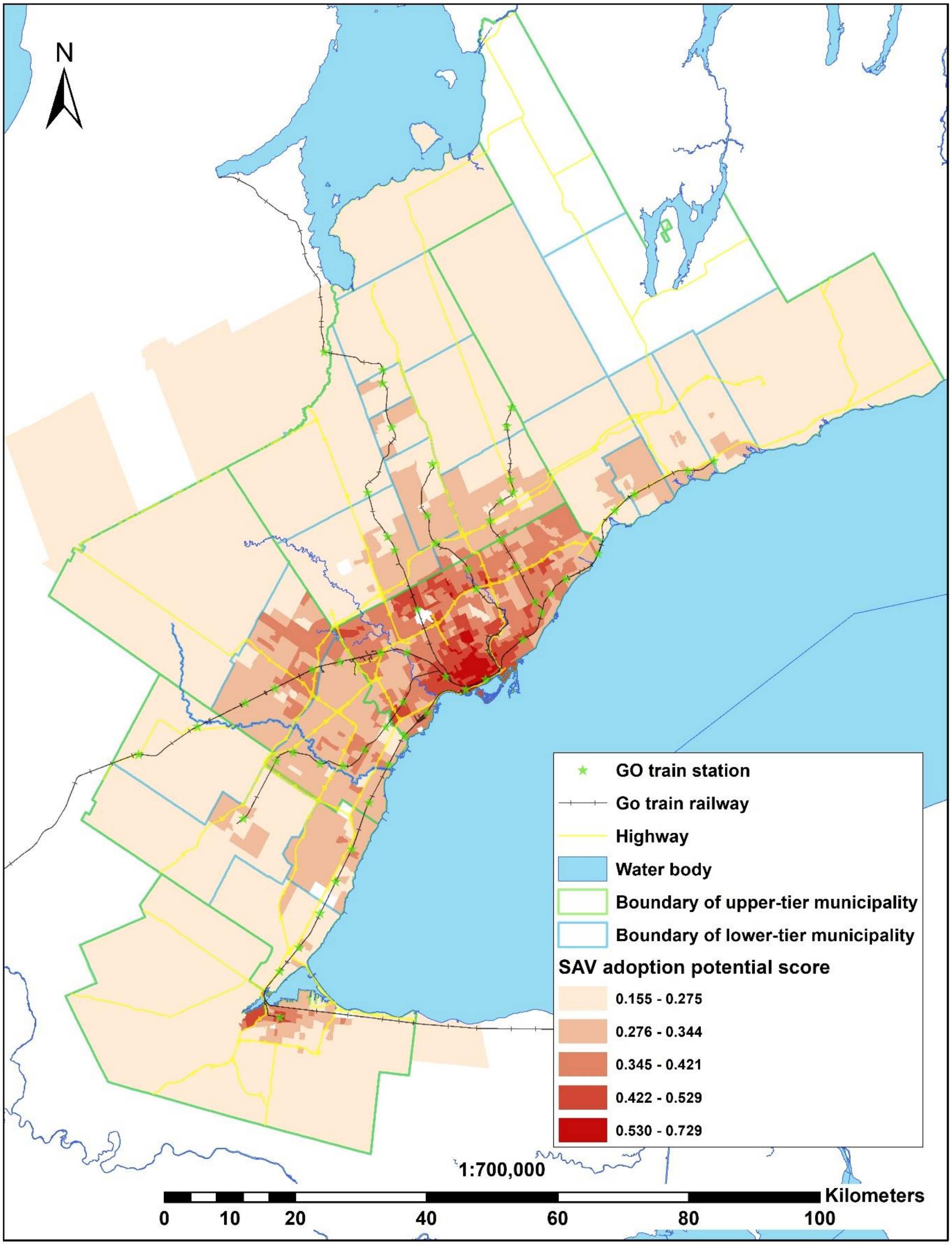


Table 5.6 Comparison between the Areas with High SAV Adoption Potential and Those Not (Fair Price)

Variable	Weight	CTs with a high SAV adoption potential score		CTs without a high SAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Not driving	0.38	0.755	0.070	0.318	0.148	0.437	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.23	0.063	0.047	0.172	0.082	-0.109	0.0000	0.0000
Education (≥ bachelor)	0.19	0.504	0.133	0.291	0.132	0.213	0.8382	0.0000
Age (15 to 34 years old)	0.10	0.403	0.098	0.256	0.042	0.147	0.0000	0.0000
Job density	0.06	16,212	31,270	935	1,548	15,277	0.0000	0.0000
Population density	0.04	18,424	12,714	4,131	3,765	14,293	0.0000	0.0000
SAV adoption potential score	1.00	0.547	0.045	0.322	0.074	0.225	0.0000	0.0000

Table 5.7 Comparison between the Areas with High SAV Adoption Potential and Those Not (High Price)

Variable	Weight	CTs with a high SAV adoption potential score		CTs without a high SAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Not driving	0.35	0.755	0.074	0.322	0.154	0.433	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.16	0.045	0.025	0.172	0.082	-0.127	0.0000	0.0000
Education (≥ bachelor)	0.24	0.558	0.095	0.290	0.130	0.268	0.0014	0.0000
Age (15 to 34 years old)	0.16	0.414	0.102	0.257	0.043	0.157	0.0000	0.0000
Job density	0.05	18,788	33,404	950	1,587	17,838	0.0000	0.0000
Population density	0.04	18,817	13,712	4,258	3,964	14,559	0.0000	0.0000
SAV adoption potential score	1.00	0.594	0.055	0.327	0.076	0.267	0.0009	0.0000

adoption potential overall have substantially less people not dependent on driving for commuting, and less highly educated and young people. The areas also overall have a lower job density and population density. It should be emphasized that these characteristics are contrary to those of the areas having high SAV adoption potential. Therefore, they are efficient in distinguishing the areas with high SAV adoption potential from those having low SAV adoption potential. In terms of their predictabilities in the geographic locations of the areas with low SAV adoption potential, independence from driving, education, age, job density, and population density are essentially the same, and quite high.

Tables 5.6 to 5.9 demonstrate that the impacts of two variables on SAV adoption potential are subject to the price change of SAVs. The first variable is education: as the price increases, the

Table 5.8 Comparison between the Areas with Low SAV Adoption Potential and Those Not (Fair Price)

Variable	Weight	CTs with a low SAV adoption potential score		CTs without a low SAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Not driving	0.38	0.171	0.046	0.410	0.166	-0.239	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.23	0.161	0.061	0.167	0.092	-0.006	0.0000	0.1877
Education (≥ bachelor)	0.19	0.263	0.104	0.320	0.150	-0.057	0.0000	0.0000
Age (15 to 34 years old)	0.10	0.236	0.032	0.277	0.063	-0.041	0.0000	0.0000
Job density	0.06	434	553	2,433	10,236	-1,999	0.0000	0.0000
Population density	0.04	1,921	1,342	6,178	6,556	-4,257	0.0000	0.0000
SAV adoption potential score	1.00	0.237	0.020	0.372	0.079	-0.135	0.0000	0.0000

Table 5.9 Comparison between the Areas with Low SAV Adoption Potential and Those Not (High Price)

Variable	Weight	CTs with a low SAV adoption potential score		CTs without a low SAV adoption potential score		Differen-ce of means	F-test	P-value of 2-sample t-test
		Mean	SD	Mean	SD			
Not driving	0.35	0.171	0.048	0.408	0.167	-0.237	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.16	0.180	0.058	0.160	0.092	0.020	0.0000	0.0000
Education (≥ bachelor)	0.24	0.228	0.087	0.332	0.147	-0.104	0.0000	0.0000
Age (15 to 34 years old)	0.16	0.237	0.032	0.276	0.063	-0.039	0.0000	0.0000
Job density	0.05	447	544	2,415	10,204	-1,968	0.0000	0.0000
Population density	0.04	1,935	1,360	6,144	6,546	-4,209	0.0000	0.0000
SAV adoption potential score	1.00	0.240	0.023	0.377	0.086	-0.137	0.0000	0.0000

proportion of highly educated people increases in the areas with high SAV adoption potential, and decreases in the areas with low SAV adoption potential. It reflects that highly educated people are not only favorable of using SAVs, but their favor is resistant to SAV price increase. The second variable is occupation: as the price increases, the proportion of people whose NOC number is either 07 or 09 decreases in the areas with high SAV adoption potential, and increases in the areas with low SAV adoption potential. It suggests that increasing the price of SAVs would strongly discourage the passion of the people having the occupations to use SAVs.

Table 5.10 and Table 5.11 reveal that the above changes on education and occupation are significant. However, the other modeling variables do not significantly change as the price fluctuates. It was previously mentioned that assuming whether the price would be fair or high

Table 5.10 Comparison between the Areas with High SAV Adoption Potential under a High SAV Price and the Areas with High SAV Adoption Potential under a Fair SAV Price

Variable	Weight in Equation (7)	Weight in Equation (5)	CTs with the highest SAV adoption potential scores from Equation (7)		CTs with the highest SAV adoption potential scores from Equation (5)		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Not driving	0.35	0.38	0.755	0.074	0.755	0.070	0.000	0.6321	0.9771
Occupation (NOC = 07 or 09)	0.16	0.23	0.045	0.025	0.063	0.047	-0.018	0.0000	0.0015
Education (≥ bachelor)	0.24	0.19	0.558	0.095	0.504	0.133	0.054	0.0034	0.0035
Age (15 to 34 years old)	0.16	0.10	0.414	0.102	0.403	0.098	0.011	0.7107	0.5040
Job density	0.05	0.06	18,788	33,404	16,212	31,270	2,576	0.5437	0.6133
Population density	0.04	0.04	18,817	13,712	18,424	12,714	393	0.4885	0.8502
SAV adoption potential score	1.00	1.00	0.594	0.055	0.547	0.045	0.047	0.0562	0.0000

Table 5.11 Comparison between the Areas with Low SAV Adoption Potential under a High SAV Price and the Areas with Low SAV Adoption Potential under a Fair SAV Price

Variable	Weight in Equation (7)	Weight in Equation (5)	CTs with a low SAV adoption potential score from Equation (7)		CTs with a low SAV adoption potential score from Equation (5)		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Not driving	0.35	0.38	0.171	0.048	0.171	0.046	0.000	0.5107	0.8758
Occupation (NOC = 07 or 09)	0.16	0.23	0.180	0.058	0.161	0.061	0.019	0.4540	0.0000
Education (≥ bachelor)	0.24	0.19	0.228	0.087	0.263	0.104	-0.035	0.0007	0.0000
Age (15 to 34 years old)	0.16	0.10	0.237	0.032	0.236	0.032	0.001	0.9385	0.6790
Job density	0.05	0.06	447	544	434	553	13	0.7535	0.7519
Population density	0.04	0.04	1,935	1,360	1,921	1,342	14	0.7950	0.8887
SAV adoption potential score	1.00	1.00	0.240	0.023	0.237	0.020	0.003	0.0129	0.0625

would unlikely cause a significant change in the SAV adoption potential score at the GTHA scale ($p = 0.1387$). Table 5.11 shows that the unlikelihood persists in the areas with low SAV adoption potential. However, Table 5.10 shows that the overall SAV adoption potential score in the areas with high SAV adoption potential would significantly increase. It does not mean that increasing the price of SAVs would encourage people to adopt SAVs because of the two previously mentioned unlikelihood. The cause of the increase may partially lie in the difference in the number of census tracts having a high score. To clarify, there are 89 census tracts having a high SAV adoption potential score when assuming the price of SAVs would be fair, whereas there are 75 (namely, 14 less) census tracts having a high SAV adoption potential score when assuming the price would be high. The reduction reflects that rising the price of SAVs would discourage some people who have a passion to use SAVs to use SAVs. However, as the favor of highly educated people for SAVs is resistant to the price change, the proportion of highly educated people significantly increases. This increase then boosts the overall SAV adoption potential score in the 75 census tracts.

When assuming the price of SAVs would be fair, there are 382 census tracts having low SAV adoption potential. When assuming the price would be high, there are 375 (7 less) such census tracts. This very small change provides a reason why the overall SAV adoption potential score in the areas with low SAV adoption potential almost do not change with the price.

Scrutinizing the land uses in the areas with high SAV adoption potential with reference to Google Maps (2019), some land uses often present in the areas. Typically, the neighbourhoods in the areas are dominated by mid-rise to high-rise apartment buildings, and their land uses are diverse. They are on or near at least one major public transit corridor, and their residents are usually within a walking distance (500 meters) from a transit station. For most of the residents, they are in a walking distance to a subway or a streetcar station. It is undeniable that the areas cover some blocks dominated by single detached houses, but these blocks are often mixed with some apartment buildings of various heights, town houses, or a number of on-street commercial or financial land uses. Proximity to a highway does not have a clear relationship with the locations of the areas with high SAV adoption potential.

Two types of neighbourhoods would likely lose their high SAV adoption potential if the price of SAVs rises. One is the neighbourhoods primarily consisting of student housing. The other is the neighbourhoods primarily consisting of single detached houses, with most of their households not having a high household income. It is noticed that both types of neighbourhoods have a commonality: most of their residents do not have a high income. Thus, people and households with a lower income would be more discouraged to adopt SAVs if the price is to be high.

Scrutinizing the land uses in the areas with low SAV adoption potential with reference to Google Maps (2019), some land uses often present in the areas. First, in the urban and suburban residential neighbourhoods having low SAV adoption potential, the land uses are typically those presenting in the areas with high PAV adoption potential. Second, almost all the census tracts with a rural landscape – dominated by farmlands or greenbelt areas, with scattered large-lot houses – have low SAV adoption potential. The rural census tracts often have quite limited or no access to public transit, and thus the residents there have to rely on private vehicles for commuting. Most of the areas with low SAV adoption potential have a close proximity to highway as most people in the areas primarily drive.

Whether assuming the modeling variables have the same weight does make discernible differences. When assuming an equal importance of all modeling variables, Equation (4) finds 52 census tracts having a high SAV adoption potential score. This number is obviously lower than the corresponding numbers from Equation (5) (89 census tracts) and Equation (7) (75 census tracts). In addition, Equation (4) finds 354 census tracts having a low SAV adoption potential score. This number is somewhat lower than the corresponding numbers from Equation (5) (382 census tracts) and Equation (7) (375 census tracts). Therefore, assuming an equal importance of the modelling variables finds less census tracts having high or low SAV adoption potential, and thus is less efficient in differentiating the census tracts with high adoption potential from those with low adoption potential. In Map 5.5, Map 5.6, and Map D2, the difference in the number of census tracts having low SAV adoption potential may not be noticeable, but the difference in the number of census tracts having high SAV adoption potential is discernible – the total area of the areas with a high score in Map D2 is less than those in Map 5.5 and Map 5.6. Nonetheless, the areas scoring high from Equation (4) always have at least above-average scores from Equation (5) or Equation (7), and vice versa. Moreover, the areas scoring low from Equation (4) always have at most below-average scores from Equation (5) or Equation (7), and vice versa.

5.1.5 Differences between the Areas with High PAV Adoption Potential and the Areas with High SAV Adoption Potential

Section 5.1.3 and Section 5.1.4 discussed lots of characteristics of the areas with high PAV adoption potential, and also lots of characteristics of the areas with high SAV adoption potential. Table 5.12 provides a qualitative comparison between the two types of areas.

Table 5.13 and Table 5.14 compare the residents and the land uses of the areas with high PAV adoption potential and those with high SAV adoption potential. Specifically, the areas with high SAV adoption potential have quite more people not relying on driving for commuting, more young people, and higher population and job densities. They also have quite less people relying on driving for commuting, and quite less high income households. Also significantly, the areas have more highly educated people, less long commuters, and less people whose NOC occupation numbers are 07 or 09. However, the differences of the means of these three variables (education, occupation, and trip distance) are less than 10%. These differences contribute to the result that the two types of areas have big differences in their average PAV and SAV adoption potential scores. This result reminds researchers to discuss PAVs and SAVs separately, which, as indicated by Chapter 2 and Chapter 3, many AV researchers do not follow.

5.1.6 Differences between the Areas with Low PAV Adoption Potential and the Areas with Low SAV Adoption Potential

Section 5.1.3 and Section 5.1.4 discussed lots of characteristics of the areas with low PAV adoption potential, and also lots of characteristics of the areas with low SAV adoption potential. Table 5.15 provides a qualitative comparison between the two types of areas.

Table 5.16 and Table 5.17 compare the residents and the land uses of the areas with low PAV adoption potential and those of the areas with low SAV adoption potential. Contrary to the findings from a comparison between the areas with high PAV adoption potential and the areas with high SAV adoption potential, the areas with low SAV adoption potential, as compared with the areas with low SAV adoption potential, have quite less people not relying on driving for commuting, and less population and job densities. They also have quite more people dependent on driving for commuting, and quite more high income households. In addition, they have less young people, but the difference of means in age is small (less than 4%). Moreover, they have obviously higher PAV adoption potential, and obviously lower SAV adoption potential. These differences emphasize again that AV researchers should distinguish PAVs from SAVs when doing research.

Similar to the findings from a comparison between the areas with high PAV adoption potential and the areas with high SAV adoption potential, the areas with low SAV adoption potential, as compared to the areas with low SAV adoption potential, have more highly educated people, less long commuters, and less people whose NOC occupation numbers are 07 or 09. Also

Table 5.12 Comparison between the Areas with High PAV Adoption Potential and the Areas with High SAV Adoption Potential

Items for comparison	Areas with high PAV adoption potential	Areas with high SAV adoption potential
Average score	Higher	Lower
Typical location in a metropolitan area	The inner suburb	The central city, especially its downtown
Proportion of all studied CTs	14%	6% (fair price); 5% (high price)
Dominant housing type	Single detached houses	Apartment buildings of various heights
Density of green space	Usually not low; often high	Often low
Presence of golf courses	Golf course is a common landmark	No presence of a golf course
Presence of farmlands or greenbelt lands	Sometimes	Rarely
Density of on-street businesses	Usually zero to very low	Usually not low; often high
Density of industrial lands	Usually not present	Often not present
Proportion of area for mixed land uses	Usually zero to very low	Usually not low
Proximity to highway	Often have at least one highway inside or nearby	Often have no highway inside or nearby
Quality of public transit services	Most of the areas are served by public transit, and many are decently or well served. However, bus is usually the only option. Some areas have no or minimal access to public transit services.	Well served by public transit, usually with multiple types of public transit services to choose, which include bus, subway, streetcar, GO train, and GO bus.

