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Identify Potential Autonomous Vehicle Adopters and Their Activity-Travel Patterns

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by

Jingyi Xiao

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Abstract

Identify Potential Autonomous Vehicle Adopters and Their Activity-Travel Patterns

by

Jingyi Xiao

AVs hold the promise to profoundly alter the way people move around by providing a safer, faster, greener, more accessible and comfortable means of transportation. Yet, the benefits of AVs could also result in undesired consequences like urban sprawl. Before AVs actually take off, how the technology will change transportation networks and urban form is far from certainty. Therefore, it is very important to identify AV adopters and their travel behavior and activity time allocation patterns, in order to make more realistic and accurate evaluations of AV impacts on transportation systems and implications for urban planning. To fill this research gap, three interrelated research questions are formulated and answered in this dissertation. Specifically, Chapter 2 shows that perceived usefulness is an important latent determinant of the intentions to use AVs and background factors such as demographics affect behavior intention both directly and indirectly through the mediator perceived usefulness. Using a multiyear cross-sectional travel survey, Chapter 3 reveals that public acceptance of AVs does change as a result of greater exposure to more information and knowledge about AVs over time. In particular, the population unfamiliar with AVs has declined over the years. Controlling for their socio-demographic characteristics, travel behavior characteristics, and built environment attributes, individuals' interest in AVs has not changed over time while their concerns have increased across time. Young well-educated male workers in wealthy households are the potential early adopters of AVs given their strong interest in AVs and less concerns. Chapter 4 explores the relationship between individuals' spatiotemporal activity-travel patterns and their stated propensity to use AVs. Using sequence analysis, clustering techniques, and statistical modeling, the results suggest that people exhibiting different activity-travel behavior patterns also express distinct attitudes towards the uses of AV (e.g., commuters perceive higher utility of AVs).

Contents

Chapter 1

Introduction

This introductory chapter begins with the background and motivation of the research, followed by three related major research questions. The structure of the dissertation is briefly outlined at the end of the chapter.

1.1 Background and Motivation

Autonomous Vehicles (AVs), also known as automated vehicles, self-driving cars, and robotic cars, are broadly defined as conveyances to transport people or goods without human intervention [1], and are considered a disruptive technology. When adopted widely, fully automated vehicles hold the promise to have tremendous impacts on transportation systems, urban form, society, and the environment, similar to the revolution in human mobility that took place at the beginning of the 20th century when internal combustion engine (ICE) vehicles replaced horse-powered carriages.

The idea of AVs dates back to the 1920s when remote-controlled "phantom autos" (driverless cars) were demonstrated in multiple U.S. cities. However, only in recent years the automotive industry and technology companies began to turn this fantasy into reality. Semi-automated vehicles equipped with Automated Driving Systems (ADS) at level 2 and 3, defined by the Society of Automotive Engineers (SAE International) [2], such as adaptive cruise control (ACC), collision avoidance, and parking assist systems, are already in the market. Examples are Tesla's Roadster, Model S, Model X, Audi A8, Mercedes-Benz S65, Infiniti Q50S, BMW 750i [3]. Waymo, formally the Google Self-Driving Car Project, has tested over 20 million real-world miles on public roads in more than 10 states in the U.S. since 2009 [4]. Waymo recently announced plans to open its fully driverless service to the general public in Phoenix in October 2020 [5]. Vehicles with varying degrees of automation have also been tested by technology companies like Aurora, DiDi, Lyft, Uber, and Zoox, to name a few.

In addition to industry, the development of AVs is also supported by different governments in countries and regions across the globe. The U.S. Department of Defense [6] conducted a series of DARPA Urban Challenge events for AV research and development in 2004, 2005, and 2007. Nevada, U.S. was the first jurisdiction to authorize the use of autonomous cars in 2011. As of now, eight states of the U.S. (California, Florida, Maryland, Michigan, Ohio, Pennsylvania, Texas, and Utah) have signed on as the first participants in the Automated Vehicle Transparency and Engagement for Safe Testing (AV TEST) Initiative [7]. Many European countries including Finland, France, Germany, Italy, the Netherlands, Spain, Sweden, and the U.K. have allowed development and testing of AVs on public roads [8]. The European Union funded a four-year CITYMOBIL2 project [9] that deployed AVs in seven selected cities to foster the implementation of Automated Road Transport System (ARTS) in European cities. The European Commission [10] also published STRIA Roadmap on Connected and Automated Transport to accelerate the deployment of automated mobility. Singapore, China, Japan, and other Asian countries are also active in the research and development of AV technologies [3].

Meanwhile, the past decades have seen a growing interest in AVs in academia, reflected by the increasing number of scientific publications. According to Gandia et al. [3], the number of publications on AVs has boosted from 140 in 1997 to 1,856 in 2017 using the Thomson Reuters' Web of Science (WoS) database. The average growth rate of publications on AVs was 39% over the analyzed periods (i.e. 1969-2018), which was much higher compared to the average science growth rate of 8-9%. Similar trend was also found in the IEEE Conference Papers database [11].

The motivation to research and develop AV technologies by industry, governments, and academia came from AVs' great potential in transforming and benefiting road transportation systems, urban dynamics, social wellbeing, and the environment. In the growing body of literature, various advantages of AVs are assessed, including more effective traffic flow and reduced traffic congestion [12, 13], increased mobility and accessibility for the disabled, senior, and children [14, 15], more open space freed from parking [16, 17]. Adoption of AVs could also dramatically reduce traffic accidents and mortality rate [18, 19], alleviate the pressure from long time commuting [11], increase utility of in-vehicle time [20], and reduce fuel use and lower greenhouse gas (GHGs) emissions [21]. Specifically, AV platoon is estimated to increase the roadway capacity, thus providing more effective traffic flows and reducing traffic congestion [12, 18, 13, 22]. According to Fagnant Kockelman [18], vehicle-miles traveled (VMT) can increase 2% and 9% and freeway congestion can be reduced by 15% and 60% if AV market penetration reaches 10% and 90%, respectively. Combined with on-demand mobility services such as ride-sharing or car-sharing, AV would further reduce the number of vehicles on roads [11].

However, the more efficient transport system might stimulate the demand for traveling, along with the new travel demand from the previously underserved population, such as children, seniors, the disabled, fatigued, drunk, inattentive [23]. The efficiency might be offset by AV-induced demand with a new equilibrium with higher VMT, leading to greater energy consumption and higher emissions. Naumov et al., [23] suggest that deployment of AVs and pooling may lead to reduced ridership and quality of public transit and more traffic congestion.

The appeal of AVs could also induce undesired consequences. While AV leads to higher quality of life through enhanced flexibility and reduced of constraints, AVs could introduce additional (long) trips and possibly make people live further from cities, exacerbating the already deleterious impacts of urban sprawl [11, 23]. The negative impacts of urban sprawl *include increased infrastructure costs and taxes, intensified segregation and inequity, increased ener*gy use, environmental degradation, and biodiversity and habitat loss [24, 25].

On the flip side, with more efficient use of roadways, cities are expected to have narrower road lanes and less street parking, which may open up space for bike lanes and sidewalk, accelerate the use of active mode [26, 27]. The adoption of shared AVs could also eliminate a large proportion of parking demand in cities [16, 17]. The current parking space can be freed up and converted to plazas, parks, and bigger living space, contributing to better land use and city form and potentially attracting people to move back to cities.

1.2 Research Questions

While the direct benefits of AVs such as safety enhancement, accessibility improvement, energy efficiency, and time freed from driving are well acknowledged, the indirect impacts associated with AVs adoptions and their effects on transportation systems and cities remain uncertain. With different assumptions and scenarios, the impacts of AV are under considerable debate and discrepancy can be found in the literature. Before AVs actually take off, one may ask *how can we make more realistic and accurate assumptions to study the implications of adopting AVs?* (*What conclusion can be drawn about the* *impacts of AVs given these assumptions?*) This question can be answered from different angles and I break it down into three smaller and concrete questions that relate to each other.