Table 5.13 Comparison between the Areas with a High PAV Adoption Potential Score and the Areas with a High SAV Adoption Potential Score (Fair Price)

Variable	**Weight in Equation (5)**	**Weight in Equation (3)**	**CTs with a high score from Equation (5)**		**CTs with a high score from Equation (3)**		**Differen-ce of means**	**F-test**	**P-value of 2-sample t-test**
			Mean	**SD**	**Mean**	**SD**			
Age (15 to 34 years old)	0.10	0.15	0.403	0.098	0.244	0.060	0.159	0.0000	0.0000
Education (≥ bachelor)	0.19	0.33	0.504	0.133	0.468	0.099	0.036	0.0007	0.0208
Household income (≥ $100,000)		0.14	0.263	0.115	0.605	0.086	-0.342	0.0008	0.0000
Occupation (NOC = 07 or 09)	0.23		0.063	0.047	0.081	0.046	-0.018	0.6079	0.0024
Driving		0.27	0.233	0.072	0.726	0.120	-0.493	0.0000	0.0000
Not driving	0.38		0.755	0.071	0.264	0.118	0.491	0.0000	0.0000
Trip distance (≥ 30 min)		0.07	0.515	0.130	0.552	0.087	-0.037	0.0000	0.0148
Job density	0.06	0.04	16,212	31,270	1,061	4,696	15,151	0.0000	0.0000
Population density	0.04		18,424	12,714	3,308	2,924	15,116	0.0000	0.0000
PAV adoption potential score		1.00	0.456	0.087	0.619	0.029	-0.163	0.0000	0.0000
SAV adoption potential score	1.00		0.547	0.045	0.291	0.067	0.256	0.0000	0.0000

Table 5.14 Comparison between the Areas with a High PAV Adoption Potential Score and the Areas with a High SAV Adoption Potential Score (High Price)

Variable	Weight in Equation (7)	Weight in Equation (3)	CTs with a high score from Equation (7)		CTs with a high score from Equation (3)		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.16	0.15	0.414	0.102	0.244	0.060	0.170	0.0000	0.0000
Education (≥ bachelor)	0.24	0.33	0.558	0.095	0.468	0.099	0.090	0.7147	0.0000
Household income (≥ $100,000)		0.14	0.298	0.109	0.605	0.086	-0.307	0.0096	0.0000
Occupation (NOC = 07 or 09)	0.16		0.045	0.025	0.081	0.046	-0.036	0.0000	0.0000
Driving		0.27	0.232	0.076	0.726	0.120	-0.494	0.0000	0.0000
Not driving	0.35		0.755	0.074	0.264	0.118	0.491	0.0000	0.0000
Trip distance (≥ 30 min)		0.07	0.489	0.125	0.552	0.087	-0.063	0.0001	0.0001
Job density	0.05	0.04	18,788	33,404	1,061	4,696	17,727	0.0000	0.0000
Population density	0.04		18,817	13,712	3,308	2,924	15,509	0.0000	0.0000
PAV adoption potential score		1.00	0.487	0.070	0.619	0.029	-0.132	0.0000	0.0000
SAV adoption potential score	1.00		0.594	0.055	0.291	0.067	0.303	0.0000	0.0000

Table 5.15 Comparison between the Areas with Low PAV Adoption Potential and the Areas with Low SAV Adoption Potential

Items for comparison	**Areas with low PAV adoption potential**	**Areas with low SAV adoption potential**
Average score	Higher	Lower
Typical location in a metropolitan area	The central city	The outer suburb
Proportion of all studied CTs	13%	27% (fair price); 26% (high price)
Dominant housing type	Outside the industrial zone: houses (primarily detached), mixed with some town houses, or apartment buildings of various heights	Large-lot single detached houses
Density of green space	Usually not high, often low; sometimes zero	Usually not low; often high
Presence of golf courses	Sometimes present	Golf course is a common landmark.
Presence of farmlands or greenbelt lands	Not present, or present in a low proportion	Commonly present
Density of on-street businesses	Usually not zero; often not low	Absent, or low
Density of industrial lands	High in many areas	Often not present
Proportion of area for mixed land uses	Usually not zero; often not low	Absent, or low
Proximity to highway	Some areas have a highway inside or nearby	Usually have at least one highway inside or nearby
Quality of public transit services	Have a decent access to transit services	Many areas have no or limited access to transit services

Table 5.16 Comparison between the Areas with a Low PAV Adoption Potential Score and the Areas with a Low SAV Adoption Potential Score (Fair Price)

Variable	Weight in Equation (5)	Weight in Equation (3)	CTs with a low score from Equation (5)		CTs with a low score from Equation (3)		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.10	0.15	0.236	0.032	0.275	0.048	-0.039	0.0000	0.0000
Education (≥ bachelor)	0.19	0.33	0.263	0.104	0.157	0.081	0.106	0.0002	0.0000
Household income (≥ $100,000)		0.14	0.505	0.118	0.164	0.068	0.341	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.23		0.161	0.061	0.241	0.076	-0.080	0.0002	0.0000
Driving		0.27	0.820	0.047	0.509	0.151	0.311	0.0000	0.0000
Not driving	0.38		0.171	0.046	0.482	0.150	-0.311	0.0000	0.0000
Trip distance (≥ 30 min)		0.07	0.498	0.093	0.563	0.128	-0.065	0.0000	0.0000
Job density	0.06	0.04	434	553	1,714	2,977	-1,280	0.0000	0.0000
Population density	0.04		1,921	1,342	7,223	7,443	-5,302	0.0000	0.0000
PAV adoption potential score		1.00	0.529	0.065	0.337	0.030	0.192	0.0000	0.0000
SAV adoption potential score	1.00		0.237	0.020	0.403	0.067	-0.166	0.0000	0.0000

Table 5.17 Comparison between the Areas with a High PAV Adoption Potential Score and the Areas with a High SAV Adoption Potential Score (High Price)

Variable	Weight in Equation (7)	Weight in Equation (3)	CTs with a low score from Equation (7)		CTs with a low score from Equation (3)		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.16	0.15	0.237	0.032	0.275	0.048	-0.038	0.0000	0.0000
Education (≥ bachelor)	0.24	0.33	0.228	0.087	0.157	0.081	0.071	0.2684	0.0000
Household income (≥ $100,000)		0.14	0.471	0.132	0.164	0.068	0.307	0.0000	0.0000
Occupation (NOC = 07 or 09)	0.16		0.180	0.058	0.241	0.076	-0.061	0.0000	0.0000
Driving		0.27	0.820	0.049	0.509	0.151	0.311	0.0000	0.0000
Not driving	0.35		0.171	0.048	0.482	0.150	-0.311	0.0000	0.0000
Trip distance (≥ 30 min)		0.07	0.484	0.092	0.563	0.128	-0.079	0.0000	0.0000
Job density	0.05	0.04	447	544	1,714	2,977	-1,267	0.0000	0.0000
Population density	0.04		1,935	1,360	7,223	7,443	-5,288	0.0000	0.0000
PAV adoption potential score		1.00	0.506	0.066	0.337	0.030	0.169	0.0000	0.0000
SAV adoption potential score	1.00		0.240	0.023	0.403	0.067	-0.163	0.0000	0.0000

similarly, the differences of the means of these three variables (education, occupation, and trip distance) are less than 11%.

5.1.7 Areas Scoring High in Both PAV and SAV Adoption Potential

Although Section 5.1.5 and Section 5.1.6 reveal that there are drastic differences between the areas with high PAV adoption potential and the areas with high SAV adoption potential, there exist census tracts high in both PAV and SAV adoption potential. There are only 3 such census tracts when assuming the price of SAVs is to be fair. They are either around Union GO train station, or Exhibition GO train station (see Map 5.7). When assuming the price of SAVs is to be high, there is one more census tract adding to the three. It is around Summerhill subway station (see Map 5.8). Considering the low number of census tracts high in both PAV and SAV adoption potential, there is little need to develop an AV adoption plan or policy for the census tracts. However, planners and policy makers may approach the residents there to better understand why they prefer to adopt both PAVs and SAVs.

Table 5.18 and Table 5.19 are two tentative efforts to explore some differences between the areas high in both PAV and SAV adoption potential and those not. Table 5.20 is a tentative effort to check the influence of SAV price change on the areas high in both PAV and SAV adoption potential. The reason why the efforts are tentative is that there are too few census tracts high in both PAV and SAV adoption potential, and thus the validity of the F-tests and the t-tests done for the three tables may not be sufficiently strong. Considering the three tables show straightforward information, the thesis would not particularly emphasize any relationships from the three tables. Nonetheless, they are some references for AV researchers, planner, and policy makers to get a sense of some possible characteristics of the areas high in both PAV and SAV adoption potential.

Scrutinizing the land uses in the areas high in both PAV and SAV adoption potential with reference to Google Maps (2019), some land uses often present in the areas. Unanimously, the areas are very well covered by multiple types of public transit services, which include bus, streetcar, subway, and inter-regional passenger train. Moreover, their land uses are mixed land uses. For the three census tracts around Union and Exhibition GO train stations, mid-rise and high-rise residential and commercial buildings are dominant. For the census tract beside Summerhill subway station, there is no mid-rise and high-rise residential and commercial buildings. However, its emergence as a census tract having high scores in both PAV and SAV adoption potential in a high-SAV-price scenario does not deny that mid-rise and high-rise residential and commercial buildings are important landmarks in the areas high in both PAV and SAV adoption potential.

Map 5.7 Areas Scoring High in Both PAV and SAV Adoption Potential (Fair SAV Price)

Map 5.8 Areas Scoring High in Both PAV and SAV Adoption Potential (High SAV Price)

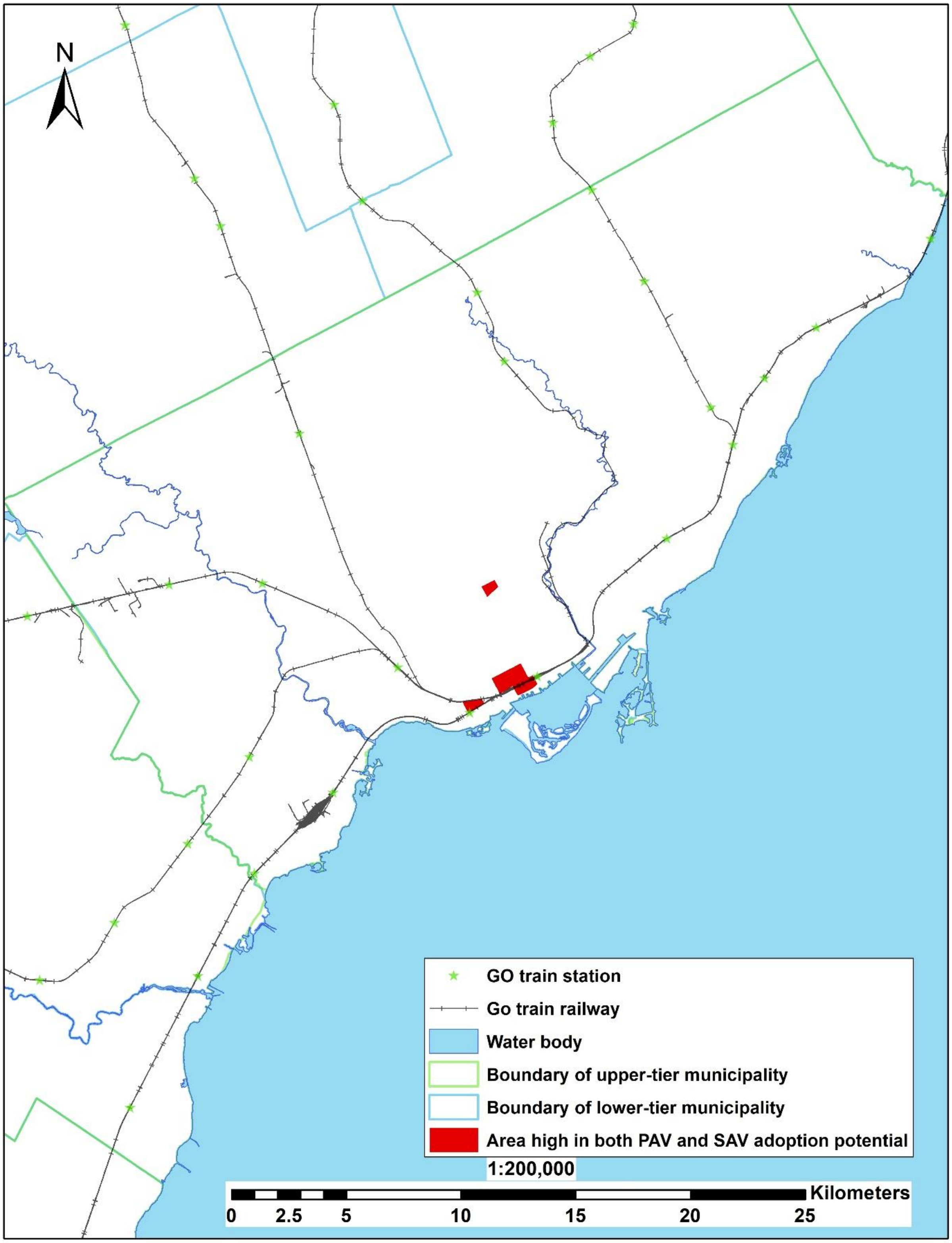


Table 5.18 Comparison between the Areas High in Both PAV and SAV Adoption Potential and Those Not (Fair SAV price)

Variable	Weight in Equation (3)	Weight in Equation (5)	CTs high in both PAV and SAV adoption potential		CTs not high in both PAV and SAV adoption potential		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.10	0.646	0.010	0.265	0.057	0.381	0.0867	0.0000
Education (≥ bachelor)	0.33	0.19	0.710	0.036	0.304	0.140	0.406	0.1833	0.0000
Household income (≥ $100,000)	0.14		0.388	0.010	0.390	0.162	-0.002	0.0113	0.8321
Occupation (NOC = 07 or 09)		0.23	0.021	0.006	0.165	0.085	-0.144	0.0133	0.0033
Driving	0.27		0.254	0.093	0.645	0.180	-0.391	0.6575	0.0002
Not driving		0.38	0.733	0.093	0.344	0.178	0.389	0.6722	0.0002
Trip distance (≥ 30 min)	0.07		0.428	0.130	0.543	0.102	-0.115	0.1705	0.0512
Job density	0.04	0.06	33,331	19,830	1,828	8,639	31,503	0.0008	0.1537
Population density		0.04	20,723	3,241	4,995	5,915	15,728	0.7246	0.0000
PAV adoption potential score	1.00		0.630	0.022	0.484	0.089	0.146	0.1676	0.0047
SAV adoption potential score		1.00	0.609	0.050	0.335	0.090	0.274	0.7302	0.0000

Table 5.19 Comparison between the Areas High in Both PAV and SAV Adoption Potential and Those Not (High SAV price)

Variable	Weight in Equation (3)	Weight in Equation (7)	CTs high in both PAV and SAV adoption potential		CTs not high in both PAV and SAV adoption potential		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.16	0.543	0.180	0.265	0.057	0.278	0.0000	0.0751
Education (≥ bachelor)	0.33	0.24	0.704	0.032	0.303	0.140	0.401	0.0490	0.0001
Household income (≥ $100,000)	0.14		0.445	0.100	0.389	0.162	0.056	0.6503	0.4901
Occupation (NOC = 07 or 09)		0.16	0.019	0.006	0.165	0.085	-0.146	0.0016	0.0000
Driving	0.27		0.276	0.089	0.646	0.180	-0.370	0.3855	0.0000
Not driving		0.35	0.713	0.088	0.344	0.178	0.369	0.3881	0.0000
Trip distance (≥ 30 min)	0.07		0.408	0.118	0.543	0.102	-0.135	0.2875	0.0079
Job density	0.04	0.05	25,921	21,439	1,826	8,642	24,095	0.0000	0.1467
Population density		0.04	16,884	7,217	4,995	5,917	11,889	0.2295	0.0001
PAV adoption potential score	1.00		0.619	0.026	0.484	0.089	0.135	0.0993	0.0025
SAV adoption potential score		1.00	0.648	0.079	0.340	0.095	0.308	0.8417	0.0000

Table 5.20 Impact of SAV Price on Some Characteristics of the Areas High in Both PAV and SAV Adoption Potential

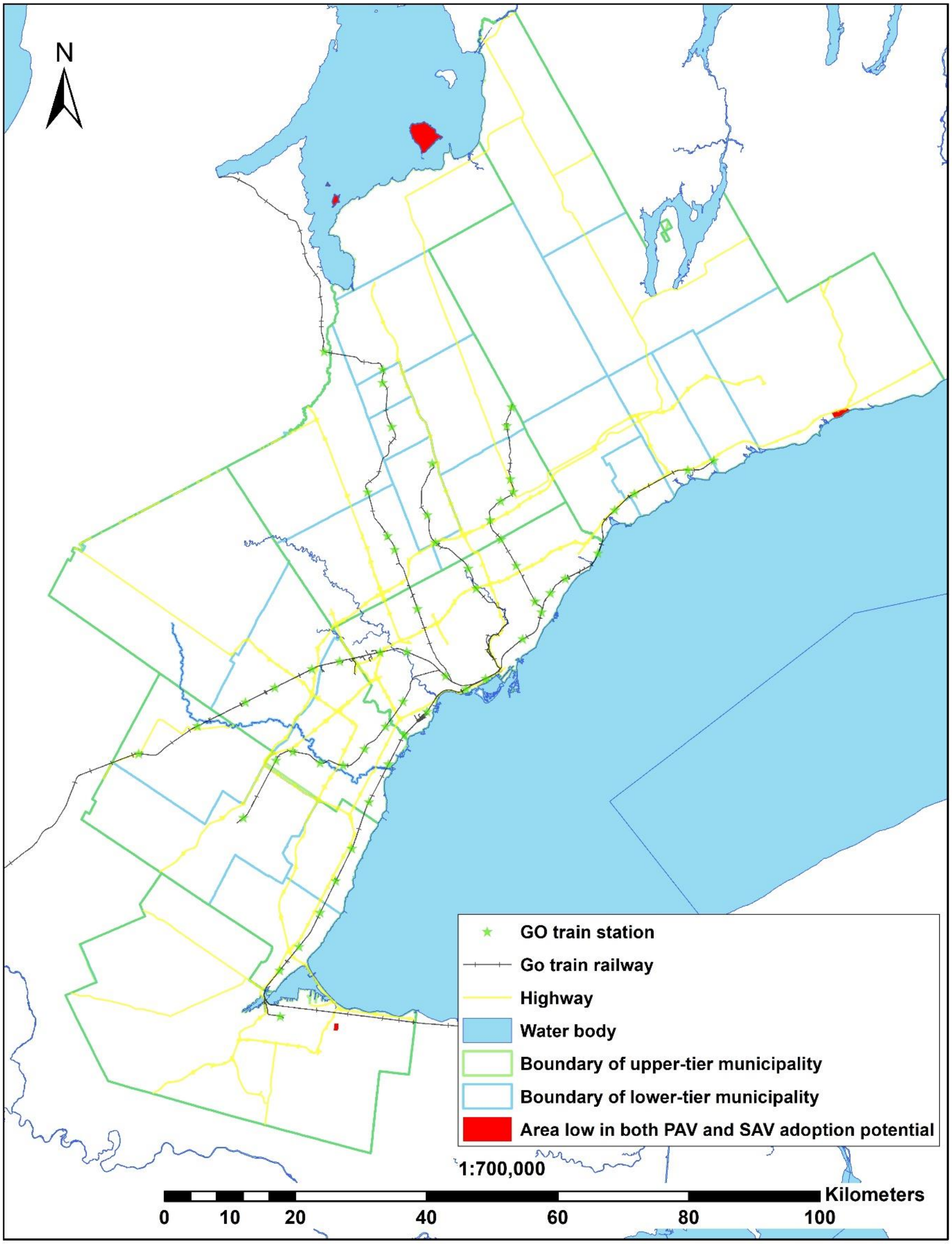
Variable	Weight in Equation (3)	Weight in Equation (7)	Weight in Equation (5)	CTs high in both PAV and SAV adoption potential (high SAV price)		CTs not high in both PAV and SAV adoption potential (fair SAV price)		Differen-ce of means	F-test	P-value of 2-sample t-test
				Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.16	0.10	0.543	0.180	0.646	0.010	-0.103	0.0067	0.3918
Education (≥ bachelor)	0.33	0.24	0.19	0.704	0.032	0.710	0.036	-0.006	0.7587	0.8603
Household income (≥ $100,000)	0.14			0.445	0.100	0.388	0.010	0.057	0.0220	0.3937
Occupation (NOC = 07 or 09)		0.16	0.23	0.019	0.006	0.021	0.006	-0.002	0.9565	0.7062
Driving	0.27			0.276	0.089	0.254	0.093	0.022	0.8154	0.8003
Not driving		0.35	0.38	0.713	0.088	0.733	0.093	-0.020	0.8034	0.8112
Trip distance (≥ 30 min)	0.07			0.408	0.118	0.428	0.130	-0.020	0.7570	0.8625
Job density	0.04	0.05	0.06	25,921	21,439	33,331	19,830	-7,410	0.9508	0.7092
Population density		0.04	0.04	16,884	7,217	20,723	3,241	-3,839	0.3809	0.5006
PAV adoption potential score	1.00			0.619	0.026	0.630	0.022	-0.011	0.9117	0.6464
SAV adoption potential score		1.00	1.00	0.648	0.079	0.609	0.050	0.039	0.6402	0.5567

5.1.8 Areas Scoring Low in Both PAV and SAV Adoption Potential

There exist census tracts low in both PAV and SAV adoption potential. There are only 3 such census tracts when assuming the price of SAVs is to be fair. They are in Hamilton, Georgia, and Clarington (see Map 5.9). Their locations are all in the outer suburb of the GTHA. When assuming the price of SAVs is to be high, the number of such census tracts increases to 15, which includes the previous 3 census tracts. The locations of the 15 census tracts are in Hamilton, Georgia, Clarington, Oshawa, Whitby, and Ajax (see Map 5.10). Thus, as the SAV price increases, the areas low in both PAV and SAV adoption potential start encroaching the inner suburb from the outer suburb. It is also noticed that even though the lower-tier municipalities of Peel, and Halton are either in the inner suburb or the outer suburb of the GTHA, they do not have any census tracts low in both PAV and SAV adoption potential. Thus, being a municipality in the suburb of a metropolitan area does not mean it would have an area low in both PAV and SAV adoption potential. Considering the low number of census tracts low in both PAV and SAV adoption potential, there is little need to develop an AV adoption plan or policy for the census tracts. However, planners and policy makers could approach the residents there so as to better understand why they have a low passion for both PAV and SAV adoptions.

Table 5.21 and Table 5.22 are two tentative efforts to explore some differences between the areas low in both PAV and SAV adoption potential and those not. Table 5.23 is a tentative

Map 5.9 Areas Scoring Low in Both PAV and SAV Adoption Potential (Fair SAV Price)



Map 5.10 Areas Scoring Low in Both PAV and SAV Adoption Potential (High SAV Price)

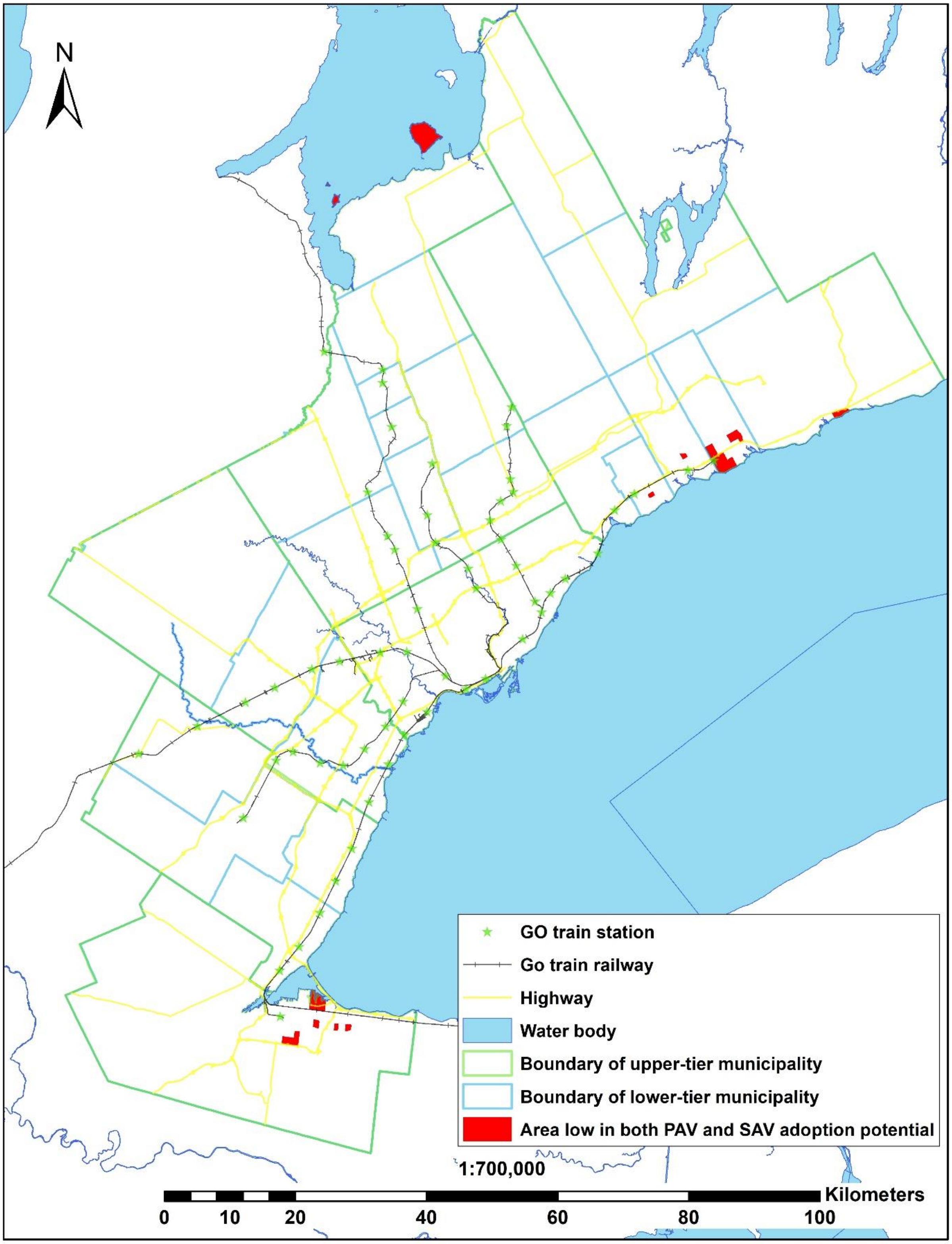


Table 5.21 Comparison between the Areas Low in Both PAV and SAV Adoption Potential and Those Not (Fair SAV price)

Variable	Weight in Equation (3)	Weight in Equation (5)	CTs low in both PAV and SAV adoption potential		CTs not low in both PAV and SAV adoption potential		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.10	0.081	0.076	0.266	0.059	-0.185	0.0761	0.0000
Education (≥ bachelor)	0.33	0.19	0.082	0.016	0.305	0.141	-0.223	0.0657	0.0040
Household income (≥ $100,000)	0.14		0.149	0.003	0.390	0.162	-0.241	0.1157	0.0198
Occupation (NOC = 07 or 09)		0.23	0.254	0.014	0.165	0.085	0.089	0.1026	0.0965
Driving	0.27		0.804	0.019	0.645	0.180	0.159	0.0235	0.0015
Not driving		0.38	0.221	0.014	0.346	0.180	-0.125	0.3851	0.0983
Trip distance (≥ 30 min)	0.07		0.379	0.092	0.543	0.101	-0.164	0.1817	0.0000
Job density	0.04	0.06	815	815	1,897	8,807	-1,082	0.0227	0.1120
Population density		0.04	1,672	1,263	5,037	5,958	-3,365	0.1363	0.2555
PAV adoption potential score	1.00		0.333	0.010	0.485	0.089	-0.152	0.0377	0.0008
SAV adoption potential score		1.00	0.219	0.035	0.336	0.091	-0.117	0.4082	0.0261

Table 5.22 Comparison between the Areas Low in Both PAV and SAV Adoption Potential and Those Not (High SAV price)

Variable	Weight in Equation (3)	Weight in Equation (7)	CTs low in both PAV and SAV adoption potential		CTs not low in both PAV and SAV adoption potential		Differen-ce of means	F-test	P-value of 2-sample t-test
			Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.16	0.219	0.066	0.266	0.059	-0.047	0.4619	0.0018
Education (≥ bachelor)	0.33	0.24	0.088	0.025	0.307	0.140	-0.219	0.0000	0.0000
Household income (≥ $100,000)	0.14		0.197	0.052	0.391	0.161	-0.194	0.0000	0.0000
Occupation (NOC = 07 or 09)		0.16	0.265	0.030	0.164	0.085	0.101	0.0001	0.0000
Driving	0.27		0.750	0.032	0.644	0.181	0.106	0.0000	0.0000
Not driving		0.35	0.242	0.022	0.346	0.180	-0.104	0.0000	0.0000
Trip distance (≥ 30 min)	0.07		0.389	0.055	0.544	0.100	-0.155	0.3603	0.0000
Job density	0.04	0.05	938	596	1,905	8,844	-967	0.0000	0.0005
Population density		0.04	2,779	1,610	5,055	5,979	-2,276	0.0000	0.0001
PAV adoption potential score	1.00		0.356	0.021	0.486	0.089	-0.130	0.0000	0.0000
SAV adoption potential score		1.00	0.246	0.033	0.342	0.096	-0.096	0.0001	0.0000

effort to check the influence of SAV price change on the areas high in both PAV and SAV adoption potential. The reason why the efforts are tentative is that there are very few census tracts low in both PAV and SAV adoption potential, and thus the validity of the F-tests and the t-tests done for the three tables may not be sufficiently strong. Considering the three tables show straightforward information, the thesis would not particularly emphasize any relationships from the three tables. Nonetheless, they are some references for AV researchers, planner, and policy makers to get a sense of some possible characteristics of the areas low in both PAV and SAV

Table 5.23 Impact of SAV Price on Some Characteristics of the Areas Low in Both PAV and SAV Adoption Potential

Variable	Weight in Equation (3)	Weight in Equation (7)	Weight in Equation (5)	CTs low in both PAV and SAV adoption potential (high SAV price)		CTs low in both PAV and SAV adoption potential (fair SAV price)		Differen-ce of means	F-test	P-value of 2-sample t-test
				Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.15	0.16	0.10	0.219	0.066	0.081	0.076	0.138	0.2189	0.0563
Education (≥ bachelor)	0.33	0.24	0.19	0.088	0.025	0.082	0.016	0.006	0.8558	0.4044
Household income (≥ $100,000)	0.14			0.197	0.052	0.149	0.003	0.048	0.8375	0.4311
Occupation (NOC = 07 or 09)		0.16	0.23	0.265	0.030	0.254	0.014	0.011	0.6350	0.3869
Driving	0.27			0.750	0.032	0.804	0.019	-0.054	0.5384	0.0309
Not driving		0.35	0.38	0.242	0.022	0.221	0.014	0.021	0.1599	0.1091
Trip distance (≥ 30 min)	0.07			0.389	0.055	0.379	0.092	0.010	0.1013	0.2657
Job density	0.04	0.05	0.06	938	596	815	815	123	0.3088	0.4555
Population density		0.04	0.04	2,779	1,610	1,672	1,263	1,107	0.9304	0.1991
PAV adoption potential score	1.00			0.356	0.021	0.333	0.010	0.023	0.5436	0.0900
SAV adoption potential score		1.00	1.00	0.246	0.033	0.219	0.035	0.027	0.4351	0.0250

adoption potential.

Scrutinizing the land uses in the areas low in both PAV and SAV adoption potential with reference to Google Maps (2019), there are three categories. Each of them does not typically exist in one or two municipalities. One category is a town or a local center surrounded by low-density or mid-density residential units. One category is an industrial center surrounded by low-density or mid-density residential units. The remaining category is the natural land or the farmland, in which a small number of single detached houses are visible. The first two categories have decent public transit services. The last category has limited or no public transit services. Thus, the population density and job density vary a lot in the areas. Therefore, there is no typical type of land use for locating where the likely areas are.

5.2 The PAV and SAV Adoption Potential around the GO Train Stations in the GTHA

As concluded in Section 4.3, areas within a 7-kilometer buffer of GO train stations are defined as the service areas of the stations for their park-and-ride and kiss-and-ride passengers. Map 5.11 shows the 1-kilometer, 4-kilometer, and 7-kilometer buffers of the stations. Approximately, 8% (110 census tracts) of the GTHA is in the 1-kilometer buffer; 66% (944 census tracts) of the GTHA is in the 4-kilometer buffer; and 87% (1239 census tracts) of the GTHA is in

Map 5.11 The Service Areas of the GO Train Stations in the GTHA for Park-and-Ride and Kiss-and-Ride Passengers

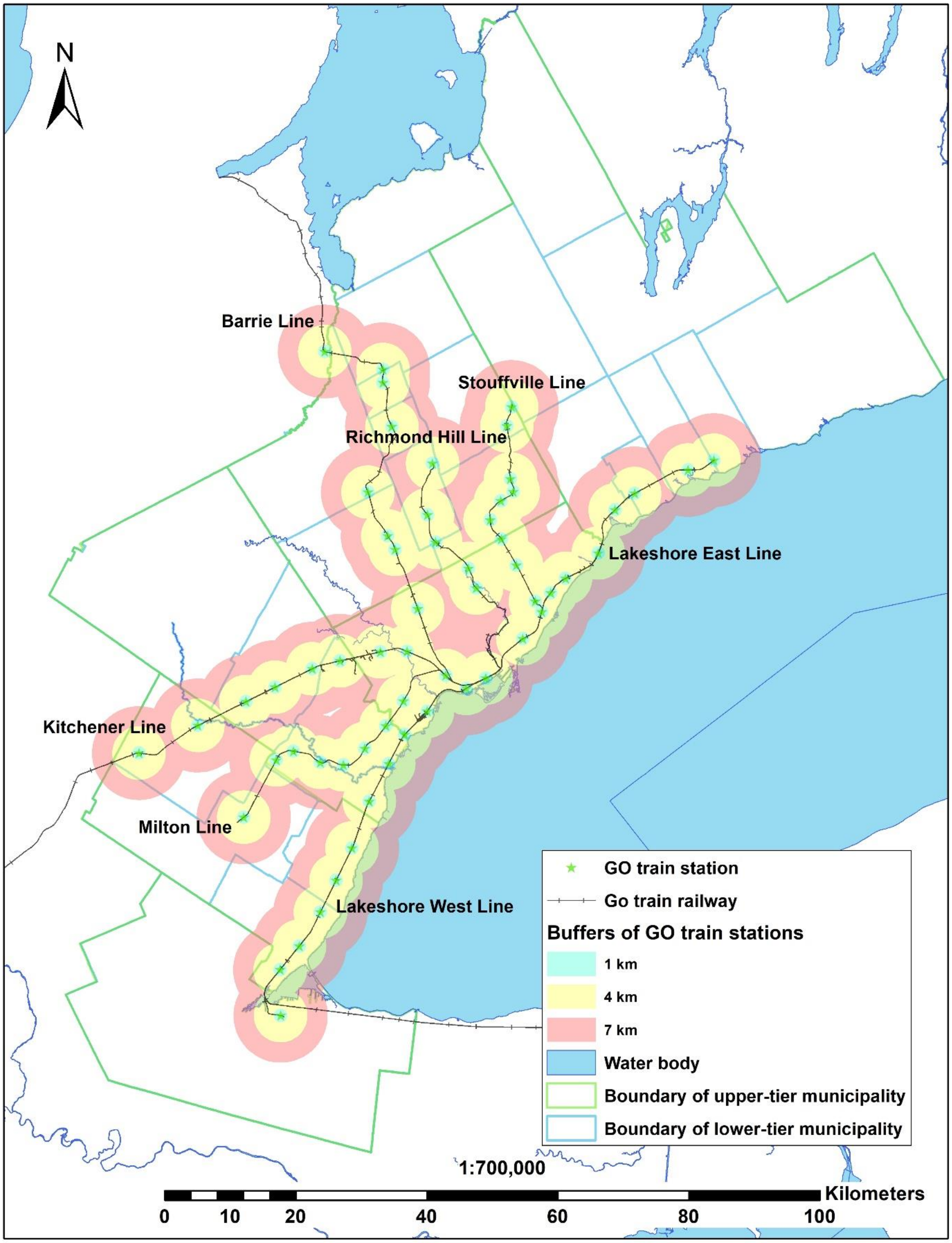


Table 5.24 The PAV and SAV Adoption Potential inside and outside the 7km Buffer of the GO Train Stations in the GTHA

Variable	Inside the buffers		Outside the buffers		Difference of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.269	0.061	0.241	0.430	0.028	0.0000	0.0000
Education (≥ bachelor)	0.319	0.143	0.202	0.076	0.117	0.0000	0.0000
Household income (≥ $100,000)	0.379	0.163	0.463	0.127	-0.084	0.0001	0.0000
Occupation (NOC = 07 or 09)	0.157	0.084	0.222	0.069	-0.065	0.0013	0.0000
Driving	0.617	0.175	0.834	0.085	-0.217	0.0000	0.0000
Not driving	0.373	0.174	0.152	0.058	0.221	0.0000	0.0000
Trip distance (≥ 30 min)	0.550	0.100	0.493	0.099	0.057	0.8235	0.0000
Job density	2,126	9,384	282	378	1,844	0.0000	0.0000
Population density	5,508	6,187	1,695	1,777	3,813	0.0000	0.0000
PAV adoption potential scores	0.482	0.092	0.501	0.063	-0.019	0.0000	0.0006
SAV adoption potential scores (fair price)	0.348	0.089	0.250	0.052	0.098	0.0000	0.0000
SAV adoption potential scores (high price)	0.355	0.093	0.243	0.045	0.112	0.0000	0.0000

the 7-kilometer buffer. As a large proportion of the GTHA is in the park-and-ride and kiss-and ride service areas of the GO train stations, it is necessary and meaningful to assess whether the PAV and SAV adoption potential in the service areas is different from those outside. Thus, comparing the potential inside and outside the 7-kilometer buffer is a major task.

Table 5.24 demonstrates whether there exist some differences between the park-and-ride and kiss-and-ride service areas of the GO train stations in the GTHA and the rest of the GTHA in terms of the modeling variables and results. Significantly, the station service areas have much more people not relying on driving for commuting, much more highly educated people, more long commuters, slightly more young people, less people whose NOC occupation numbers are 07 or 09, less high-income households, and much less people dependent on driving for commuting. In addition, they have higher population and job densities. These differences comprehensively lead to two statistically significant results. First, the overall PAV adoption potential in the station service areas is slightly (1.9%) lower than that outside. Second, the overall SAV adoption potential in the station service areas is approximately 10% more than that outside in both price scenarios. Therefore, their difference in SAV adoption potential is much more prominent than their difference in PAV adoption potential. In addition, a fluctuation of SAV price would not change their difference in SAV adoption potential much.

Table 5.25 indicates that all the significant differences true at the 7-kilometer buffer are also true at the 4-kilometer buffer. Particularly, the difference of means of the PAV adoption potential scores do not change much. However, the difference of means of SAV adoption potential scores approximately reduces by a half in both price scenarios. The reduction reveals that the people living between 4 kilometers and 7 kilometers from their home GO train stations are much more willing to adopt SAVs than those living less than 4 kilometers from their home stations. Major contributing factors to the reduction include large reductions in the differences of means of the proportion of highly educated people, and the proportion of people not relying on driving for commuting as the radius is reduced from 7 kilometers to 4 kilometers. The minor contributing factors include noticeable reductions in the differences of means of the proportion of young people, job density, and population density.

Table 5.26 indicates that in the 1-kilometer buffer of the stations, most of the significant differences true at the 7-kilometer and the 4-kilometer buffers are also true at the 1-kilometer buffer. Particularly, the difference of means of PAV adoption potential scores do not change much as the radius reduces from 4 kilometers to 1 kilometers. However, the difference of means of SAV adoption potential scores further reduces by approximately in both price scenarios. Therefore, SAV adoption potential noticeably decreases as one gets closer to a GO train station, though this potential keeps being much significantly higher than that outside the buffer radius. In terms of the decrease in the overall SAV adoption potential near the stations between the 1-kilometer and the 4-kilometer buffers, the contributing factors are small decreases in the differences of means of the proportion of highly educated people, the proportion of people not relying on driving for commuting, and population density. It is noticed that from the 4-kilometer buffer to the 1-kilometer buffer, there is a large drop in the proportion of long commuters, but it does not cause a large change in the difference of means of the PAV adoption potential.