- ***Research Question 1***: How is individuals' intention to adopt AV affected by the observable background factors such as socio-demographic characteristics directly and indirectly through latent psychological constructs?
- ***Research Question 2***: How do public interest and concerns towards AV change over time when controlling for socio-demographic characteristics, travel behavior characteristics, and built environment attributes?
- ***Research Question 3***: How do individuals' daily activity-travel patterns relate to their disposition to-wards the use of AVs?

With these questions answered, this research identifies the population segments of AV adopters and how they will adopt AVs for activities and travel. The findings can be incorporated into transportation simulation models to assess the impacts of AVs on travel demand and transportation supply more realistically and accurately. The understanding of latent constructs in the mental process of forming behavior intention could help in making more efficient interventions to change people's attitudes towards AVs and behaviors to attain a socially and environmentally desired outcome, i.e., transportation systems and cities that are more accessible to people with safety, security, equity, and sustainability.

1.3 Dissertation Synopsis

This dissertation is comprised of three research articles, which are Chapters 2, 3, and 4 respectively. These three articles answer the three research questions posed in section

1.2. The remainder of this dissertation is organized as follows.

Drawing on theories from behavior science, Chapter 2 presents a study that establishes a conceptual model to investigate the direct and indirect effects of a wide variety of observable background factors on public intentions to adopt AVs (buying or sharing) with a mediator perceived usefulness. The proposed conceptual model can help pinpoint how background factors like socioeconomic status affect behavioral intention via its antecedent cognitive construct more accurately in the mental process of intention formation.

Few research attempts have been made to examine the change of public attitudes towards AVs over time. To close this knowledge gap, Chapter 3 investigates the change of people's interest and concerns towards AVs over time at aggregate and individual level using a multiyear cross-sectional Travel Study data. In particular, various socio-demographic characteristics, travel behavior characteristics, and built environment attributes are examined in terms of their relationship with individuals' disposition towards AVs. The identification of the market segment for AVs and customers preferences of various AV technologies and services can help achieve a more realistic evaluation of the potential impacts of AVs on transportation systems and the environment.

Chapter 4 explores whether and to what extent people's exhibited spatiotemporal activity-travel patterns correlate with their stated perceptions about AVs using travel diaries data. Particularly, five distinct daily activity-travel patterns are identified and we find systematic differences in the positive and negative attitudes towards AVs that depend on the timing of travel decisions in a day and the variety of modes used. The findings can be used for AV demand prediction and travel demand models and will help AV develop solutions for niche markets.

Finally, Chapter 5 concludes this dissertation with key findings. Contributions including the theoretical and practical implications made by this research are discussed. Limitations and several possible directions for future work are presented.

Chapter 2

Perceived Usefulness and Intentions to Adopt Autonomous Vehicles

[1] **Abstract**. Understanding the mental process of public acceptance of autonomous vehicles (AVs) is important to the prediction and change of adoption behavior. We present a conceptual model to incorporate background factors such as demographic variables and travel behaviors attributes to the understanding of AV perceived usefulness and intention to adopt AVs. Using data from the 2019 California Vehicle Survey (CVS), we investigate the relationships between observed and latent variables with regard to AV acceptance via structural equation modeling (SEM) techniques. The results show that perceived usefulness is an important determinant of behavioral intention. Householders who are young, well-educated, and males perceive higher usefulness of AVs than other population segments. Households that have telecommuters, transit riders, transportation network company (TNC; e.g., Uber Lyft) riders, and electric vehicles (EVs) owners, and households that own or plan to install photovoltaic cell (solar) panels also anticipate high

[1] The content of this chapter is an revised version of a published article: Xiao, J., Goulias, K. G. (2022). Perceived usefulness and intentions to adopt autonomous vehicles. *Transportation Research Part A: Policy and Practice, 161,* 170-185. https://doi.org/10.1016/j.tra.2022.05.007

benefits of AVs. Living or working at places with access to infrastructure such as EV charging stations and hydrogen fueling stations also add to positive perception of AVs' advantages. Controlling for perceived usefulness, households having higher annual income and EVs express a stronger interest in buying an AV but not in ridesharing. Young educated households with more TNC riders show a greater propensity to AV sharing services but not for owning AVs. The proposed conceptual model can help pinpoint how background factors such as socioeconomic status affects behavioral intention via its antecedent cognitive construct more accurately to represent the mental process of intention formation. The practical discoveries can assist policymakers identifying population segments that will be the first adopters of this technology.

2.1 Introduction

A future with autonomous vehicles (AVs) is appealing because it offers unprecedented opportunities to people and society with improved road safety, increased accessibility and equity, lower travel costs, reduced air pollution and greenhouse gas (GHGs) emissions, leading to more efficient transportation systems and sustainable urban design and land use [12]. But the ease of use and access to AVs could also induce travel demand and stimulate urban sprawl [11], which might transform the urban landscape in an undesired way. Although the ubiquity of AVs is still beyond reach, understanding the public's attitudes towards AV is critical for the adoption of AVs and the potential impacts and consequences of AVs on cities, transportation networks and the environment.

The research on public acceptance and market readiness of AVs has been growing over the past decades. The approaches of studies can be broadly grouped into two types: regression analysis using only observable variables and structural equation models (SEMs) using latent variables based on behavioral science theory. The former method identifies possible AV users by correlating people's various socio-demographic, trip and travel characteristics with their attitudes to AVs usually through regression analysis. For example, young men with high education attainment and high income are found to be receptive to the use of AVs [28, 29]. While the finding itself is valuable to the identification of the AV niche market, it is rather hard to uncover the underlying fundamentals that form the attitudes, which is essential to the prediction and change of adoption behaviors. Research shows that findings with theoretical basis usually lead to more effective behavior-change intervention design than non-theoretical ones [30]. However, the majority theory-based research on AV acceptance focuses only on the conceptual determinants of intention and behavior without examining background factors such as demographic variables, personality traits and current travel behaviors, which could affect intention and behavior indirectly via the more proximal conceptual precursors of intention.

Combining the strengths of both approaches, we introduce a conceptual model to study both observed and latent determinants of the intentions to adopt AVs. With a SEM, the relationships among household socio-demographic characteristics, vehicle ownership, intention to use AVs and its conceptual antecedents (*perceived usefulness*) are explored simultaneously through an empirical study in California using data from the 2019 California Vehicle Survey (CVS). In view of its leading role in many technology revolutions, California might be the first area around the world to widely adopt AVs. This study deepens our understanding of households' attitudes towards AV in California. The findings also provide new insights into policy implications and guidance for behavior-change interventions.

2.2 Literature Review

To estimate the future market penetration rate of AVs, numerous variables are assessed on their correlations with people's predispositions of AVs through regression analysis. Some of the demographic and socioeconomic characteristics of individuals such as gender, age, race, education attainment and income are found to be correlated with their disposition. Studies show that well-educated white young men with high income are more receptive to the adoption of AVs [28, 29, 31, 32, 33]. However, the discoveries differ substantially considering the variations in context, data measurement, methodology and geography. Travel behavior and built environment indicators are also scrutinized. For example, public transit riders and ridesourcing users exhibit stronger interest in the various uses of AVs [34] (Rahimi et al., 2020). Furthermore, people with complex schedules and diverse travel modes are also more inclined to use AVs [35]. Living in areas with high population density and road traffic could also have a positive influence on individuals' sentiments concerning AVs [36, 37]. The change of attitudes over time is also investigated with multi-wave survey data [37, 33]. Using the multiyear household travel surveys in Seattle Metropolitan area, Xiao and Goulias [33] show that individuals' interest in AVs has not changed from 2015 to 2019 while the concerns have increased across time when their demographic, socioeconomic and activity-travel variables are controlled for.