Building connections to Map 5.4, Map 5.5, and Map 5.6, the three maps actually reflect the findings that near the GO train stations, there is lower PAV adoption potential, and higher

Table 5.25 The PAV and SAV Adoption Potential inside and outside the 4km Buffer of the GO Train Stations in the GTHA

Variable	Inside the buffers		Outside the buffers		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.272	0.065	0.253	0.043	0.019	0.0000	0.0000
Education (≥ bachelor)	0.317	0.137	0.279	0.148	0.038	0.0427	0.0000
Household income (≥ $100,000)	0.366	0.159	0.437	0.158	-0.071	0.8898	0.0000
Occupation (NOC = 07 or 09)	0.156	0.080	0.183	0.090	-0.027	0.0027	0.0000
Driving	0.605	0.176	0.723	0.165	-0.118	0.1124	0.0000
Not driving	0.385	0.175	0.266	0.160	0.119	0.0332	0.0000
Trip distance (≥ 30 min)	0.557	0.098	0.514	0.103	0.043	0.1571	0.0000
Job density	2,405	10,665	875	1,822	1,530	0.0000	0.0000
Population density	5,722	6,480	3,645	4,422	2,077	0.0000	0.0000
PAV adoption potential scores	0.476	0.091	0.500	0.084	-0.024	0.0342	0.0000
SAV adoption potential scores (fair price)	0.353	0.090	0.301	0.083	0.052	0.0551	0.0000
SAV adoption potential scores (high price)	0.360	0.094	0.303	0.088	0.057	0.1369	0.0000

SAV adoption potential. Visible from Map 5.4, the colored patches around many GO train stations, such as Brampton, Bramalea, and Richmond Hill are overall lighter than their surroundings. It means that the PAV adoption potential near the stations are lower than those farther from them. Also visible from Map 5.5 and Map 5.6, the colored patches around many GO train stations, such as Hamilton, Newmarket, and Whitby are overall darker than the surroundings. It means that the SAV adoption potential near the stations are higher than those farther from them.

Now that the GO train station service areas have less PAV adoption potential, and more SAV adoption potential, it is necessary to check whether the seven GO train lines differ a lot in their nearby potential.

Table 5.27, Table 5.28, and Table 5.29 are some works done for the check. Generally speaking, around Richmond Hill Line and Milton Line, there are obviously higher PAV adoption potential, compared to other lines (see Table 5.27). The higher potential do not fluctuate much inside their park-and-ride and kiss-and-ride service areas. Near Milton Line, there is also an obviously less SAV adoption potential at all radii of the three buffers and in both SAV price

Table 5.26 The PAV and SAV Adoption Potential inside and outside the 1km Buffer of the GO Train Stations in the GTHA

Variable	Inside the buffers		Outside the buffers		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Age (15 to 34 years old)	0.291	0.084	0.263	0.056	0.028	0.0000	0.0012
Education (≥ bachelor)	0.334	0.142	0.302	0.141	0.032	0.8733	0.0212
Household income (≥ $100,000)	0.328	0.151	0.395	0.162	-0.067	0.4220	0.0000
Occupation (NOC = 07 or 09)	0.143	0.067	0.167	0.086	-0.024	0.0010	0.0008
Driving	0.554	0.181	0.652	0.179	-0.098	0.7877	0.0000
Not driving	0.435	0.178	0.338	0.177	0.097	0.8486	0.0000
Trip distance (≥ 30 min)	0.558	0.112	0.541	0.101	0.017	0.1164	0.0984
Job density	6,151	25,816	1,536	5,115	4,615	0.0000	0.0651
Population density	6,454	5,663	4,909	5,963	1,545	0.5324	0.0089
PAV adoption potential scores	0.466	0.086	0.486	0.089	-0.020	0.7063	0.0246
SAV adoption potential scores (fair price)	0.378	0.097	0.332	0.090	0.046	0.2032	0.0000
SAV adoption potential scores (high price)	0.387	0.107	0.337	0.094	0.050	0.0379	0.0000

scenarios, and this difference increases as one shrinks the service radius (see Table 5.28 and Table 5.29). However, the SAV adoption potential near Richmond Hill Line is significantly lower only if the service radius is reduced to 1 to 4 kilometers. It reflects a previous finding that within the service area of a typical GO train station, the SAV adoption potential decreases as one approaches the station. Thus, the GO train lines having higher PAV adoption potential nearby does not necessarily have lower SAV adoption potential nearby.

Table 5.28 and Table 5.29 show that Kitchener Line is the only line having an obviously higher SAV adoption potential nearby. The significance is essentially stable across its park-and-ride and kiss-and-ride service areas. In addition, Kitchener Line has an obviously lower PAV adoption potential nearby, and this difference is overall stable internally in its station service area (see Table 5.27).

Table 5.27 shows that Lakeshore East Line and Stouffville Line have obviously lower PAV adoption potential nearby, and this difference is the largest within the 1-kilometer buffer.

Table 5.27 The PAV Adoption Potential of the Seven GO Train Lines in the GTHA

GO train line	In the 7km buffer of the line		In the 7km buffers of other lines		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Lakeshore West	0.476	0.102	0.483	0.090	-0.007	0.0152	0.3533
Lakeshore East	0.445	0.078	0.489	0.093	-0.044	0.0028	0.0000
Milton	0.536	0.070	0.475	0.092	0.061	0.0000	0.0000
Kitchener	0.449	0.080	0.490	0.093	-0.041	0.0060	0.0000
Barrie	0.493	0.100	0.481	0.091	0.012	0.1243	0.1707
Richmond Hill	0.553	0.070	0.474	0.091	0.079	0.0004	0.0000
Stouffville	0.455	0.081	0.487	0.093	-0.032	0.0156	0.0000
GO train line	**In the 4km buffer of the line**		**In the 4km buffers of other lines**		**Differen-ce of means**	**F-test**	**P-value of 2-sample t-test**
	Mean	**SD**	**Mean**	**SD**			
Lakeshore West	0.469	0.097	0.477	0.090	-0.008	0.1584	0.3075
Lakeshore East	0.439	0.074	0.483	0.092	-0.044	0.0012	0.0000
Milton	0.531	0.072	0.468	0.091	0.063	0.0017	0.0000
Kitchener	0.438	0.077	0.485	0.092	-0.047	0.0044	0.0000
Barrie	0.483	0.104	0.475	0.090	0.008	0.0437	0.5443
Richmond Hill	0.550	0.070	0.468	0.089	0.082	0.0049	0.0000
Stouffville	0.454	0.079	0.481	0.093	-0.027	0.0111	0.0003
GO train line	**In the 1km buffer of the line**		**In the 1km buffers of other lines**		**Differen-ce of means**	**F-test**	**P-value of 2-sample t-test**
	Mean	**SD**	**Mean**	**SD**			
Lakeshore West	0.456	0.104	0.469	0.080	-0.013	0.0571	0.5128
Lakeshore East	0.402	0.066	0.477	0.085	-0.075	0.2640	0.0012
Milton	0.505	0.059	0.460	0.088	0.045	0.1294	0.0710
Kitchener	0.435	0.054	0.472	0.090	-0.037	0.0292	0.0322
Barrie	0.479	0.061	0.465	0.087	0.014	0.6710	0.7370
Richmond Hill	0.534	0.050	0.459	0.086	0.075	0.1043	0.0090
Stouffville	0.444	0.081	0.471	0.087	-0.027	0.8160	0.1961

Table 5.28 The SAV Adoption Potential of the Seven GO Train Lines in the GTHA (Fair Price)

GO train line	In the 7km buffer of the line		In the 7km buffers of other lines		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Lakeshore West	0.312	0.080	0.356	0.089	-0.044	0.0677	0.0000
Lakeshore East	0.340	0.075	0.350	0.091	-0.010	0.0009	0.0824
Milton	0.311	0.043	0.353	0.092	-0.042	0.0000	0.0000
Kitchener	0.388	0.077	0.339	0.089	0.049	0.0060	0.0000
Barrie	0.326	0.081	0.351	0.089	-0.025	0.2334	0.0039
Richmond Hill	0.342	0.075	0.349	0.090	-0.007	0.0103	0.3516
Stouffville	0.358	0.069	0.346	0.092	0.012	0.0000	0.0381
GO train line	In the 4km buffer of the line		In the 4km buffers of other lines		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Lakeshore West	0.312	0.080	0.358	0.090	-0.046	0.3614	0.0001
Lakeshore East	0.346	0.072	0.354	0.093	-0.008	0.0002	0.2352
Milton	0.313	0.045	0.359	0.093	-0.046	0.0000	0.0000
Kitchener	0.392	0.076	0.344	0.090	0.048	0.0068	0.0000
Barrie	0.326	0.086	0.356	0.090	-0.030	0.6365	0.0037
Richmond Hill	0.336	0.073	0.355	0.091	-0.019	0.0088	0.0228
Stouffville	0.354	0.068	0.353	0.094	0.001	0.0000	0.8103
GO train line	In the 1km buffer of the line		In the 1km buffers of other lines		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Lakeshore West	0.379	0.088	0.377	0.100	0.002	0.5278	0.9085
Lakeshore East	0.383	0.067	0.377	0.101	0.006	0.0892	0.8110
Milton	0.319	0.058	0.386	0.099	-0.067	0.0480	0.0016
Kitchener	0.423	0.080	0.369	0.098	0.054	0.4467	0.0357
Barrie	0.293	0.019	0.382	0.097	-0.089	0.0087	0.0000
Richmond Hill	0.329	0.049	0.382	0.099	-0.053	0.0359	0.0135
Stouffville	0.364	0.072	0.381	0.102	-0.017	0.0825	0.4690

Table 5.29 The SAV Adoption Potential of the Seven GO Train Lines in the GTHA (High Price)

GO train line	In the 7km buffer of the line		In the 7km buffers of other lines		Differen-ce of means	F-test	P-value of 2-sample t-test
	Mean	SD	Mean	SD			
Lakeshore West	0.319	0.083	0.363	0.093	-0.044	0.0462	0.0000
Lakeshore East	0.340	0.077	0.358	0.096	-0.018	0.0002	0.0033
Milton	0.324	0.042	0.360	0.097	-0.036	0.0000	0.0000
Kitchener	0.382	0.085	0.349	0.094	0.033	0.0616	0.0000
Barrie	0.328	0.072	0.354	0.094	-0.026	0.0003	0.0000
Richmond Hill	0.371	0.076	0.354	0.095	0.017	0.0034	0.0235
Stouffville	0.364	0.064	0.354	0.097	0.010	0.0000	0.0662
GO train line	**In the 4km buffer of the line**		**In the 4km buffers of other lines**		**Differen-ce of means**	**F-test**	**P-value of 2-sample t-test**
	Mean	**SD**	**Mean**	**SD**			
Lakeshore West	0.336	0.089	0.365	0.094	-0.029	0.3941	0.0004
Lakeshore East	0.346	0.073	0.363	0.097	-0.017	0.0000	0.0199
Milton	0.325	0.044	0.366	0.098	-0.041	0.0000	0.0000
Kitchener	0.385	0.085	0.354	0.095	0.031	0.0822	0.0001
Barrie	0.324	0.072	0.364	0.095	-0.040	0.0022	0.0000
Richmond Hill	0.364	0.074	0.360	0.096	0.004	0.0021	0.6077
Stouffville	0.360	0.062	0.360	0.099	0.000	0.0000	0.9334
GO train line	**In the 1km buffer of the line**		**In the 1km buffers of other lines**		**Differen-ce of means**	**F-test**	**P-value of 2-sample t-test**
	Mean	**SD**	**Mean**	**SD**			
Lakeshore West	0.394	0.099	0.385	0.110	0.009	0.5973	0.7128
Lakeshore East	0.381	0.066	0.389	0.113	-0.008	0.0309	0.7069
Milton	0.324	0.060	0.397	0.110	-0.073	0.0232	0.0012
Kitchener	0.425	0.093	0.381	0.108	0.044	0.5666	0.1205
Barrie	0.286	0.025	0.392	0.107	-0.106	0.0159	0.0000
Richmond Hill	0.353	0.058	0.391	0.111	-0.038	0.0532	0.2975
Stouffville	0.369	0.064	0.392	0.115	-0.023	0.0045	0.2176

However, in terms of difference of means, the two lines do not differ much from other lines in nearby SAV adoption potential (see Table 5.28 and Table 5.29).

Table 5.28 and Table 5.29 indicate that Lakeshore West Line has an obviously lower SAV adoption potential nearby, but most of the lower adoption potential concentrate between the 4-kilometer and the 7-kilometer buffers of its stations. Somewhat differently, the two tables also indicate that Barrie Line has a noticeably lower SAV adoption potential nearby, and the difference is the largest in the 1-kilometer buffer. For both lines, they do not differ much from other lines in nearby PAV adoption potential. Synthesizing all the differences as well as the similarities of the lines, it is found that a line having a relatively higher PAV adoption potential does not necessarily have a relatively lower SAV adoption potential, and vice versa. In addition, a line having a relatively lower PAV adoption potential does not necessarily have a relatively higher SAV adoption potential, and vice versa.

Appendix F reminds that even in a line, different stations can have obviously different PAV and SAV adoption potential around them. For instance, in Kitchener Line, the park-and-ride and kiss-and-ride service area of Georgetown GO train station has much higher PAV adoption potential, and much lower SAV adoption potential, relative to the service areas of other stations in Kitchener Line.

Four stations are worth a particular mentioning. The park-and-ride and kiss-and-ride service area of Gormley GO train station has the highest PAV adoption potential (0.616), whereas the park-and-ride and kiss-and-ride service area of Weston GO train station has the lowest PAV adoption potential (0.370). The park-and-ride and kiss-and-ride service area of Union GO train station has the highest SAV adoption potential (0.539 for the fair-price scenario, and 0.579 for the high-price scenario), whereas the park-and-ride and kiss-and-ride service areas of Lincolnville GO train station has the lowest SAV adoption potential (0.212 for the fair-price scenario, and 0.219 for the high-price scenario). The maximums and minimums reflect again that the highest PAV adoption potential scores often occur in the inner suburb of the GTHA, while the lowest often occur in Toronto. They also reflect again that the highest SAV adoption potential scores often occur at and round the downtown area in Toronto, while the lowest often occur in the outer suburb of the GTHA.

Chapter 6: Conclusions

As mentioned in Chapter 1, this thesis is one of the first works to explore the geography of PAV or SAV adoption potential, indexing the potential, and providing insights and implications on AV adoption for planners and policy makers. In this Chapter, Section 6.1 will summarize the answers to the three research questions as posed in Chapter 1. Section 6.2 will brief the limitations of the research, while Section 6.3 will discuss the areas for further research.

6.1 Findings

6.1.1 Factors influencing the Potential Adoptions of PAVs and SAVs

To find the factors influencing the potential adoptions of PAVs and SAVs respectively, Chapter 2 reviewed the technology adoption theories relevant to AV adoption. Table 2.1 and Table 2.2 summarize the arguments of the theories relevant to AV adoption, and provide an overview of the key factors encouraging or discouraging people's intention to adopt AVs. However, the theories do not clearly distinguish PAVs from SAVs, while many scholars as mentioned in Chapter 3 found that the impact of a factor on PAV adoption may differ from its impact on SAV adoption. Therefore, AV researchers and technology theorists need to expand the current AV adoption theories so as to recognize the difference between PAVs and SAVs. Particularly, the theorists need to test the impacts of the factors as summarized in Table 2.1 and Table 2.2 on PAV and SAV adoptions.

As efforts to expand the theories, some scholars – as mentioned in Chapter 3 – have modeled the impacts of at least one of three types of factors on AV, PAV and SAV adoption respectively. The three types of factors are (1) the socioeconomic characteristics of a population, (2) the travel characteristics of a population, and (3) the land use characteristics of where the population live. The nature of these factors' impacts are summarized in Table 3.2, which clearly indicates that many factors differ in their influence on potential PAV adoption and potential SAV adoption. For this reason, potential PAV adoption and potential SAV adoption are two relatively independent concepts, and that it is meaningless to find and model the factors influencing potential AV adoption.

6.1.2 Assessing Potential PAV and SAV Adoptions in the Urban Context

Chapter 3 identifies three approaches that AV researchers have used to understand AV adoption. First and most commonly used, a survey, an interview, or both are conducted to quantify the influences of a set of variables on people's intention to adopt PAVs and SAVs. Second, a few studies, including this thesis, synthesize some common influential factors on people's decision making on PAVs and SAVs through a systematic review of the literature. Third, some researchers model how the general availability of PAVs and SAVs would impact the residential locations of a population, which they believe would have a long term impact on the PAV and SAV adoption potential of a place. However, before this thesis, there has been no study indexing the adoption potential of PAVs and SAVs to a specific geographic unit, such as a census geographic unit. In addition, no one has mapped the potential across a city or a metropolitan area. Therefore, there has been no study generating findings and suggestions for planners and policy makers through the two approaches. Thus, the thesis is the first effort to narrow the two research gaps.

Coping with the data availability of the 2016 Canadian Census at the census tract level, and implementing a systematic literature review, the thesis selected 6 variables that are key factors reflecting the locations of the people favoring PAVs, and assigned a weight to each of them. The two steps helped produce a linear equation, indexing the PAV adoption potential of a census tract. The range of the indexed potential is from 0.000 to 1.000, both inclusively. The closer to 1.000 the potential is, the higher the potential. After the PAV potential of all the census tracts in the GTHA was indexed, ArcMap was used to map their potential using the 5-class natural-break classification scheme. The produced map demonstrates where, in the GTHA, there exists high PAV adoption potential, and where there exists low PAV adoption potential. The same process was utilized to produce the map showing the SAV adoption potential in the GTHA in two scenarios: the price of SAVs would be fair, and the price would be high.

Although the thesis only models the PAV and SAV adoption potential in the GTHA, the same processes can be implemented in any other urban areas in Canada using the 2016 Canadian Census data. In the future, when new Canadian Census data become available, the same processes can be done in the GTHA as well as other Canadian urban areas to monitor the change of the potential.

Outside Canada, researchers can check whether they have data for the variables as described in Equations (3), (5), and (7) for their studied urban area. If they have the data, they would be able to go through the same processes to assess the PAV and SAV adoption potential there. If the data of one or more variables are not available, they would have two approaches for consideration. First, they may check whether there exist data of a reasonable alternative variable. For example, if there exists no data for household income, but for personal income, the researcher may use the data for personal income to model the impact of income. Second, researchers may reference to Table 3.2 and Table 4.1, and see which variables are significant for an adoption scenario, and have data available. Then, they need to find a new weight for each of selected variable.

6.1.3 Implications for Planners and Policy Makers

Chapter 2 introduces lots of factors either encouraging or discouraging people's intention to adopt AVs. From these factors, planners and policy makers can learn the lessons as tabulated in Table 6.1.

Chapter 5 provides a case study of the PAV adoption potential and the SAV adoption potential in the GTHA. From the case study, planners and policy makers, especially those in the GTHA, can learn lots of lessons.

The first lesson is on the choices of PAV and SAV testing corridors. Places with high PAV adoption potential tends to cluster in the inner suburb, while places with high SAV adoption potential tends to cluster in the Downtown. Thus, before allowing a general operation of AVs due to a concern of the safety of the vehicles (the concern was discussed in Chapter 2), planners are recommended to choose some roads in the inner suburb for testing PAV operation, and some roads in the Downtown for testing SAV operation.

The second lesson is on the target groups of people who may be approached in a plan or policy development. In the areas with high PAV adoption potential, there are more highly educated people, more high-income households, and more people heavily dependent on driving

Table 6.1 Lessons from Chapter 2 for Planners and Policy Makers

Finding	Suggestion
PAVs and SAVs are relatively independent concepts.	Plan and policy making on AVs should take into consideration the differences of PAVs and SAVs; and may design different goals, objectives, rules, principles, and items for PAV adoption and SAV adoption.
Some people have concerns on the life safety and cyber security of AVs.	The government develops safety standards for PAVs and SAVs. In addition, the government may consider providing funding for the research on AV safety, especially on the technology improving AV safety.
Many people wish that drivers would not be responsible for the accidents caused by PAVs.	The government needs to assess this wish, and decide whether drivers can be conditionally waived of their responsibilities for an accident. More importantly, the government should identify the roles and responsibilities of the drivers and the passengers in a PAV or SAV.
Policy incentives would encourage people to adopt AVs.	The government comprehensively uses incentives and deterrents to guide people's consumptions on PAVs and SAVs, so as to maintain or realize a good traffic condition and a sustainable transportation.
AVs would improve the mobility of seniors, but many seniors do not prefer AVs, especially SAVs, due to various reasons.	The government may design a project to broaden seniors' knowledge of PAVs and SAVs, and teach them how to use the two types of vehicles.
The preparedness of the traffic infrastructure for AV adoption is a key factor influencing AV adoption.	The government should make a long term plan to install the necessary facilities to assist AV operation, and maintain them. Particularly, the government should consistently provide enough budget for the installation and maintenance.
Some people hesitate adopting AVs because they do not know how to interact with non-AVs.	The government should be aware that there would be a transition period when both non-AVs and AVs would operate on road. Thus, the government may conduct a research to find the approximate length of the period, and design new traffic rules or modify current traffic rules to facilitate a harmonious interaction between AVs and non-AVs.
People can do things not relevant to driving in an AV.	The government may need to detail the allowed activities in an AV.
A better fuel efficiency would facilitate AV adoption.	The government may financially support the research on improving the fuel efficiency of AVs. The government may also assess the potential impacts of PAVs and SAVs on the environment, and take action accordingly.
Household income directly influences one's decision making on PAVs.	The government may comprehensively utilize taxing and financial incentives to regulate the demand for PAVs as well as SAVs, and the traffic volume of PAVs as well as SAVs.

for commuting, whereas there are less young people. In the areas with low PAV adoption potential, there are less highly educated people, less high-income households, and less people heavily dependent on driving for commuting. Thus, planners and policy makers may approach these people, and take care of their concerns on PAVs in the process of AV adoption plan and policy development. In the areas with high SAV adoption potential, there are more people not relying on driving for commuting, and highly educated and young people, whereas there are less people whose occupations fall in one of the two categories: trades, transport and equipment operators and related occupations (NOC = 07); and occupations in manufacturing and utilities (NOC = 09). In the areas with low SAV adoption potential, there are less people not dependent on driving for commuting, and highly educated and young people. Thus, planners and policy makers may approach these people, and take care of their concerns on SAVs in the process of AV adoption plan and policy development.