Meanwhile, theory-based research on AV acceptance has advanced substantially recently. According to the theory of reasoned action (TRA) [38], *attitudes toward the behavior* and *subjective norm* are the two conceptually independent determinants of individual's intention to perform a given behavior under volitional control. Later, the theory of planned behavior (TPB) [39] is developed as an extension of TRA with an additional determinant *perceived behavioral control*, which is used together with behavioral intention to predict behavior. With this theoretical underpinning, Ge et al. [40]

define a set of psychometric latent constructs related to the adoption of AVs and develop survey questions that could measure them reliably. Du et al. [41] show that mass media affect self-efficacy and subjective norm, which affect the intention to use AV directly and through the mediating effect of trust using questionnaire responses from 173 Chinese college students.

Another widely adopted theoretical foundation is the technology acceptance m[42], which proposes *perceived ease of use* and *perceived usefulness* as the fundamental constructs of user acceptance of information technology. A unified model, the unified theory of acceptance and use of technology (UTAUT) [43] is developed to integrate the core constructs from behavioral science models including TRA, TPB and TAM. It theorizes four direct determinants of behavioral intention: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*. Enormous extensions based on TAM and/or UTAUT have been applied to a wide range of contexts and studies. For example, perceived usefulness and perceived safety are found to impact the intention of older adult drivers to use automated driver assistance systems (e.g., adaptive cruise control) while perceived usefulness also impacts the intention to use a fully automated driving system [44]. Syahrivar et al. [45] examine the negative impact of drivers' desire for control and the positive impact of locus of control on their acceptance to AV with a cultural mediator called power distance based on a study in Hungary and Indonesia. Waung et al. [46] find that people's trust in AV performance mediates the effect of perceived AV performance on intention to use AV and the trust in regulation also mediates the impact of perceived privacy and security risk on their behavioral intention.

The majority of theory-based studies are focused on the relationships among latent psychological constructs and their accurate measures through meticulous questionnaire design. However, it is also critical to quantify the direct effects of the observable background factors such as socio-demographic characteristics and travel-activity attributes on the latent constructs and the indirect effects on behavioral intention through these theoretical antecedents, because the understanding of these effects can bring about more specific and effectual behavior-change interventions and policies for AV adoption. Therefore, this study investigates the relationships among the observable variables, latent constructs, and the behavioral intention (to adopt AVs) using the 2019 CVS data, which is introduced in the following section.

2.3 Data

As the most populous U.S. state, California has a population of 39.5 million [2]. As the largest sub-national economy and the fifth-largest economy in the world, California is home to many large technology companies including Google and Apple. Being a global trendsetter in economics, information, innovation, and environmentalism, California could be a big market for the early adoption of autonomous vehicles. As vehicles with autonomous features (including highly autonomous vehicles), in conjunction with ridesharing services, continue to grow in California, vehicle ownership and preference in technologies are changing rapidly.

This research uses data from the 2019 CVS [47], which is the most recent survey conducted by the California Energy Commission on residential and commercial light-duty vehicle ownership. The survey has taken place periodically over the past two decades to update light-duty vehicle ownership and preferences and forecast the shift in use behavior. To the best of our knowledge, the 2017 and 2019 CVS are the first set of public agency surveys (used for decision making about car ownership and type policies) that contain attitudinal questions of AVs in California. The 2019 survey has more questions on AVs compared to the one in 2017, therefore, it is used in this study. It is notable that the

[2] https://www.census.gov/quickfacts/fact/table/CA,US/PST045219

questions of AVs are asked only in the residential survey and not in the commercial one and are asked at household level rather than person level.

2.3.1 Survey Household Characteristics

The 2019 CVS dataset used in this study contains data from 4,248 completed residential surveys, including household demographic, socioeconomic, and car ownership information. Demographics such as gender, race and education attainment and travel behavior characteristics were collected for every household member above 15 years old. Residence location is known at county level because part of the survey was conducted online without collecting finer location information. The descriptive statistics of the sample households are presented in Table 2.1. The population statistics were obtained from the American Community Survey (ACS) 2015-2019 5-year estimates. Compared to the population, the survey oversampled two-person households whose householder is a senior with no children living together. While the low income and zero-car households are a bit underrepresented in the data, households living in single family housing and in northern California are overrepresented. While there are small discrepancies between the CVS sample and US Census/ACS population reported characteristics, the representativeness of the sample is adequate for statistical models that controls for many social and demographic characteristics. There are a total of 8,365 persons and 8,049 vehicles in the 4,248 households in CVS. Some variables such as number of adult males and females, number of transportation network companies (TNC) riders, and whether or not owning electric vehicles (EVs) in the household were derived from person- and vehicle-level data and were aggregated to household level, and they are used in this study as well. Descriptive statistics at person- and vehicle-level are shown in Appendix A (see Table A.1 and A.2).

To capture built environment indicators of the households, the percentage of public transit commuters and telecommuters (i.e., people who work from home), employment rate, and average commute time at county level were computed based on data obtained from the ACS 2015-2019 5-year estimates. The public transit commuter percentage is the number of public transit commuters in a county divided by the total number of commuters in that county. Higher ratio of transit commuters indicates higher accessibility of public transit. The top five counties with the highest transit ridership rate are all in the Bay Area, including San Francisco (37.2%), Alameda (16.9%), Contra Costa (11.6%), San Mateo (11.6%), except for county Mono (22.6%).The values look reasonable because the Bay Area has several public transportation systems including BART (Bay Area Rapid Transit), Caltrain, AC Transit, and San Francisco Muni, making it more accessible to public transit than other areas in California. The average commute time is the aggregated travel time (in minutes) to work regardless of commute modes divided by the total number of commuters. The indicator is used as a proxy for accessibility to the road network connectivity as a whole. High average commute time may imply traffic along major commuting routes. The top five counties (i.e., Contra Costa, Calaveras, San Benito, Alameda, and San Joaquin) with the longest commute time are also in the Bay Area and its periphery. In addition, the telecommuter percentage is calculated as the number of telecommuters over the total number of employed people. Employment rate is to divide the number of employed people by the total number of people age 16 years and above. These indicators are mapped in Figure 2.1 (a)-(d) and the exact values are presented in Table A.3 in Appendix A.