The third lesson is on the land use planning for AV adoption. Usually in the areas with high PAV adoption potential, there are low-density residential development, lots of green spaces, and one or more golf courses. In addition, they usually have a highway going through or nearby. Moreover, they usually have a low job density. Usually in the areas with low PAV adoption potential, the typical land uses fall in one of two categories. The first category is a mixture of industrial, business, and commercial uses, with no or a few households. The second category is the residential use mixed with some on-street businesses, or adjacent to a local or town center. Usually in the areas with high SAV adoption potential, there are mixed land uses, high-density development, transit-oriented development, and one or more transit corridors. In addition, they have higher job density and population density. Usually in the areas with low SAV adoption potential, there are rural lands, and natural lands. In addition, they have one or more highways going through or nearby. Moreover, transit-friendly development and infrastructure are often invisible.

Planners and policy makers should be aware that a land use characteristic is often associated with contrasting levels of PAV adoption and SAV adoption. Thus, the places that would have a high PAV volume would likely to have a low SAV volume, and vice versa. Hence, this implication may need to be considered when forecasting future vehicle volume. This implication also echoes Chapter 5's findings that there are very few census tracts high in both PAV and SAV adoption potential, and also very few census tracts low in both PAV and SAV adoption potential. In addition, planners and policy makers may use the typical land use characteristics as a guide to find the stakeholders more favoring or disliking either PAV adoption or SAV adoption. If the planners and policy makers of a municipality consider it a necessity to have certain ranges of PAV volume and SAV volume in an area, they may consider integrating certain land use policies into their long term plans.

The fourth lesson is on the pricing of SAVs. Changing the price of SAVs from a fair level ($0.37/km to $0.85/km) to a high level ($0.86/km to $2.00/km) would usually not much change the SAV adoption potential of a census tract. It reflects that the pricing of SAVs on SAV adoption is quite minor. Nonetheless, the people whose NOC is 07 or 09, students, and low-income households for SAV adoption are passionate to adopt SAVs, but their passion would dramatically drop if the price level of SAVs rises. To help them have a decent access to SAVs, planners may need to coordinate with SAV operators in terms of the pricing. If necessary, policy makers may make a policy on subsidizing the three groups' expenditures on SAVs.

The fifth lesson is on the necessity of distinguishing PAVs from SAVs. Comparing the areas high in PAV adoption potential with those high in SAV adoption potential, their residents have different socioeconomic and travel characteristics, and their land uses are different. Therefore, planners and policy makers should bear in mind that PAVs and SAVs are two independent concepts. In addition, their plans and policies should sufficiently distinguish the two concepts.

The sixth lesson is on regional rail transit planning. This lesson is more specifically for the planners at Metrolinx. In the park-and-ride and kiss-and-ride service areas of the GO train stations serving the GTHA residents, there is a higher SAV adoption potential, and a lower PAV adoption potential. This finding suggests that it may be feasible to use SAVs to increase the accessibility of the GO train stations as well as the ridership of GO train. However, the PAV and SAV adoption potential varies from line to line and from station to station. Thus, Metrolinx's AV adoption plan may classify its train stations into some categories based on the PAV and SAV adoption potential in their park-and-ride and kiss-and-ride service areas, and then prepare planning items specific for each categories. To supplement, Metrolinx may also consider drafting some planning items specific for each train station, such as the number of parking spaces for PAVs and SAVs respectively, and the redesign of the station areas. If necessary, Metrolinx may utilize its right to price its parking spaces, and guide more people to use SAVs to access GO train stations.

6.2 Limitations

6.2.1 Choices of the Modeling Variables

The thesis created three indices to model the adoption potential of PAVs and SAVs in a CGU. Each index consists of 6 variables belonging to one of three types of factors: (1) the socioeconomic characteristics of a population, (2) the travel characteristics of a population, and (3) the land use characteristics of where the population live. Chapter 2 reminds us that there are many other important factors influencing people's decision making on PAVs and SAVs, such as vehicle characteristics, one's personality and habits, peer influences, media information dissemination, and government incentives and policies (see details in Table 2.1 and Table 2.2), but the equations do not reflect the impacts of these factors. This limitation is not inevitable because these factors either are difficult to be quantified, or do not have data from the 2016 Canadian census. Thus, the equations are arguably the best models utilizing the census data and facilitating mapping.

6.2.2 Weights of the Modeling Variables

The weights in Equation (3), Equation (5), and Equation (7) are not necessarily the same, and they were established through review of three selected studies. The number of selected studies is low, but they are the usable studies that could be found so far. Thus, it is inevitable to use the findings of only three studies to help create the equations that are supposed to be generally true in modeling the PAV and SAV adoption potential in the urban context. As AV research efforts continue, it would be possible to offer more refined weights.

It is also noticed that there is more than one way to decide the weights of modeling variables, such as sensitivity analysis. However, due to time constraint, the thesis does not manage to use more methods to generate more sets of weights, and do a comparison.

6.3 Opportunities for future studies

6.3.1 Model Improvements

As mentioned before, as more relevant studies are published, AV researchers could re-evaluate the prominence of quantifiable variables, and consider whether the indices in the thesis need to be modified or refined. In addition, AV researchers may do a sensitivity analysis to generate a new set of weights, and compare their modeling results with the ones in the thesis.

As mentioned before, the weights in Equation (3), Equation (5), and Equation (7) are based on the findings of three studies. After some years, there would likely to more academic works like the three studies, with their study areas covering other urban areas. At that time, a new literature review can be conducted to check whether a variable should replace an existing modeling variable, and whether the weights of the existing variables should be fine-tuned.

6.3.2 Technology Adoption Theoretical Models for PAV Adoption and SAV Adoption

There has been theoretical models on the adoption of AVs. However, there has been no complete theoretic models on the adoption of PAVs and the adoption of SAVs, though many researchers have evaluated the prominence of some types of factors with respect to people's intention to adoption PAVs or SAVs, such as those reviewed in Chapter 3. AV theorists may do more case studies in unstudied urban areas, and see whether the findings from the thesis and the reviewed literatures referenced in the thesis also exist there. In addition, they may test the prominence of other types of factors that may have been ignored. These works would contribute to the theorization. Nevertheless, after AVs become available, AV researchers should verify the theories, and make necessary refinement.

6.3.3 Understanding Carpooling SAVs

Table 3.1 reflects that there is a very limited number of researches having studied carpooling SAVs in particular. Although on-demand SAVs and carpooling SAVs are not exclusive from each other, only focusing on-demand SAVs may not be sufficient in understanding SAVs. Thus, AV researchers are encouraged to do more studies on carpooling SAVs, and clarify the relationship between on-demand SAVs and carpooling SAVs.

6.3.4 Planning the Urban Parking Spaces

By running the models in the thesis, all planners in Canada would know the current demands for PAVs and SAVs across their cities or metropolitan areas. The demands provide implications on how much parking space is needed for PAVs, and how much for SAVs. Building upon these implications, planners could study whether and how they should re-design and plan their urban parking spaces.

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Appendix A: Estimated Driving Cost in Ontario (2016)

Vehicle category	Annual mileage (km)	Unit cost ($/km)
Compact	10,000	0.65
	20,000	0.38
	30,000	0.28
Crossover	10,000	0.79
	20,000	0.45
	30,000	0.36
Intermediate	10,000	1.05
	20,000	0.60
	30,000	0.45
Luxury	10,000	1.22
	20,000	0.67
	30,000	0.51
Pickup trucks	10,000	0.77
	20,000	0.45
	30,000	0.36
Sport	10,000	0.84
	20,000	0.48
	30,000	0.38
Subcompact	10,000	0.58
	20,000	0.34
	30,000	0.26
SUV	10,000	0.88
	20,000	0.51
	30,000	0.39
Van	10,000	0.84
	20,000	0.48
	30,000	0.38
Average	**10,000**	**0.85**
	20,000	**0.48**
	30,000	**0.37**

Source: Canadian Automobile Association (2018); Bank of Canada (2018). Tabulated by Jiajun Zhang.

The table above shows the cost of driving a private vehicle in Ontario in 2016. All the costs were generated following a few steps. Frist, the cost of driving a private vehicle in Ontario in 2018 was retrieved from Canadian Automobile Association (2018), using its default setting. The setting assumes that people travel 45% of their trips on city roads and 55% on highways. It also assumes that the fuel cost is $1.026/L. In addition, the setting has various assumptions for the purchasing and maintenance costs for different vehicle categories. After the retrieval, all the costs were converted into their values in 2016 using the inflation calculator of the Bank of Canada (2018).

It is noticed that the average annual travel distance of light vehicles was 16,000 km in Ontario in 2008 (Natural Resources Canada, 2008). Then, it is meaningful to estimate the unit cost ($/km) for an average private vehicle travelling 16,000 km a year. It is known from the table that the unit cost of driving a private vehicle does not decrease linearly, so it is reasonable to find a parabolic equation to estimate the cost. Two models have been tried.

One model generates an exponential equation by assuming the unit cost decreases exponentially in the range of 10,000 km to 20,000 km. The equation is $y = \frac{0.75146915^{(10000+x)}}{0.85}$, where x is the annual kilometers traveled in a year by a private vehicle, and y is the unit cost in $/km. It gives y ≈ $0.00/km when x = 16,000 km. As this result is lower than $0.48/km, this model is not accurate.

The other model generates a quadratic equation by modeling a quadratic parabola most closely passing through three points (10000, 0.85), (20000, 0.48), and (30000, 0.37). The equation is $y = \frac{13}{1 \times 10^{10}} x^2 - \frac{19}{250000} x + \frac{37}{25}$, where x is the annual kilometers traveled in a year by a private vehicle, and y is the unit cost in $/km (Free Mathematics Tutorials, 2018). It gives y = $0.5968/km when x = 16,000 km. Comparing the result with the unit costs of a private vehicle travelling 10,000 km and 20,000 km, this result is a reasonable estimation. Therefore, it is reasonably assumed that in 2016, GTHA private vehicle drivers spend $0.60/km in driving on average.

Appendix B: More Relationships between Land Use and AV Adoption

Nodjomian and Kockelman (2018) is one of the very few (if not the only one) article that exclusively models how land uses affect AV adoption. For the modeling, the authors used two datasets. One dataset includes 1,423 samples containing household location data. The other dataset contains 2,588 samples about their decision making on AVs in long distance (>50 mile, i.e. > 80 km) travel.

Particularly, Nodjomian and Kockelman (2018) studied the impacts of 5 land use variables on AV adoption. The 5 variables are density, diversity of land uses, urban design, destination accessibility, and distance to transit. They found three of them are important for the AV adoption in America.

The first variable is diversity of land uses. Nodjomian and Kockelman (2018) measured it in three ways: (1) a common measure, which equals $\frac{\#\ housing\ units\ in\ a\ census\ block}{\#\ jobs\ in\ the\ census\ block}$, and which suggests the importance of household density and job density; (2) trip equilibrium index, which equals $\frac{\#\ trips\ from\ a\ census\ block}{\#\ trips\ to\ the\ census\ block}$, and which suggests the importance of travel frequency and trip distance; and (3) regional diversity index, which is a function of population and employment. The explicit expression of this function is not introduced in their paper. All of the measures indicate that a good diversity of land uses would significantly discourage AV adoption, and a poor diversity of land uses would significantly encourage people to move farther from the central city.

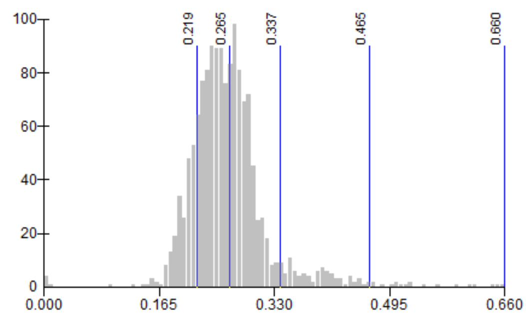
The second variable is destination accessibility. Nodjomian and Kockelman (2018) measured it in five ways: (1) number of jobs within a 45-minute drive, (2) number of jobs within a 45-minute transit ride, (3) distance to the nearest grocery store, (4) distance to work or school, and (5) distance to downtown. These measures indicate the importance of some reviewed variables in this thesis: job density, trip purpose, trip distance, and distance from the central city. Nodjomian and Kockelman (2018) use these measures to indicate that a good access to non-residential land uses would significantly discourage AV adoption. Moreover, a long distance to destination would significantly influence people to move closer to the central city.

The third variable is design. Nodjomian and Kockelman (2018) measured it in two ways: (1) density of transportation facilities, in facility miles/acre; and (2) intersection density. Only density of transportation facilities is significantly as well as positively associated with AV adoption, whereas intersection density has no significant relationship with AV adoption in America.

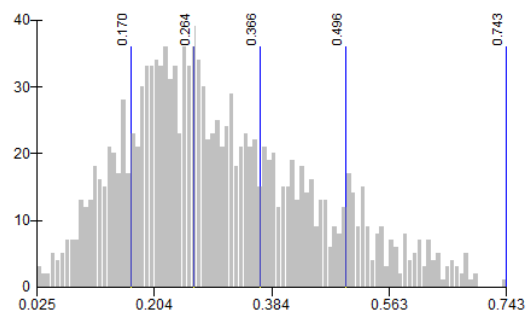
Although Nodjomian and Kockelman (2018) reveal lots of important relationships between land use and AV adoption, their findings may not provide too much meaningful information to this thesis. That is because most of their conclusions do not distinguish SAVs from PAVs, whereas Chapter 3 demonstrates that PAVs and SAVs often have different relationships with the same variable. Thus, it is unknown whether the significances persist when PAVs and SAVs are discussed separately. Second, as Chapter 3 shows, the findings true at a national scale may not be true at an urban scale.

Appendix C: Graphs of Statistical Distributions

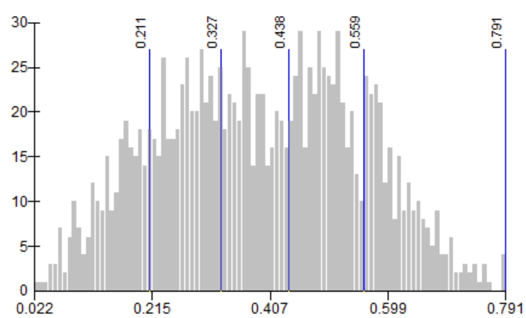
Age (15 to 34 years old)



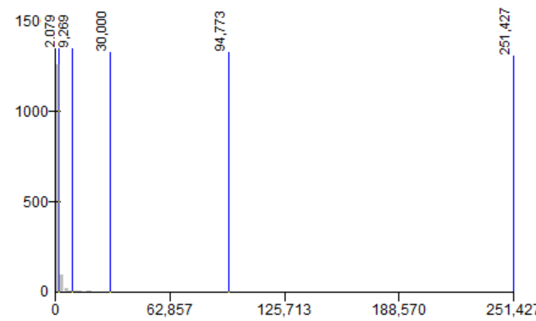
Education (bachelor or higher)



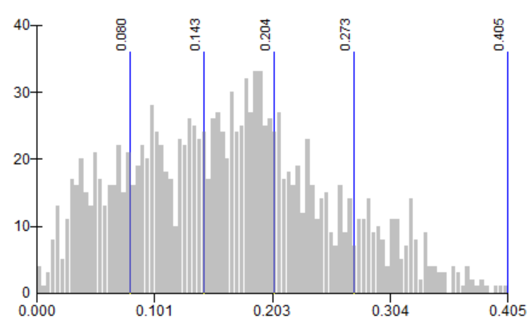
Household income ($100,000 or above)



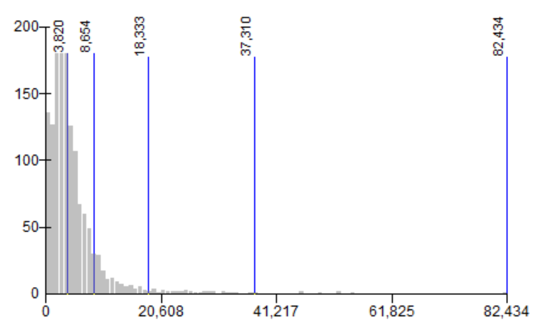
Job density



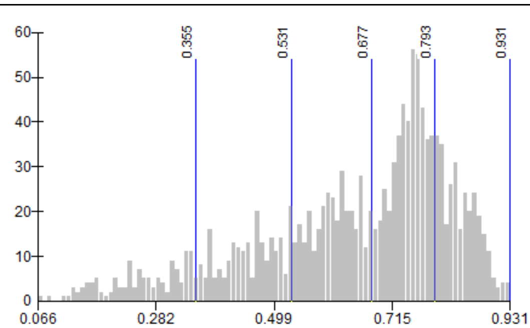
Occupation (NOC = 07 or 09)



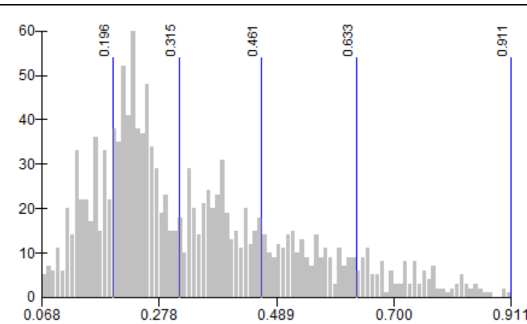
Population density



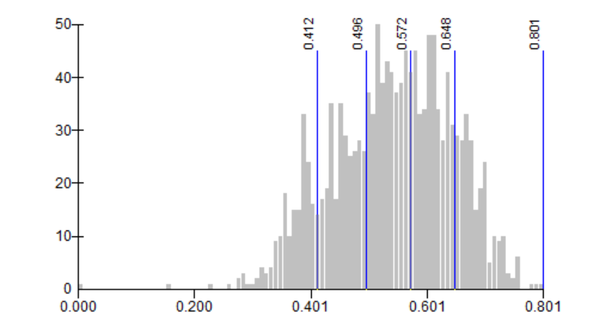
Transportation mode (driving)



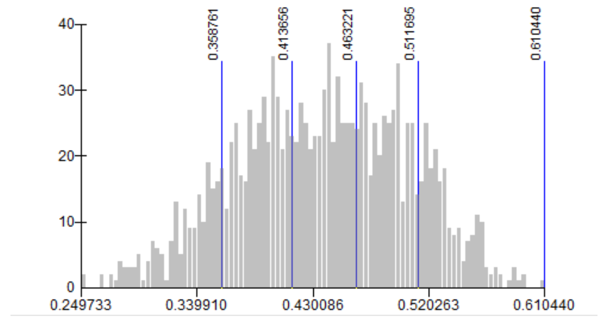
Transportation mode (not driving)