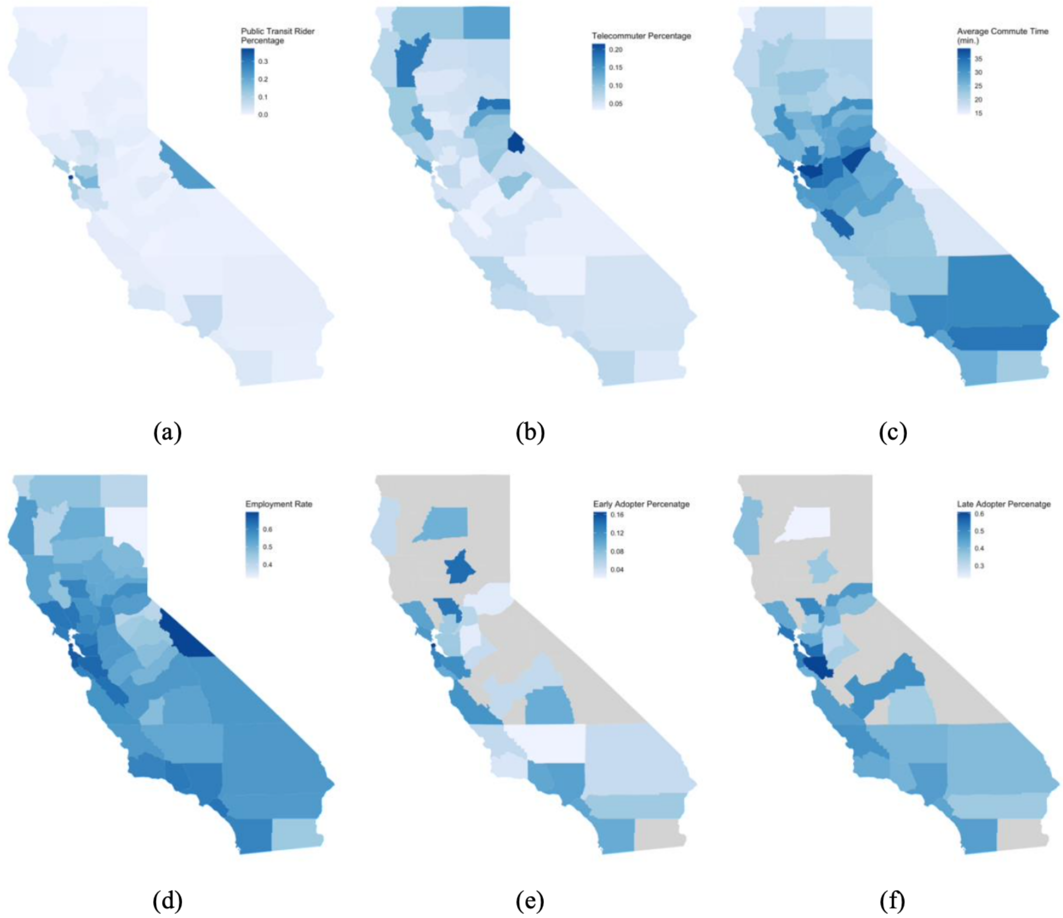

Figure 2.1: (a) Public transit rider percentage, (b) telecommuter percentage, (c) average commute time in minutes, (d) employment rate, (e) early adopter percentage, and (f) late adopter percentage, at county level in California, USA (a-d are from ACS 2015-2019 5-year estimates and e-f are from the 2019 CVS data. Counties colored in grey have less than 20 observations.)

2.3.2 Survey Questions About AVs

The survey contains seven attitudinal questions about AVs. The responses are 4-point Likert-scale from “strongly disagree” to “strongly agree” and are shown in Figure 2.2. The responses vary considerably according to the questions. For instance, more than half of the households agree that a self-driving vehicle could enable them to enjoy traveling more and travel more often in situations when driving by themselves is not easy, safe, or even possible. However, the majority of people don't think they could work on an AV to reduce their time at the workplace and/or they would send an AV to pick up or drop off their children. Part of the reason could be that the data used in this study oversampled households whose householder is senior and probably retired and households with no children, which indicates that people with different socioeconomic status may perceive the usefulness of AVs differently.

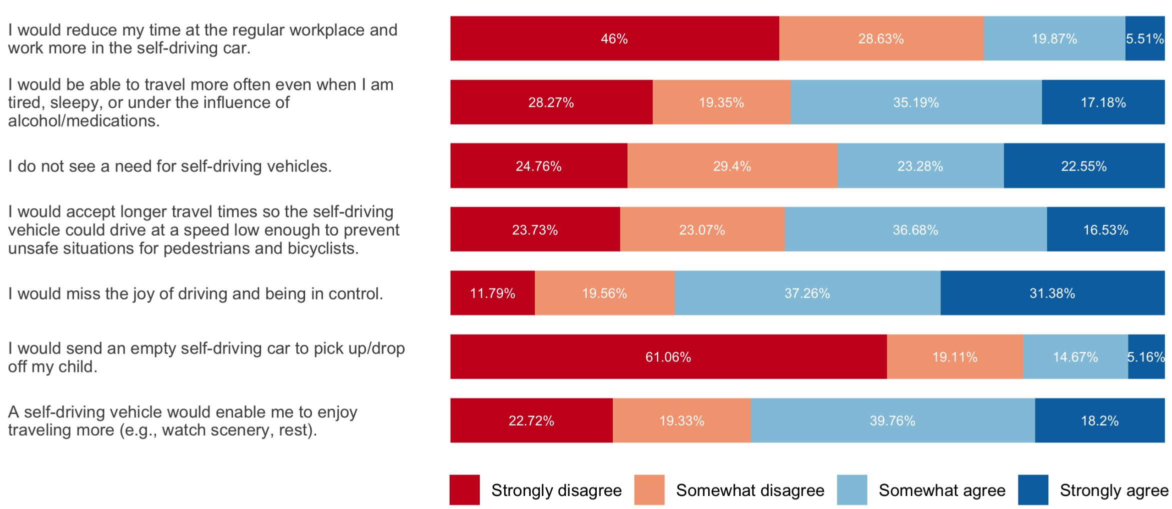

Figure 2.2: Survey Responses of Attitudinal Questions About AVs

Another four survey questions are about people's intentions to use AVs in different ways, including owning an AV, riding AV through ride-hailing services (standard or carpool), and about their relative preference in owning or sharing an AV. The second question about on-demand driverless services has missing responses from 112 (2.64%) no-car households because it assumes respondents to have at least one car. Simply removing these observations is not proper since all households with no cars will be excluded systematically. Given that the correlation between the responses of the first two questions (i.e., buying a self-driving vehicle and using driverless services) is moderately high (polychoric correlation = 0.63), the missing responses were imputed using the same ordered responses from the first question. The questions and responses (after missing data imputation) are presented in Table 2.2. Only a small percentage (less than 10%) of households has the intention to own and/or use AVs proactively. A large portion (around 45%-50%) of households are indifferent whereas the rest are resistant to adoption. in Figure 2.1 (e) and (f) display the spatial distributions of ”early adopter” and ”late adopter” for California at county-level. About half of the households are more interested in buying an AV whereas the other half are more positively disposed to on-demand driverless services.

Table 2.1: Household-level Descriptive Statistics (n = 4,248)

Variable	**Category**	**Sample**	**Sample (%) (n = 4,248)**	**Population %) (N = 13,044,266)**
Household size	1	1,090	25.66	23.81
	2	1,867	43.95	30.42
	3	593	13.96	16.69
	4	482	11.35	15.25
	5 or more	216	5.08	13.83
Number of children [ab]	0	3,453	81.28	65.63
	1 or more	795	18.72	34.37
Householder age [b]	18 to 64	2,774	65.30	76.06
	65 and over	1,474	34.70	23.94
Household Income	Less than $24,999	294	6.92	16.39
	$25,000 to $49,999	575	13.54	17.96
	$50,000 to $99,999	1,213	28.55	27.93
	$100,000 to $149,999	779	18.34	16.63
	$150,000 to $199,999	430	10.12	8.93
	$200,000 or more	582	13.70	12.16
	Prefer not to answer	375	8.83	-
Total Housing Units	1 (detached or attached)	3,191	75.12	65.34
	2 to 4	214	5.04	7.82
	5 to 19	313	7.37	11.17
	20 or more	397	9.34	12.13
	Mobile home	104	2.45	3.43
	Boat, RV, Van, etc.	9	0.21	0.12
	Others	20	0.47	-
Number of vehicles	0	112	2.64	7.11
	1	1,529	35.99	30.42
	2	1,713	40.32	37.20
	3	607	14.29	16.20
	4 or more	287	6.76	9.07
Owns electric vehicle(s)		1,174	27.64	-
Has solar panels installed		667	15.70	-
Region	Central Valley	249	5.86	9.87
	Los Angeles	1,922	45.25	46.23
	San Diego	388	9.13	8.63
	San Francisco	1,005	23.66	20.94
	Sacramento	343	8.07	6.82
	Rest of State	336	7.91	7.51
	I don't know	5	0.12	-

Note: a: children are defined as individuals below 16 years old in the sample (CVS) and below 18 years old in the ACS data.
b: due to the differences in the categorizations of the sample and ACS data, the statistics are based on aggregated categories for comparison purposes. The finer categories will be used in analysis and modeling.

Table 2.2: Questions About Intention to Adopt AVs and Their Responses (N=4,248)

Stated Behavioral Intention	**Question**	**Choice**	**%**
AV ownership	Now, consider your current situation with the vehicles your household now owns (if any), and imagine that driverless vehicles have become widely available for purchase. Which of the following scenarios best describes your household?	We would wait as long as possible and try to avoid ever buying a self-driving vehicle (denoted as *early adopter*)	46.07
		We would eventually buy a self-driving vehicle, but only after they are in common use (denoted as *late adopter*)	44.96
		We would be one of the first to buy a self-driving vehicle (either as a replacement or additional household vehicle)	8.97
AV shared services	If on-demand driverless ride-hailing services were widely available today, which of the following best describes how your household would use these services and how it would impact the vehicle(s) you currently own?	Keep current vehicles and not use any driverless services	42.04
		Keep current vehicles, but also use these driverless services whenever needed or convenient	48.78
		Get rid of one (or more) household vehicles and use driverless ride-hailing services instead	9.18
AV pooled services	I would be unlikely to use shared driverless services (even at lower cost) because I would not want to share a vehicle with strangers.	Strongly agree	34.37
		Somewhat agree	32.58
		Somewhat disagree	22.57
		Strongly disagree	10.48
AV owning vs sharing	Overall, what would be your relative interest in owning a driverless vehicle versus using on-demand ride-hailing services?	Much more interested in owning a driverless vehicle	16.29
		Somewhat more interested in owning a driverless vehicle	35.50
		Somewhat more interested in using on-demand driverless services	35.59
		Much more interested in using on-demand driverless services	12.62

2.4 Methodology

2.4.1 Perceived Usefulness

The seven Likert-scale attitudinal items about AVs measure people's opinions from different perspectives; some items such as "a self-driving vehicle would enable me to enjoy traveling more (e.g., watch scenery, rest)" are more specific than others (e.g., "I do not see a need for self-driving vehicles."). Noticing that four of the items are about specific use of driverless cars, we conduct a Confirmatory Factor Analysis (CFA) to validate if these items are manifested by a single latent construct *perceived usefulness*, according to TAM [42]. The other fundamental determinant *perceived ease of use* in TAM is not examined in this study given the nature of autonomous vehicles (requiring no human control). Latent constructs such as *subjective norm* and *perceived behavioral control* in TPB and *performance expectancy* and *facilitating conditions* in UTAUT cannot be examined due to the lack of data available in the questionnaire. Table 2.3 contains the outcome of a single-factor CFA model estimated by WLSMV (diagonally weighted least squares with mean- and variance-adjusted; widely used for ordinal response variables with skewed distributions) using the R package Lavaan version 0.6-8 [48]. (See section 2.4.3 for more details about model estimation.)

The Chi-square test is first used to assess the model fit. As an accept-support test, chi-square test supports a model when it fails to reject the null hypothesis that there is no statistical difference (e.g., at level of α=0.05) between the model-implied covariance matrix and the sample covariance matrix. Our model has a chi-square of 42.616 with a degree of freedom of 2 and p-value less than 0.001, giving preliminary evidence against the model since the null hypothesis is rejected. However, studies [49, 50] have shown that the chi-square test is sensitive to sample size and is prone to reject the null hypothesis with large sample size. Given our large sample size (N=4,248), we also evaluate the model fit by widely used fit statistics including Comparative Fit Index (CFI), Tucker-Lewis index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). According to literature [51, 52, 53], a model with CFI and TLI greater than 0.90, and RMSEA and SRMR less than 0.08 is considered an acceptable fit. Our 4-item single-factor model (CFI = 0.993, TLI = 0.979, RMSEA = 0.102, 90% CI = [0.085, 0.121], SRMR = 0.025) is shown to fit the data quite well based on these fit indices except for RMSEA.

The results show that the factor loadings for the four items, i.e., *enjoy traveling more*, *travel more often*, *work in an AV*, and *escort children*, are all statistically significant and greater than 0.7 (from 0.718 to 0.819) after standardization. For example, the underlying latent response variable of *enjoy traveling more* increases by 0.819 in standard deviation unit given an one standard deviation unit increase in *perceived usefulness*. The positive values of factor loadings suggest that higher perceived usefulness corresponds to stronger agreement with AV's capabilities, as expected. Furthermore, more than 50% (51.6%-67.0%) of the variances of the latent response variables can be explained by *perceived usefulness*, demonstrating a good measurement model [52]. None of the correlation residuals (i.e., the difference between model-implied correlations and sample correlations; not shown in the paper) is greater than 0.1 in absolute value, indicating a close reproduction of sample correlations. Cronbach's alpha of 0.85 also implies high internal consistency.

Table 2.3: Confirmatory Factor Analysis Results

Indicator	**Description**	**Std.Est.**	**S.E.**	**z-value**	$P(>\|z\|)$	**Var.**	**R2**
Enjoy traveling more	A self-driving vehicle would enable me to enjoy traveling more (e.g., watch scenery, rest).	0.819	0.009	87.330	0.000	0.330	0.670
Travel more often	I would be able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications.	0.810	0.009	88.380	0.000	0.343	0.657
Work in an AV	I would reduce my time at the regular workplace and work more in the self-driving car.	0.718	0.010	69.296	0.000	0.484	0.516
Escort children	I would send an empty self-driving car to pick up/drop off my child.	0.739	0.011	67.714	0.000	0.454	0.546

Fit indices
Robust chi-square = 90.952, df = 2, p $<$ 0.001
CFI = 0.993, TLI = 0.979
RMSEA = 0.102, 90% CI = [0.065, 0.121]
SRMR = 0.025

Note: Std.Est. = Standardized Estimate, S.E. = Standard Error, Var. = Residual Variance.
Factor loadings are estimated using variance standardization method by fixing the variance of the latent variable to 1 and freely estimating all loadings.

2.4.2 SEM Model of Intention to Use AVs

After establishing a valid and reliable measure of perceived usefulness using the 4-point items, we propose a SEM to simultaneously capture the relationship among observed household characteristics, the latent construct perceived usefulness, and the stated behavioral intentions of adopting AVs. We hypothesize that households' socio-demographic, mobility and built environment characteristics will affect their intentions to adopt AVs both directly and indirectly through the mediator of perceived usefulness. Perceived usefulness is hypothesized to positively affect the intentions to buy AV(s) and also use AV(s) in on-demand ride-hailing services. We also think the residuals of these intentions and preferences are correlated due to some unobserved variables they have in common. The conceptual model is depicted in Figure 2.3.