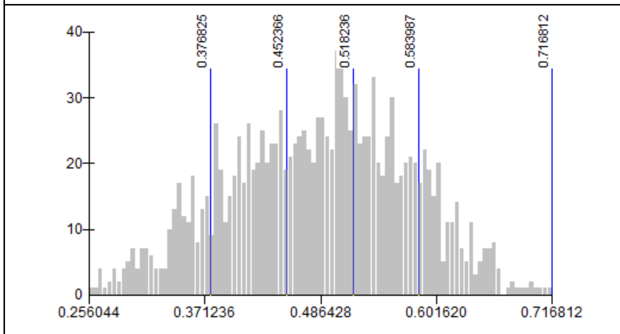
Trip distance (30 min or longer)



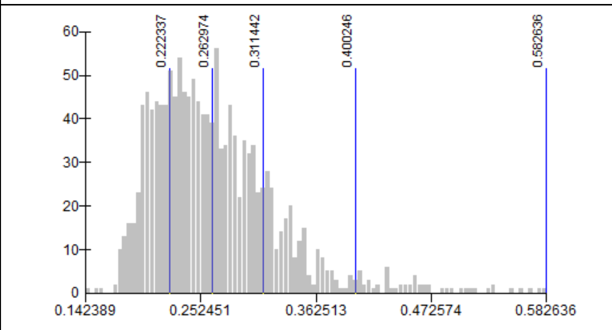
Equation (2)



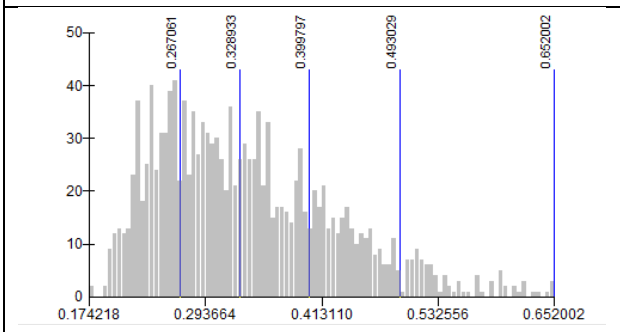
Equation (3)



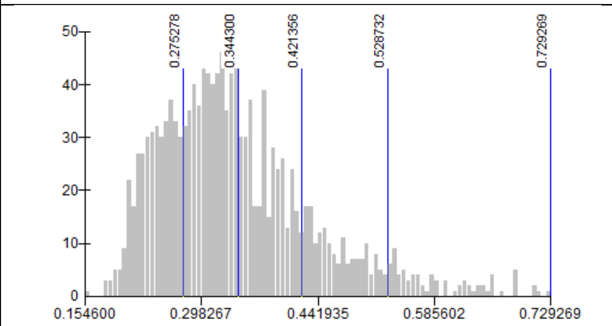
Equation (4) or (6)



Equation (5)



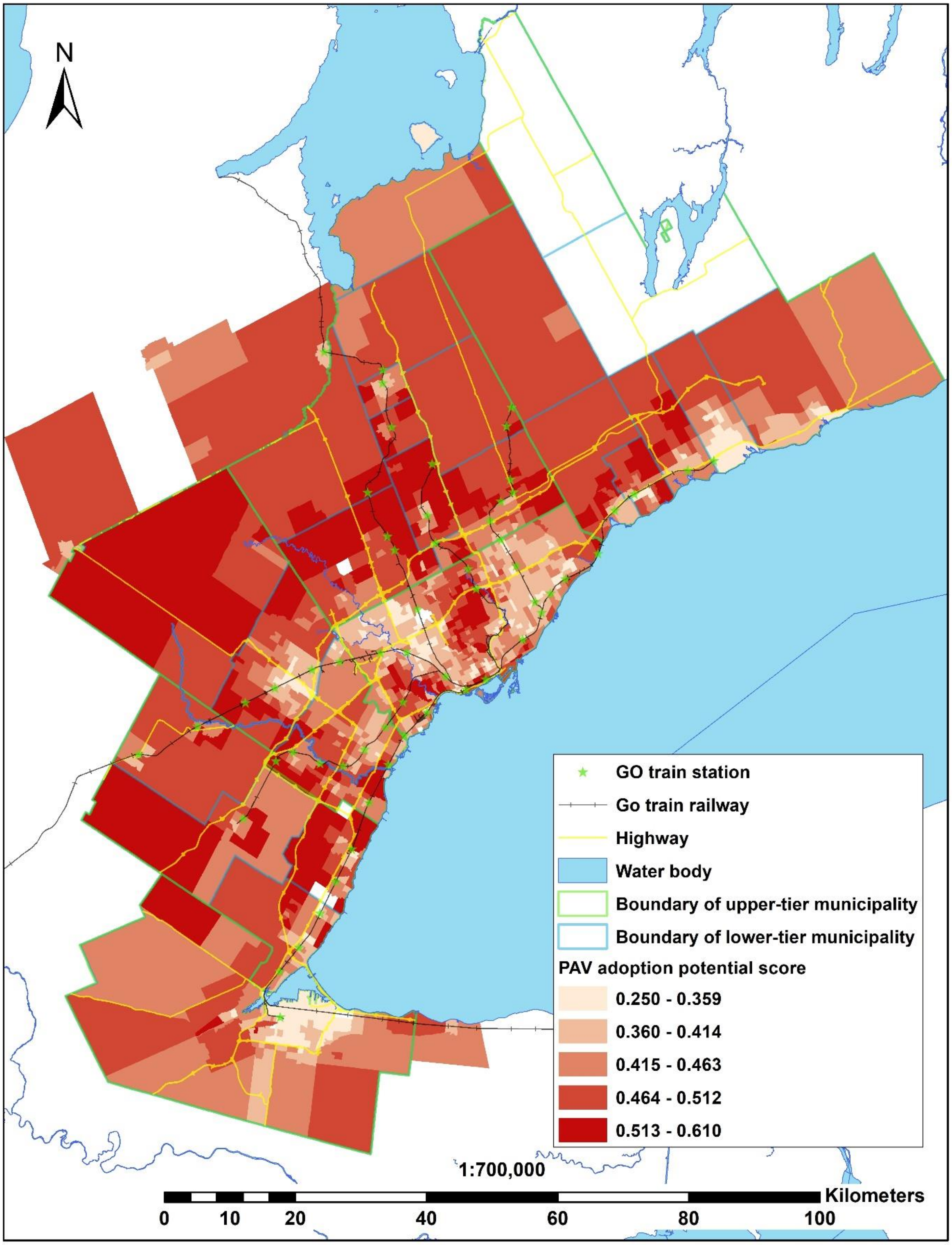
Equation (7)



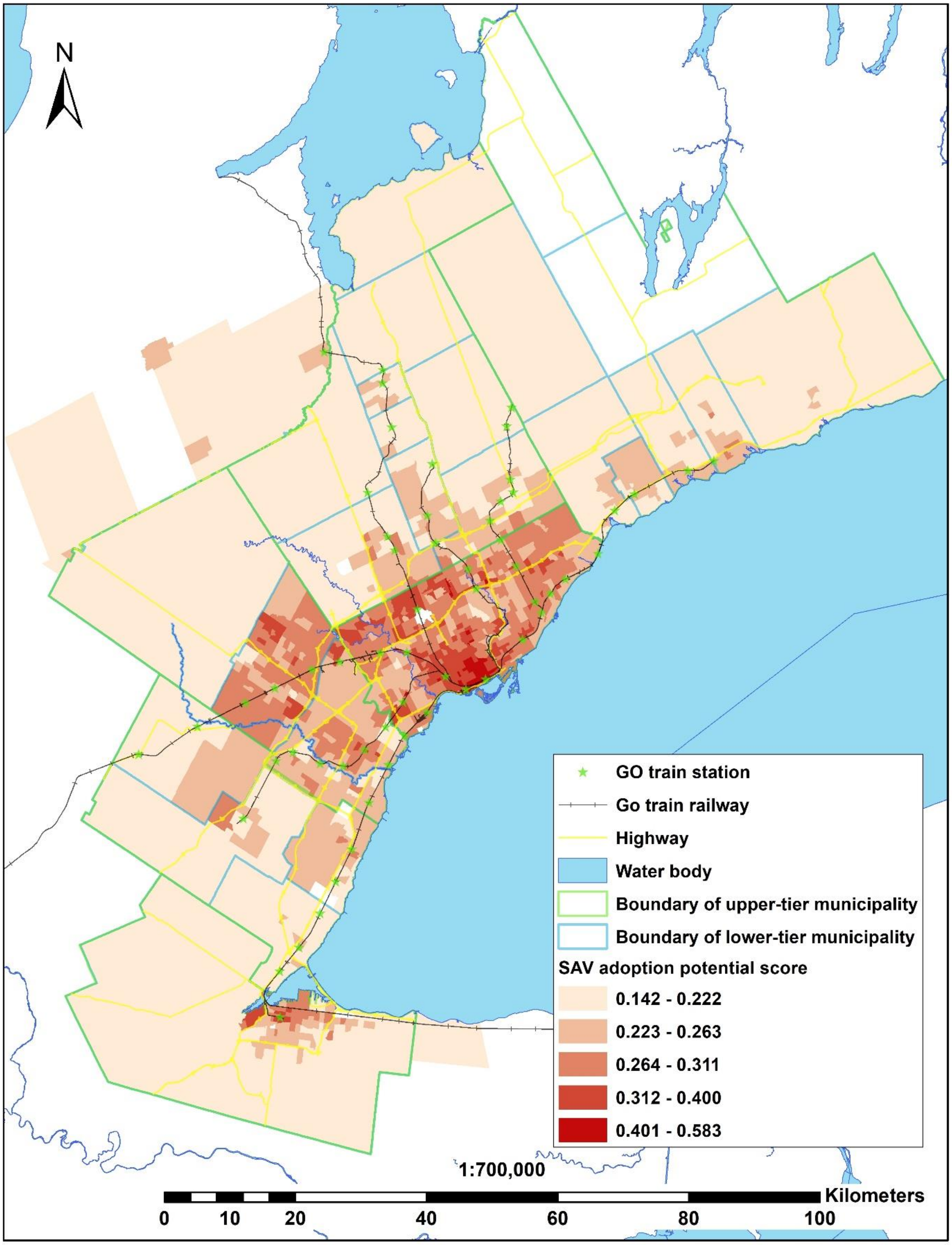
Appendix D: The PAV and SAV Adoption Potential in the GTHA, Produced by Equation (2) and Equation (4)

See the maps on the next 2 pages.

Map D1 The PAV Adoption Potential in the GTHA, Produced by Equation (2)



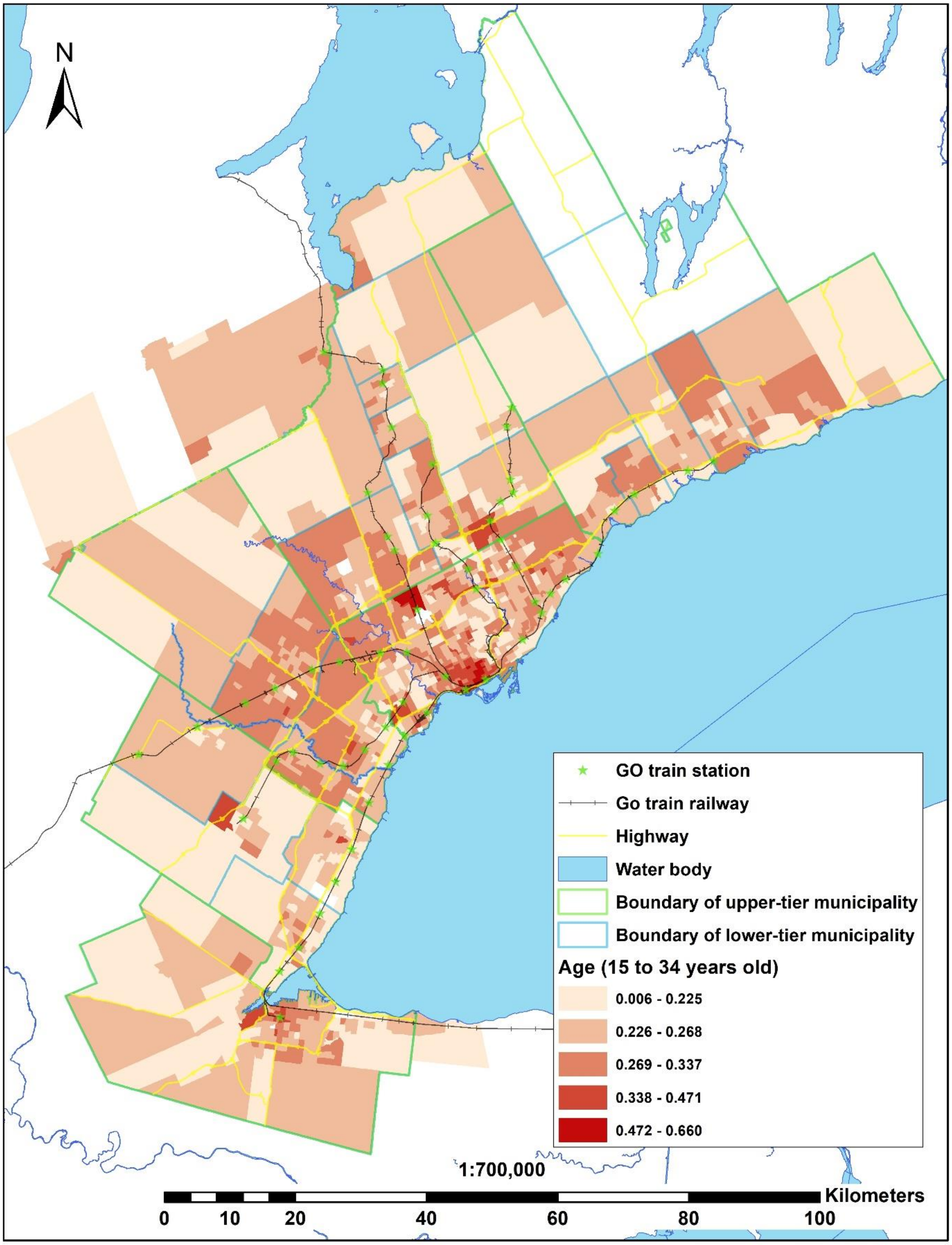
Map D2 The SAV Adoption Potential in the GTHA, Produced by Equation (4)



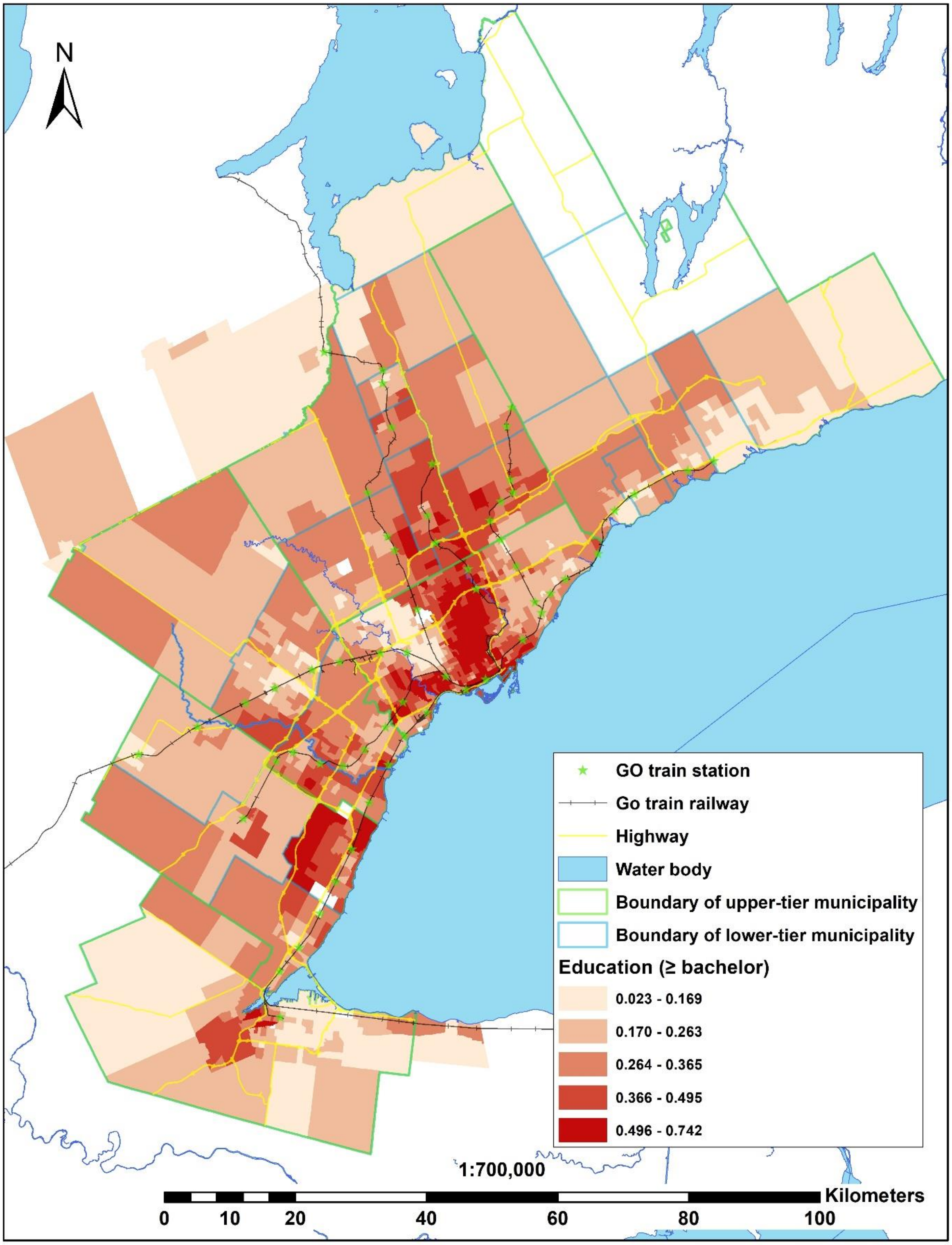
Appendix E: Atlas of the Maps on the Modeling Variables

This appendix lists 9 maps about the spatial distribution of the population having a specific socioeconomic or travel characteristics, or the spatial distribution of a land use identity. All the numbers in the legends are the normalized values generated during the modeling process. Census tracts having a higher proportion of population having a certain characteristic, or a higher job or population density have a redder color.