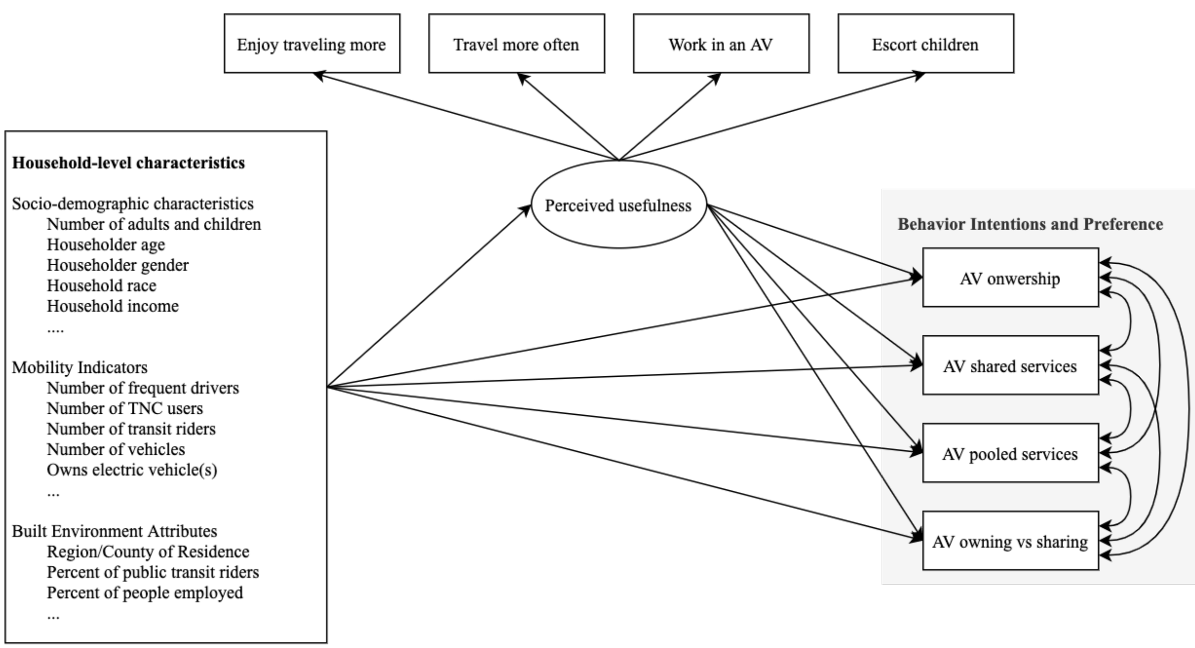

Figure 2.3: The Proposed Conceptual Model

The proposed model can be specified as a combination of a measurement model in Equation 2.1 and a path model in Equation 2.2.

$$\mathrm{z} = \lambda\eta + \epsilon \tag{2.1}$$

$$\mathrm{y} = \mathrm{Bx} + \gamma\eta + \zeta \tag{2.2}$$

where z is a $k \times 1$ vector of observed indicators;

η is a latent exogenous variable (perceived usefulness);

λ is an $k \times 1$ vectors of factor loadings on the latent variable for indicators z;

ϵ is an $k \times 1$ vector of errors of measurement for indicators z. The errors are assumed to be uncorrelated and to have mean zero;

y is a $q \times 1$ a vector of observed dependent variables;

x is a $p \times 1$ vector of observed independent variables;

B is a $q \times p$ matrix of path coefficients of the independent variables x to the dependent variables y;

γ is a $q \times 1$ vector of path coefficients of the latent exogenous variable to the dependent variables y;

η is an $q \times 1$ vector of errors for the dependent variables y. The errors are assumed to be correlated with each other.

2.4.3 Model Estimation

Both the four Likert-scale indicators and the stated behavioral intentions can be treated as ordered categorical variables. Notable is that all of these variables have only three or four categories and the majority of them have severely asymmetrical distributions. Thus, estimation methods for normally distributed continuous variables such as maximum likelihood may not be appropriate. Weighted least squares (WLS) estimator that makes no normality assumptions of the responses is developed to estimate ordinal variables with only a few (i.e., five or fewer) categories and has gained popularity over the years. In a typical framework of WLS, the observed ordinal response variable is assumed to be generated from a latent continuous variable, which is normally distributed with thresholds that divide the distribution into the observed response categories [54]. Polychoric correlation (between two ordinal variables), polyserial correlation (between an ordered variable and a continuous variable) and other correlations are estimated for the observed variables. From these correlations obtained is an asymptotic covariance matrix, the inverse of which is used as the weight matrix in WLS estimation [52]. However, WLS might not be a viable alternative in cases when the asymptotic covariance matrix cannot be estimated due to small sample size and/or the large weight matrix cannot be derived through matrix inversion [55].

Diagonally weighted least squares (DWLS), as a robust WLS-based estimator, is developed to overcome the computational limitations of WLS. It uses only the diagonal of the asymptotic covariance matrix and its inverse for parameter estimates and uses the full asymptotic covariance matrix (not inverse) to accurately estimate the robust standard errors of parameters and model test statistics such as chi-square [56]. Muthén, du Toit, & Spisic [57] show that DWLS estimators outperform WLS in terms of little bias in parameter estimations and more accurate estimations in standard errors with large sample sizes. WLSM (diagonally weighted least squares with mean-adjusted) and WLSMV (diagonally weighted least squares with mean- and variance-adjusted) are two kinds of DWLS that produce the same parameter estimates and robust standard errors, yet different chi-square; WLSMV uses a scaling factor to adjust the chi-square to approximate the mean and variance of the expected chi-square distribution while WLSM only adjusts for the mean [58]. Fit statistics based on chi-square such as CFI, TLI, RMSEA and SRMR would vary because of the differences in adjusted robust chi-square of WLSM and WLSMV. Computational simulation results generally favor WLSMV over WLSM for most fit indices [59, 55]. Thus, WLSMV estimator is used in this study.

2.5 Results

2.5.1 Model Fit

Our proposed SEM model was estimated in Lavaan 0.6-8 [48] using the WLSMV estimator. The path model specification and estimation were an iterative process: the model was first estimated with all variables and paths, the variables that are not significant at =0.05 for all dependent variables were removed using backward elimination, then insignificant paths were removed from model specification for model estimation in the next iteration. The process stops when no insignificant variable or path exists in the model. Results including the direct effects (path coefficients) and indirect effects (from an explanatory variable x_1 to the dependent variable y via a mediator x_2) are presented in Table 2.4, along with thresholds, variances, and fit statistics.

The model fit is assessed using the same fit indices and threshold standards discussed above (chi-square test with p-value > 0.05, CFI > 0.9, TLI > 0.9, RMSEA < 0.08 and SRMR < 0.08). Again, the chi-square test (robust chi-square is 488.575, df $= 221$, p-value $= 0.000$) does not support a good fit, presumably due to the large sample size. However, the high CFI (0.985), TLI (0.998), and low RMSEA (0.017, 90% CI [0.015, 0.019]) and SRMR (0.027) suggest that our model fits the data very well even using a stricter rule (CFI > 0.95, TLI > 0.95, RMSEA < 0.05 and SRMR < 0.05). According to the results, 60.4% of the variance of the intention to buy an AV and 42.8% of the variance of the intention to use shared driverless services can be explained by our model. However, our model is not good at explaining the attitudes towards pooled driverless services and preference for owning versus sharing an AV; only 16.1% and 7.6% of the variances are explained by our model, respectively.

Table 2.4: Model Results

Measurement Model

	Enjoy traveling more		Travel more often		Work in an AV		Escort children	
	Std.Est.	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**
Variable								
Perceived usefulness	0.866	117.746	0.785	90.364	0.695	62.328	0.744	67.986
Thresholds [a]								
1 | 2	-0.324	-0.967	-0.432	-1.27	0.915	2.471	1.122	2.874
2 | 3	0.223	0.664	0.075	0.219	1.707	4.598	1.713	4.383
3 | 4	1.33	3.955	1.068	3.132	2.68	7.172	2.523	6.447
Residual variance	0.25	19.575	0.384	28.117	0.516	33.27	0.446	27.337

Note: Std.Est. = Standardized Estimate. Estimates in italics are not significant at 0.05 level.
a: thresholds [a]re the cutoff points for the underling latent continuous variables. For example, threshold 1 | 2 of "enjoy traveling more" is the cutoff points for the responses "strongly disagree" and "somewhat disagree".

Regression Model

	Perceived usefulness		AV ownership				AV shared services			
	Direct Effect		Direct Effect		Indirect Effect		Direct Effect		Indirect Effect	
	Std.Est.	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**
Variable										
Perceived usefulness			0.673	51.848			0.591	41.518		
Male Householder (reference: non-male)	0.106	6.444			0.071	6.377			0.062	6.369
Householder 18-34 years (reference: 65 years and over)	0.184	9.849	0.054	3.285	0.124	9.568			0.109	9.583
Householder 35-64 years	0.12	6.005	-0.006	-0.373	0.081	5.923			0.071	5.94
householder race as Asian	0.076	4.722			0.051	4.685			0.045	4.691
Householder with bachelor's degree and above (0/1)	0.053	3.143			0.036	3.138	0.06	3.908	0.031	3.136
Family household (reference: non-family)			-0.052	-3.346			-0.043	-2.497		

Number of adults (16 years and over)			-0.078	-3.695						
Number of children (under 16 years)	0.043	2.743			0.029	2.739			0.025	2.736
Number of students (16 years and over)			0.057	3.065						
Number of telecommuters	0.037	2.317			0.025	2.314			0.022	2.314
Household income \$100,000 to \$149,999 (reference: household income below \$100,000)	0.057	3.399	0.044	3.089	0.039	3.389			0.034	3.377
Household income \$150,000 to \$199,999	0.039	2.352	0.047	3.209	0.026	2.348			0.023	2.344
Household income \$200,000 to \$249,999	0.032	1.879	0.039	2.566	0.021	1.879			0.019	1.876
Household income \$250,000 or more	0.069	4.011	0.056	3.796	0.047	3.995			0.041	3.98
Number of vehicles	-0.091	-4.382			-0.061	-4.371	0.062	3.364	-0.054	-4.357
Zero-car household (0/1)			0.037	2.261						
Owns EV(s) (0/1)	0.073	3.253	0.042	2.065	0.091	3.876	0.047	2.158	0.043	3.231
Has owned or leased EV(s) (0/1)			0.052	3.205						
Has vehicle(s) used for TNCs (0/1)			0.047	2.708			-0.065	-4.236		
Vehicles' average Miles-Per-Gallon (MPG) (normalized [b])			0.074	3.328						
Number of transit riders	0.052	2.81			0.035	2.803			0.031	2.801
Number of TNC riders	0.098	5.499			0.066	5.45	0.052	2.722	0.058	5.437
Has solar panels installed (0/1)	0.046	2.682			0.031	2.676			0.027	2.677
Plan to install solar panels within 5 years (0/1)	0.104	6.554	0.034	2.459	0.07	6.469			0.062	6.463
Aware of hydrogen fueling stations nearby (0/1)	0.043	2.474	0.059	3.852	0.029	2.47			0.026	2.47
Has EV charge spot(s) at workplace (0/1)	0.047	2.564	0.032	2.087	0.031	2.56			0.028	2.558
Has EV chargers in the neighborhood (0/1)	0.098	3.889			0.066	3.869			0.058	3.862
Percent of public transit riders			-0.052	-2.816						

Average commute time (min.)							0.083	4.066		
thresholds [a]										
1 | 2			0.451	1.316			1.346	3.778		
2 | 3			1.965	5.701			2.881	8.104		
Residual Variances	0.797	55.463	0.396	27.733			0.572	33.271		

	Perceived usefulness		AV pooled services				AV owning vs sharing [c]			
	Direct Effect		Direct Effect		Indirect Effect		Direct Effect		Indirect Effect	
	Std.Est.	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**	**Std.Est.**	**z-value**
Variable										
Perceived usefulness			0.294	16.973			-0.213	-11.597		
Male Householder (reference: non-male)	0.106	6.444			0.031	6.032	-0.036	-2.168	-0.023	-5.601
Householder 18-34 years (reference: 65 years and over)	0.184	9.849	0.053	2.71	0.054	8.453	-0.06	-3.024	-0.039	-7.449
Householder 35-64 years	0.12	6.005	0.047	2.396	0.035	5.624	0.027	1.319	-0.026	-5.303
householder race as Asian	0.076	4.722			0.022	4.565			-0.016	-4.347
Householder with bachelor's degree and above (0/1)	0.053	3.143	0.086	5.031	0.016	3.082	0.037	2.132	-0.011	-3.027
Family household (reference: non-family)			-0.043	-2.591	-0.043	-2.591				
Number of children (under 16 years)	0.043	2.743			0.013	2.711	-0.048	-2.685	-0.009	-2.663
Number of telecommuters	0.037	2.317			0.011	2.294			-0.008	-2.274
0.3Household income $100,000 to $149,999 (reference: household income below $100,000)	0.057	3.399			0.017	3.319			-0.012	-3.267
Household income $150,000 to $199,999	0.039	2.352			0.012	2.329			-0.008	-2.3
Household income $200,000 to $249,999	0.032	1.879			0.009	1.868			-0.007	-1.858
Household income $250,000 or more	0.069	4.011			0.02	3.898			-0.015	-3.791
Number of vehicles	-0.091	-4.382			-0.027	-4.23			0.019	4.086
Zero-car household (0/1)							0.038	2.248		
Owns EV(s) (0/1)	0.073	3.253			0.021	3.184			-0.015	-3.106

Has vehicle(s) used for TNCs (0/1)			-0.034	-2.102						
Number of transit riders	0.052	2.81			0.015	2.763			-0.011	-2.716
Number of TNC riders	0.098	5.499	0.071	3.706	0.029	5.226	0.057	3.011	-0.021	-4.945
Has solar panels installed (0/1)	0.046	2.682			0.013	2.649			-0.01	-2.612
Plan to install solar panels within 5 years (0/1)	0.104	6.554			0.031	6.089	-0.047	-2.679	-0.022	-5.696
Aware of hydrogen fueling stations nearby (0/1)	0.043	2.474			0.013	2.445			-0.009	-2.423
Has EV charge spot(s) at workplace (0/1)	0.047	2.564			0.014	2.533			-0.01	-2.504
Has EV chargers in the neighborhood (0/1)	0.098	3.889			0.029	3.763	0.064	2.5	-0.021	-3.674
Percent of public transit riders			-0.055	-2.98						
Average commute time (min.)			0.054	2.597						
Employment rate			0.101	4.813						
thresholds [a]										
1 | 2			0.271	0.78			-0.477	-1.346		
2 | 3			1.123	3.238			0.565	1.591		
3 | 4			1.941	5.6			1.67	4.703		
Residual Variances			0.839	62.919			0.924	94.633		

Fit Indices (N = 4,248)
Robust chi-squared = 488.575, df = 221, p-value = 0.000
CFI = 0.985, TLI = 0.998
RMSEA = 0.017, 90% CI [0.015, 0.019]
SRMR = 0.027

Note: Est. = Estimate. S.E. = Standard Error. (0/1) indicates binary variable; the coefficients are estimated for the “true” categories. Estimates in italics are not significant at 0.05 level. Empty cells are not estimated in the model.
a: thresholds are the cutoff points for the underling latent continuous variables. For example, threshold 1 | 2 of “AV pooled services” is the cutoff points for the responses “strongly disagree” and “somewhat disagree”.
b: Vehicles’ average Miles-Per-Gallon (MPG) are normalized [b]y the mean of the variables.
c: The higher the ordered category, the higher the preference for sharing AVs than owning.

2.5.2 Perceived usefulness

The estimated factor loadings of the measurement part of the SEM model and the standalone measurement model (in section 2.4.1) are not exactly the same as a result of simultaneous estimations of the SEM model. Yet, the discrepancy in the loadings is minor. All standardized loadings are well above or close to 0.7, reflecting a valid and reliable measurement of the latent construct *perceived usefulness*.