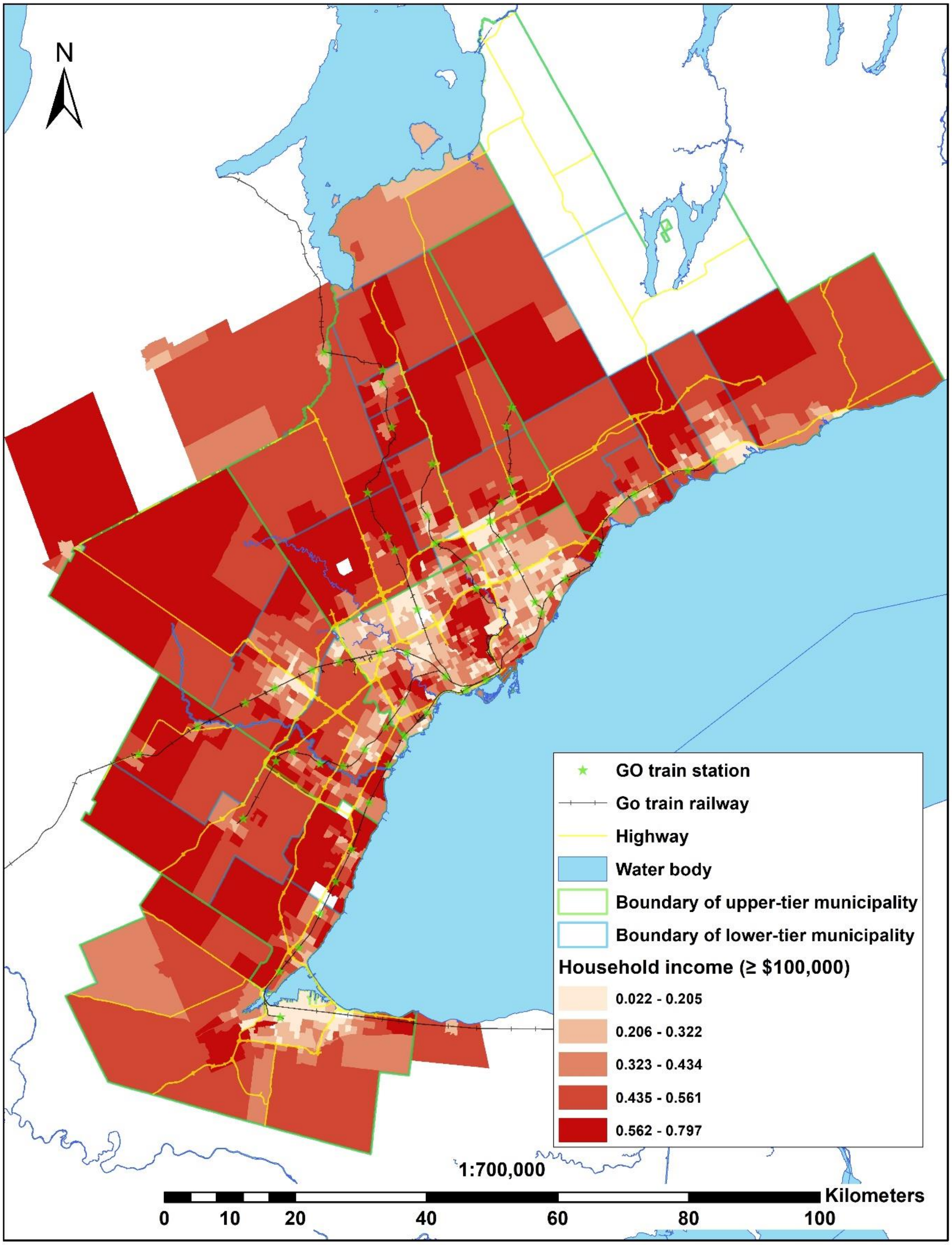
Map E1 Age: Spatial Distribution of People Aged 15 to 34 in 2016



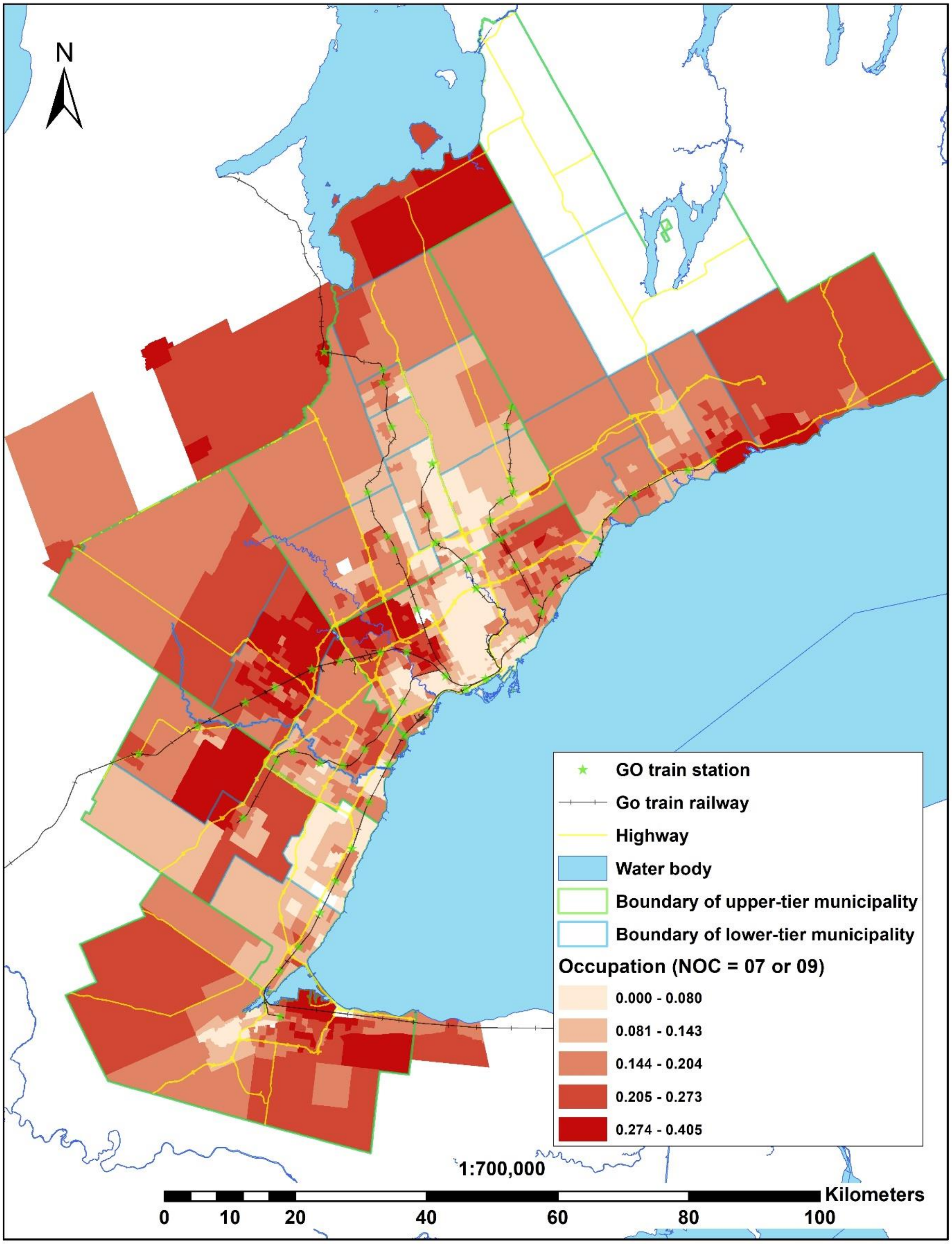
Map E2 Education: Spatial Distribution of People Having at least a Bachelor's Degree in 2016



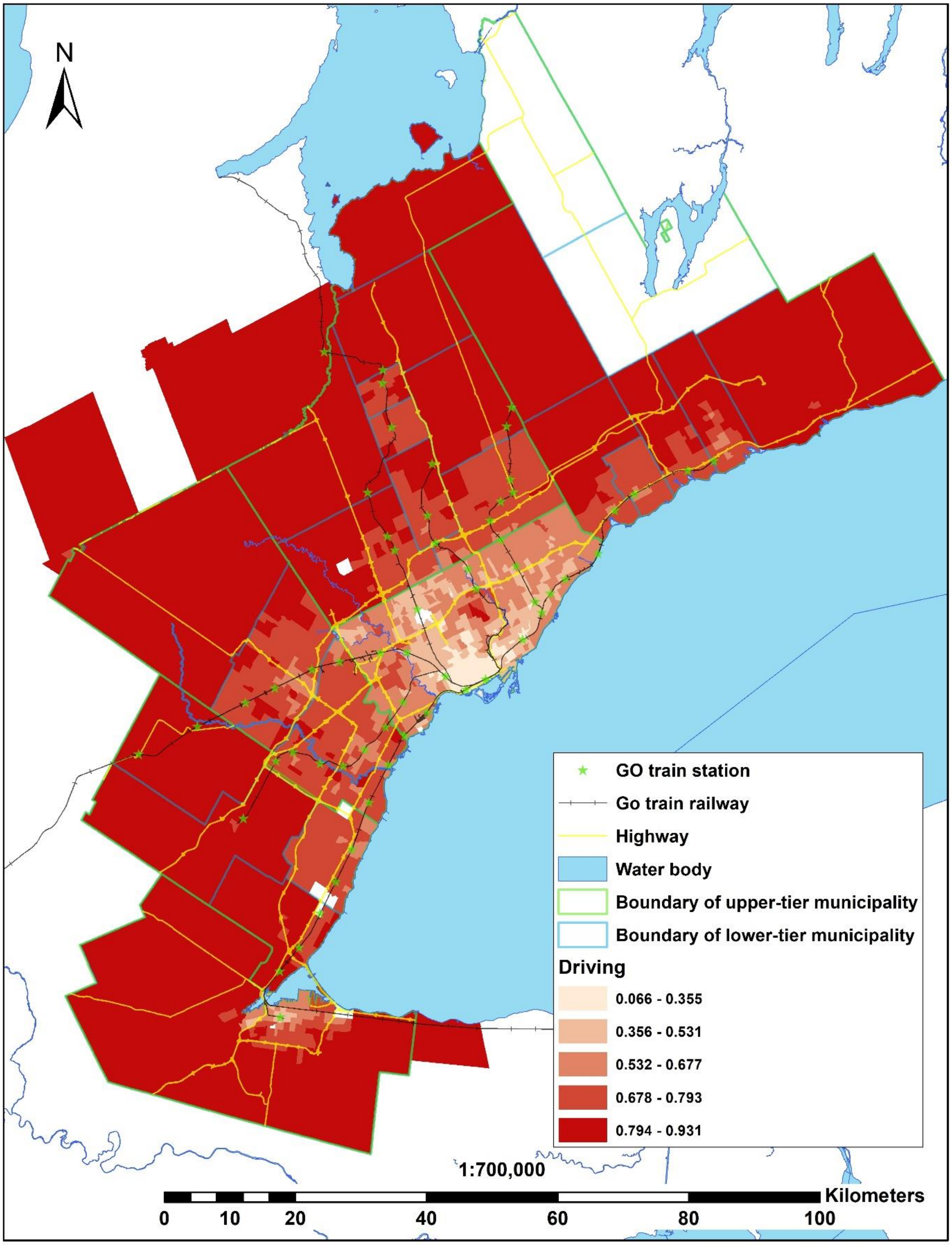
Map E3 Household Income: Spatial Distribution of Households with a Total Income of at Least $100,000 in 2015



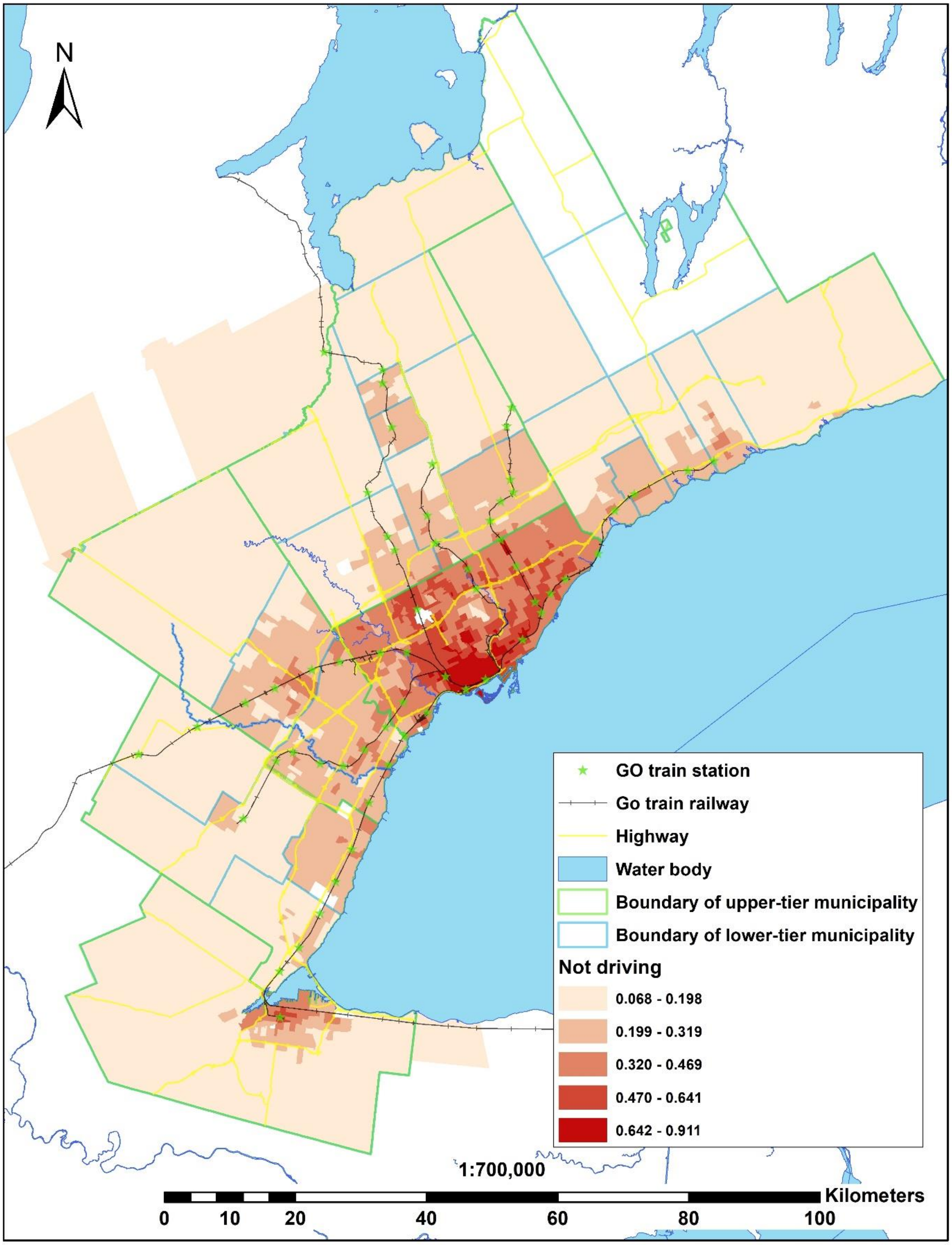
Map E4 Occupation: Spatial Distribution of People Whose NOC is 07 or 09 in 2016



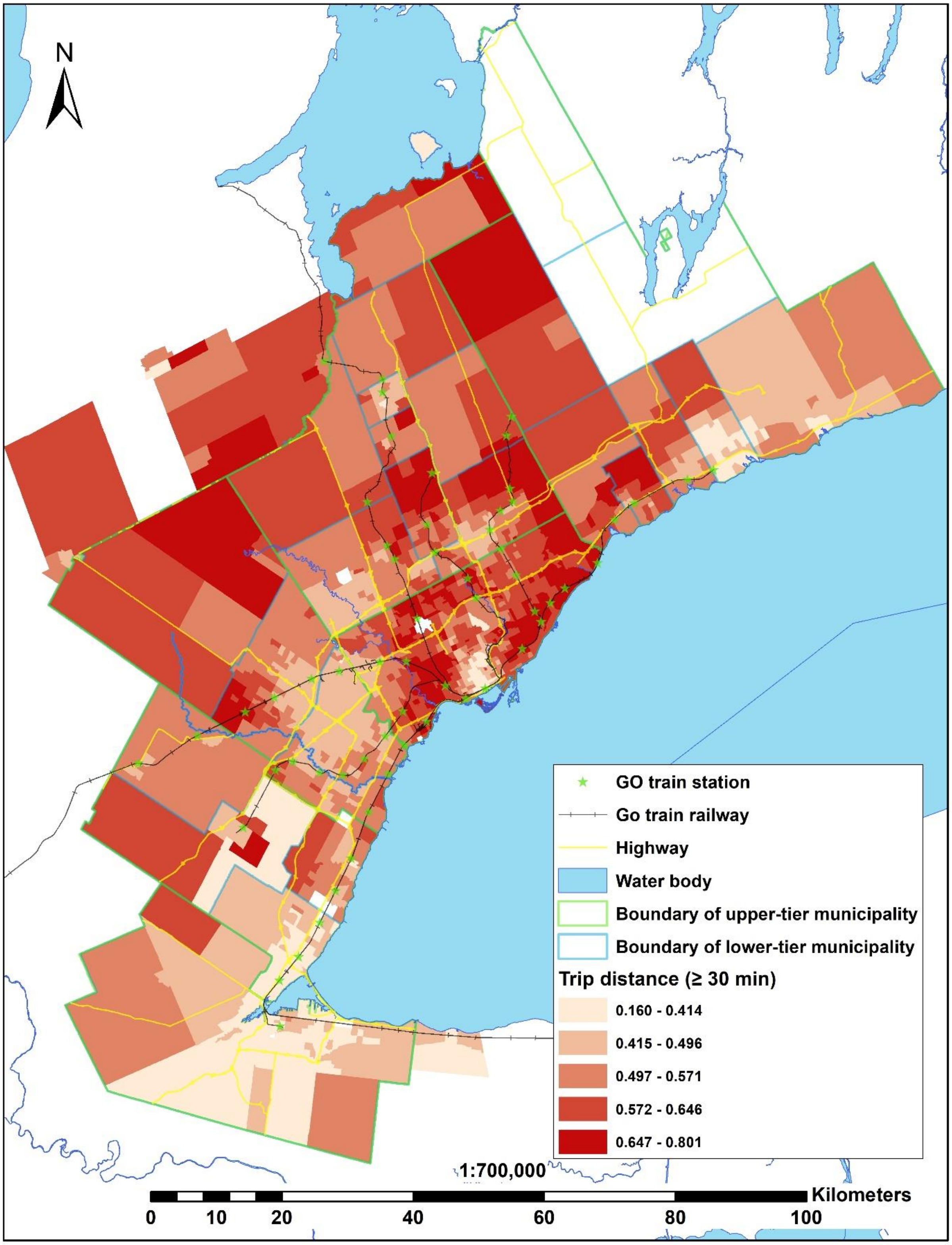
Map E5 Transportation Mode: Spatial Distribution of People who Primarily Drove between Home and Workplace in 2016



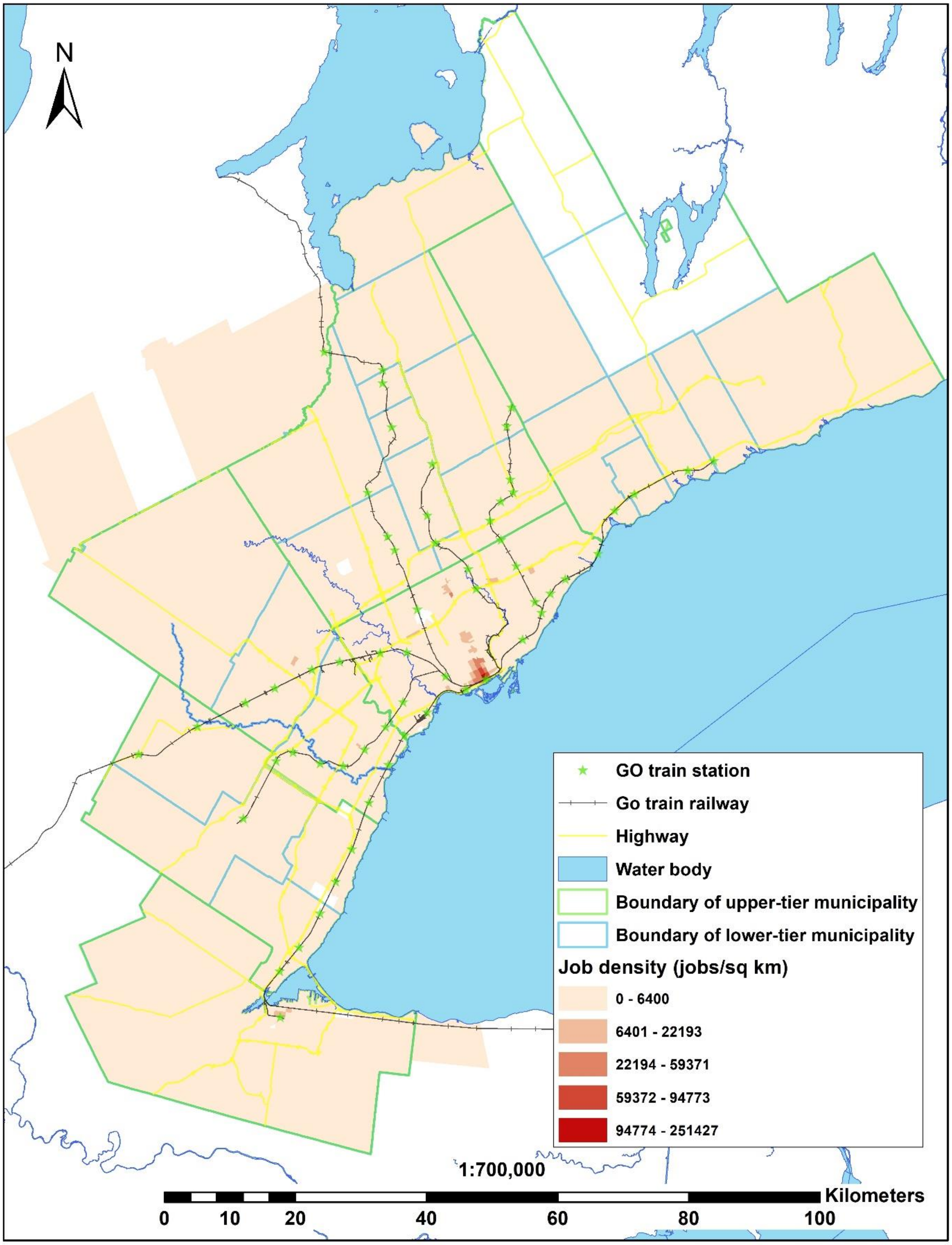
Map E6 Transportation mode: Spatial Distribution of People who Primarily Did not Drive between Home and Workplace in 2016



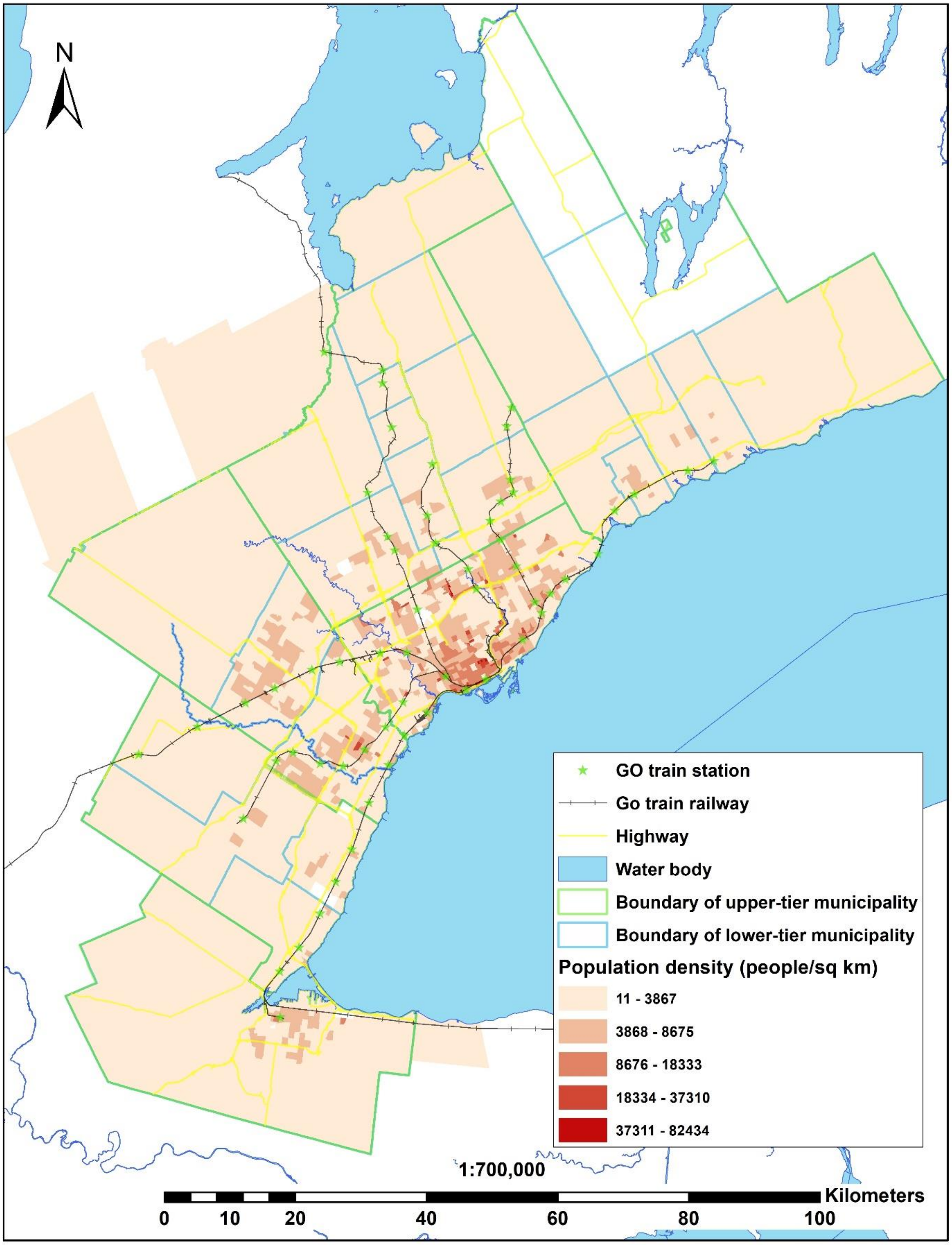
Map E7 Trip Distance: Spatial Distribution of People Who Usually Spent 30 Minutes for Commuting from Home to Workplace in 2016



Map E8 Job Density: Spatial Distribution in 2016



Map E9 Population Density: Spatial Distribution in 2016



Appendix F: The PAV and SAV Adoption Potential around Each GO Train Station in the GTHA

Part 1: The Potential in the 7-Kilometer Buffer

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	SD	Mean	SD	Mean	SD
Union	0.486	0.090	0.539	0.073	0.579	0.082
Lakeshore West Line						
Hamilton	0.405	0.079	0.321	0.064	0.313	0.066
Aldershot	0.487	0.118	0.249	0.070	0.251	0.046
Burlington	0.498	0.056	0.244	0.020	0.252	0.020
Appleby	0.566	0.056	0.236	0.017	0.259	0.015
Bronte	0.577	0.059	0.273	0.015	0.294	0.021
Oakville	0.566	0.074	0.287	0.022	0.311	0.022
Clarkson	0.542	0.071	0.294	0.027	0.309	0.021
Port Credit	0.536	0.093	0.298	0.028	0.311	0.027
Long Branch	0.464	0.037	0.311	0.035	0.309	0.035
Mimico	0.479	0.073	0.363	0.027	0.373	0.020
Exhibition	0.434	0.102	0.512	0.023	0.543	0.040
Lakeshore East Line						
Oshawa	0.400	0.068	0.276	0.043	0.258	0.034
Whitby	0.494	0.062	0.263	0.019	0.265	0.014
Ajax	0.500	0.055	0.276	0.026	0.279	0.025
Pickering	0.504	0.058	0.270	0.018	0.275	0.015
Rouge Hill	0.513	0.046	0.302	0.026	0.312	0.024
Guildwood	0.404	0.052	0.381	0.045	0.373	0.041
Eglinton	0.386	0.051	0.388	0.037	0.378	0.031
Scarborough	0.393	0.052	0.367	0.030	0.359	0.027
Danforth	0.439	0.079	0.412	0.053	0.423	0.048
Milton Line						
Milton	0.566	0.067	0.255	0.028	0.265	0.030
Lisgar	0.587	0.019	0.288	0.016	0.304	0.015
Meadowvale	0.543	0.058	0.289	0.025	0.298	0.025
Streetsville	0.587	0.034	0.296	0.022	0.319	0.021
Erindale	0.519	0.051	0.310	0.030	0.319	0.022
Cooksville	0.483	0.045	0.341	0.035	0.346	0.038
Dixie	0.463	0.047	0.323	0.038	0.318	0.032
Kipling	0.554	0.083	0.339	0.048	0.362	0.046

Part 1 Continued

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	SD	Mean	SD	Mean	SD
Kitchener Line						
Acton	0.499	0.044	0.238	0.002	0.227	0.007
Georgetown	0.542	0.054	0.224	0.019	0.228	0.010
Mount Pleasant	0.536	0.030	0.318	0.026	0.311	0.024
Brampton	0.477	0.045	0.336	0.048	0.320	0.043
Bramalea	0.437	0.045	0.354	0.037	0.330	0.033
Malton	0.417	0.038	0.405	0.032	0.383	0.027
Etobicoke North	0.407	0.052	0.381	0.047	0.361	0.038
Weston	0.370	0.072	0.391	0.053	0.370	0.040
Bloor	0.460	0.088	0.462	0.044	0.478	0.052
Barrie Line						
Bradford	0.486	0.044	0.262	0.036	0.245	0.029
East Gwillimbury	0.509	0.028	0.235	0.002	0.240	0.003
Newmarket	0.512	0.063	0.259	0.025	0.264	0.020
Aurora	0.567	0.044	0.251	0.013	0.268	0.015
King City	0.593	0.032	0.246	0.019	0.263	0.022
Maple	0.555	0.047	0.281	0.027	0.288	0.023
Rutherford	0.559	0.060	0.275	0.036	0.287	0.037
Downsview Park	0.428	0.105	0.405	0.054	0.398	0.043
Richmond Hill Line						
Gormley	0.616	0.020	0.243	0.011	0.273	0.013
Richmond Hill	0.564	0.069	0.281	0.022	0.303	0.018
Langstaff	0.572	0.050	0.288	0.023	0.318	0.019
Old Cummer	0.522	0.058	0.370	0.061	0.394	0.061
Oriole	0.552	0.079	0.386	0.074	0.419	0.075
Stouffville Line						
Lincolnville	0.553	0.014	0.212	0.010	0.219	0.013
Stouffville	0.559	0.023	0.233	0.011	0.246	0.009
Mount Joy	0.564	0.021	0.271	0.014	0.290	0.014
Markham	0.562	0.031	0.272	0.029	0.286	0.021
Centennial	0.534	0.055	0.276	0.020	0.292	0.017
Unionville	0.569	0.045	0.263	0.024	0.294	0.022
Milliken	0.426	0.042	0.345	0.033	0.337	0.024
Agincourt	0.427	0.040	0.374	0.034	0.371	0.032
Kennedy	0.380	0.033	0.399	0.037	0.391	0.035
Scarborough	0.393	0.052	0.367	0.030	0.359	0.027
Danforth	0.439	0.079	0.412	0.053	0.423	0.048

Part 2: The Potential in the 4-Kilometer Buffer

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Union	0.470	0.089	0.555	0.066	0.595	0.079
Lakeshore West Line						
Hamilton	0.382	0.070	0.354	0.058	0.346	0.061
Aldershot	0.484	0.101	0.245	0.068	0.247	0.046
Burlington	0.484	0.051	0.247	0.020	0.253	0.021
Appleby	0.545	0.058	0.243	0.014	0.259	0.015
Bronte	0.554	0.056	0.268	0.016	0.286	0.021
Oakville	0.543	0.069	0.290	0.023	0.310	0.024
Clarkson	0.542	0.076	0.295	0.028	0.310	0.022
Port Credit	0.536	0.093	0.298	0.028	0.311	0.027
Long Branch	0.464	0.037	0.311	0.035	0.309	0.035
Mimico	0.479	0.073	0.363	0.027	0.373	0.020
Exhibition	0.434	0.102	0.512	0.023	0.543	0.040
Lakeshore East Line						
Oshawa	0.371	0.072	0.299	0.043	0.277	0.032
Whitby	0.464	0.055	0.270	0.017	0.267	0.013
Ajax	0.486	0.052	0.273	0.028	0.275	0.026
Pickering	0.491	0.057	0.270	0.017	0.273	0.014
Rouge Hill	0.522	0.039	0.302	0.027	0.313	0.025
Guildwood	0.400	0.049	0.386	0.048	0.378	0.045
Eglinton	0.386	0.051	0.388	0.037	0.378	0.031
Scarborough	0.393	0.052	0.367	0.030	0.359	0.027
Danforth	0.438	0.070	0.411	0.051	0.422	0.047
Milton Line						
Milton	0.565	0.067	0.255	0.030	0.266	0.030
Lisgar	0.586	0.021	0.285	0.014	0.300	0.014
Meadowvale	0.529	0.055	0.286	0.023	0.294	0.022
Streetsville	0.586	0.037	0.294	0.024	0.318	0.024
Erindale	0.519	0.051	0.310	0.030	0.319	0.022
Cooksville	0.480	0.046	0.342	0.037	0.346	0.039
Dixie	0.457	0.043	0.325	0.039	0.319	0.033
Kipling	0.557	0.086	0.343	0.048	0.366	0.046

Part 2 Continued

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	SD	Mean	SD	Mean	SD
Kitchener Line						
Acton	0.470	0.017	0.240	0.000	0.222	0.003
Georgetown	0.528	0.054	0.228	0.019	0.229	0.010
Mount Pleasant	0.536	0.030	0.327	0.015	0.319	0.014
Brampton	0.466	0.047	0.333	0.039	0.317	0.035
Bramalea	0.411	0.024	0.369	0.032	0.342	0.031
Malton	0.406	0.021	0.409	0.015	0.384	0.018
Etobicoke North	0.417	0.052	0.365	0.034	0.351	0.026
Weston	0.371	0.075	0.390	0.055	0.369	0.042
Bloor	0.445	0.078	0.468	0.042	0.480	0.053
Barrie Line						
Bradford	0.477	0.050	0.283	0.021	0.264	0.010
East Gwillimbury	0.509	0.028	0.235	0.002	0.240	0.003
Newmarket	0.512	0.063	0.259	0.025	0.264	0.020
Aurora	0.564	0.045	0.253	0.012	0.271	0.013
King City	0.590	0.020	0.229	0.006	0.246	0.002
Maple	0.554	0.052	0.284	0.028	0.292	0.023
Rutherford	0.577	0.065	0.277	0.029	0.295	0.030
Downsview Park	0.383	0.079	0.426	0.046	0.407	0.042
Richmond Hill Line						
Gormley	0.631	0.012	0.245	0.013	0.279	0.007
Richmond Hill	0.557	0.069	0.282	0.023	0.303	0.019
Langstaff	0.579	0.048	0.288	0.022	0.319	0.018
Old Cummer	0.527	0.057	0.367	0.061	0.393	0.063
Oriole	0.541	0.084	0.380	0.081	0.411	0.081
Stouffville Line						
Lincolnville	0.567	0.000	0.222	0.000	0.232	0.000
Stouffville	0.559	0.023	0.233	0.011	0.246	0.009
Mount Joy	0.559	0.019	0.272	0.016	0.289	0.016
Markham	0.575	0.018	0.253	0.018	0.275	0.016
Centennial	0.534	0.055	0.276	0.020	0.292	0.017
Unionville	0.566	0.047	0.265	0.025	0.296	0.023
Milliken	0.425	0.042	0.344	0.033	0.336	0.024
Agincourt	0.431	0.043	0.370	0.035	0.370	0.034
Kennedy	0.377	0.034	0.402	0.035	0.394	0.034
Scarborough	0.393	0.052	0.367	0.030	0.359	0.027
Danforth	0.438	0.070	0.411	0.051	0.422	0.047

Part 3: The Potential in the 1-Kilometer Buffer

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	SD	Mean	SD	Mean	SD
Union	0.566	0.030	0.613	0.028	0.669	0.030
Lakeshore West Line						
Hamilton	0.361	0.037	0.429	0.026	0.436	0.019
Aldershot	0.499	0.000	0.236	0.000	0.236	0.000
Burlington	0.483	0.024	0.270	0.013	0.279	0.012
Appleby	0.473	0.000	0.258	0.000	0.266	0.000
Bronte	0.525	0.000	0.246	0.000	0.254	0.000
Oakville	0.519	0.107	0.325	0.028	0.347	0.010
Clarkson	0.418	0.000	0.329	0.000	0.317	0.000
Port Credit	0.582	0.075	0.318	0.006	0.344	0.014
Long Branch	0.437	0.000	0.357	0.000	0.036	0.000
Mimico	0.473	0.068	0.356	0.010	0.363	0.007
Exhibition	0.476	0.151	0.512	0.022	0.554	0.048
Lakeshore East Line						
Oshawa*	0.359	0.000	0.286	0.000	0.264	0.000
Whitby*	0.449	0.000	0.257	0.000	0.260	0.000
Ajax	0.461	0.026	0.275	0.030	0.273	0.033
Pickering	0.414	0.000	0.276	0.000	0.275	0.000
Rouge Hill*	0.545	0.000	0.320	0.000	0.337	0.000
Guildwood	0.422	0.080	0.347	0.046	0.346	0.035
Eglinton	0.345	0.018	0.416	0.017	0.402	0.014
Scarborough	0.371	0.017	0.392	0.001	0.377	0.003
Danforth	0.426	0.069	0.432	0.046	0.443	0.037
Milton Line						
Milton	0.489	0.021	0.228	0.019	0.224	0.013
Lisgar	0.577	0.000	0.316	0.000	0.325	0.000
Meadowvale*	0.480	0.000	0.276	0.000	0.279	0.000
Streetsville	0.588	0.067	0.275	0.007	0.301	0.008
Erindale	0.497	0.024	0.325	0.007	0.321	0.002
Cooksville	0.466	0.045	0.381	0.023	0.385	0.029
Dixie	0.501	0.000	0.255	0.000	0.254	0.000
Kipling	0.515	0.000	0.331	0.000	0.344	0.000

Part 3 Continued

GO train station	PAV adoption potential scores of the CTs in the buffer		SAV adoption potential scores of the CTs in the buffer (fair price)		SAV adoption potential scores of the CTs in the buffer (high price)	
	Mean	SD	Mean	SD	Mean	SD
Kitchener Line						
Acton*	0.453	0.000	0.240	0.000	0.220	0.000
Georgetown*	0.527	0.000	0.219	0.000	0.220	0.000
Mount Pleasant	0.548	0.000	0.336	0.000	0.336	0.000
Brampton	0.425	0.008	0.302	0.021	0.292	0.013
Bramalea	0.429	0.000	0.368	0.000	0.348	0.000
Malton	0.437	0.000	0.431	0.000	0.406	0.000
Etobicoke North	0.386	0.000	0.368	0.000	0.349	0.000
Weston	0.390	0.051	0.362	0.035	0.352	0.023
Bloor	0.447	0.048	0.500	0.019	0.518	0.020
Barrie Line						
Bradford	0.442	0.000	0.301	0.000	0.274	0.000
East Gwillimbury*	0.481	0.000	0.238	0.000	0.243	0.000
Newmarket	0.429	0.014	0.286	0.017	0.277	0.016
Aurora*	0.489	0.000	0.268	0.000	0.274	0.000
King City*	0.609	0.000	0.222	0.000	0.244	0.000
Maple	0.511	0.000	0.272	0.000	0.270	0.000
Rutherford	0.583	0.000	0.318	0.000	0.331	0.000
Downsview Park*	0.348	0.000	0.427	0.000	0.397	0.000
Richmond Hill Line						
Gormley*	0.643	0.000	0.232	0.000	0.272	0.000
Richmond Hill	0.471	0.014	0.285	0.004	0.293	0.007
Langstaff	0.549	0.023	0.296	0.017	0.318	0.023
Old Cummer	0.513	0.017	0.369	0.016	0.392	0.013
Oriole	0.604	0.033	0.365	0.063	0.408	0.069
Stouffville Line						
Lincolnville*	0.567	0.000	0.222	0.000	0.232	0.000
Stouffville*	0.582	0.000	0.237	0.000	0.253	0.000
Mount Joy	0.537	0.000	0.267	0.000	0.283	0.000
Markham	0.568	0.011	0.248	0.011	0.269	0.012
Centennial	0.538	0.048	0.274	0.004	0.290	0.006
Unionville	0.540	0.000	0.286	0.000	0.324	0.000
Milliken	0.433	0.001	0.331	0.012	0.329	0.014
Agincourt	0.441	0.043	0.379	0.041	0.379	0.038
Kennedy	0.357	0.011	0.417	0.005	0.406	0.004
Scarborough	0.371	0.017	0.392	0.001	0.377	0.003
Danforth	0.426	0.069	0.432	0.046	0.443	0.037

* The 1-kilometer buffer of the station does not contain the centroid of any census tracts. Thus, the score of the census tract whose centroid is closest to the station is used as the overall potential in the 1-kilometer buffer of the station.