As a mediator, *perceived usefulness* is found to be associated with a variety of household demographic, socioeconomic and mobility-related characteristics. Male householders perceive greater usefulness of AVs compared to their counterparts. Compared to older householders aged 65 years and above, householders below 35 years old see more utility in AVs; the perceived utility also decreases with the increase of householder age. Asian householders with high educational attainment also consider AVs more useful. Households with more children and telecommuters also have a higher perception of usefulness of AVs. One plausible explanation is that telecommuters can take advantage of working when traveling in AVs, yet it is not the case for commuters requiring physical presence at the workplace. Households with annual income more than $100,000 acknowledge the worth of AVs more than those with income less than $100,000, especially households with more than $250,000 annual income. The results display consistency with the findings that young, educated, wealthy male telecommuters are generally more receptive to AV technology in previous work [29, 37].

As for mobility related indicators, households with more vehicles tend not to find necessity for AVs, presumably the vehicles they own fulfill all their needs. But less car-dependent households with more transit riders and TNC users embrace AV technologies more than other households. Households that own EV(s) also perceive greater usefulness of AVs compared to those who do not. Households having solar panels installed or planning to do so rate AVs higher. So do the households that are aware of hydrogen fueling stations and EV charge stations nearby and in the workplace. This could be attributed to these households' awareness of energy conservation, tech-savviness, green lifestyle [29, 31]. Location of residence (at county level) is not found to be associated with AV usefulness probably because of the coarse geographic unit or because variables such as "has EV chargers in the neighborhood (0/1)" also contains locational information at an even finer level.

2.5.3 Intentions to Adopt AVs

Perceived usefulness is found to be significantly correlated with the intention to adopt AVs in owning and ridesharing services (both standard and pooled), which provides evidence to support our hypothesis that perceived usefulness positively affects the behavioral intentions regardless of form. The amount of influence differs: the impacts of perceived usefulness on buying or sharing an AV are substantial and are relatively small on a pooled driverless service, implying that other latent variables such as perceived privacy and value of time could also affect the development of intention. However, this assumption cannot be verified due to the lack of data that measures these variables.

Depending on the use of AVs, household characteristics and built environment factors affect the intentions differently. As for the intention to buy an AV, householder age, household annual income, the plan to install solar panels within 5 years, and EV ownership are the top four important factors in terms of standardized total effects (i.e., the sum of direct and indirect effects) besides perceived usefulness. They all affect the intention both directly and indirectly through the mediator perceived usefulness. Wealthy households are more interested in purchasing AVs; particularly, the direct effect of household income indicates that while perceiving the same level of usefulness, households with higher annual income have stronger intention to buy AVs, which can be attributed to their higher *perceived behavioral control* [39] of having the ability to actually buy it. Young households and households having EVs (including plug-in hybrid EVs and battery EVs) and/or plan to install solar panels are more receptive to AVs, which could be explained by the latent constructs of *technology savviness* and *environmental awareness* examined in many studies [29, 60]. It is worth noting that zero-car households also show interest in owning AVs, possibly leading to a higher rate of privately owned vehicles. In addition, the predisposition of owning AVs is also positively associated with household average vehicle MPG, experience with EVs, awareness of green vehicle fueling/charging stations. Meanwhile, it is negatively related to the number of adults in a family and the percentage of transit riders in the residence county.

Contrasting with buying AVs, the important covariates that affect the intentions to use on-demand driverless services (either standard or pooled) are unalike. They are the number of TNC riders in a household, householder's age and educational attainment, EV ownership, and average commute time at county-level. TNC riders exhibit stronger interest in using on-demand AV sharing services likely due to their positive experience with TNC. High average commute time also increase people's intention to use AV sharing services. Having EV experience, the awareness of green vehicle fueling/charging stations, and the plan to install solar panels also contribute to greater intentions for AV sharing services. But, households that use vehicle(s) for TNC services are opposed to on-demand driverless services since they can use their own vehicles for travel. Furthermore, the intention to use pooled driverless services is positively related to the employment rate and negatively associated with the percentage of public transit ridership in the home county.

The preference for owning versus sharing AVs also varies between households with different characteristics. Higher perceived usefulness of AV is associated with higher preference for buying AVs, suggesting that higher perceived usefulness makes the possession of an AV more desirable. Moreover, consistent with findings above, households that are wealthy and that have EVs, solar panel installation plan and more children and telecommuters prefer buying AVs to sharing, while households with more TNC riders and vehicles are the opposite.

The residual covariance between the intentions to buy and share an AV is 0.360, implying that there might still be some other variables that impact the overall acceptance of AVs, either directly or indirectly through other determinants that are not observed or estimated with current data.

2.6 Discussion and Conclusions

2.6.1 Findings and Implications

With the aid of SEM, this empirical study in California confirms that perceived usefulness is an important latent determinant of the intentions to use AVs. Consistent with many other research [28, 29, 31, 32, 33], we find that young male householders with high educational attainment are more receptive to AV adoption in general. Furthermore, we point out that these demographics only affect the behavioral intentions indirectly through the latent construct perceived usefulness. Our study is in agreement with a few other analyses finding that race and ethnicity are important determinants of attitudes towards autonomous cars. Examples include the higher sensitivity of non-Hispanic whites on privacy when sharing AVs [61], lower concerns with AV reliability by African American segments [62], and different weights assigned to AV design features and perceived benefits by many different ethnic/race segments [34]. In this study, we show that Asians perceive higher utility of AVs than non-Asians. Yet, these differences may be due to spatial heterogeneity. We also discover that households with more children, telecommuters and transit riders anticipate more benefits of AVs.

While the aforementioned variables affect the adoption intention indirectly, certain variables exhibit both direct and indirect effects, differing by the form of adoption. Household annual income is a pivotal determinant for the intention to purchase an AV, as existing literature also supports [36, 63, 64, 65, 33]. In this study, we decompose its effects into indirect and direct ones, and show that income could affect the purchase intention directly, which is not the case for the intention to use shared services (with only indirect effects). This implies that less wealthy households develop lower intention to buy AVs than well off ones, even with the same level of perceived usefulness. We conjecture that financial barrier is the anticipated impediment for buying AVs but not for sharing AVs. While the correlation between EV ownership and AV ownership intention has been found in related work [66, 67], we find also having solar panels (and installation plans) and green vehicle fueling/charging stations nearby are also crucial to household's decision to buy AVs. Meanwhile, we find that young people and people with higher education attainment who have TNC car/ridesharing experience have higher perceived usefulness and intentions to use AV sharing services. All this shows that age, educational attainment, and previous ride-hailing experience are essential for AV sharing intention to a much higher degree than buying AVs. These findings on the direct effects can possibly be strongly related to other latent variables like perceived behavioral control, habit strength, technology savviness and green lifestyle, which cannot be examined in this study due to the lack of data available that measure them.

The maturity of technology advancement does not guarantee the wide adoption of AVs (the slow adoption of EVs is an example). While unraveling public acceptance of AVs can be quite challenging, we hope the findings and implications from this study can help provide guidance to the deployment and market uptake of AVs. *First*, enhancing people's understanding of the benefits of AVs and their advantages over conventional cars through market campaigns could improve their perceived usefulness of AVs and therefore can help develop a stronger interest in AV adoptions. *Second*, the strategies to promote AVs should be customized to use cases; strategies encouraging AV ownership are different from the ones for on-demand AV ridesharing. The presumably high upfront cost required to purchase an AV especially at an early stage can inhibit people from even considering it even if they perceive high usability of AVs. Reducing financial barriers for low- and mid- income households through tax incentives, rebates and loan financing programs to make AV more affordable could promote the possession of AVs to mimic similar strategies for EVs. *Third*, non-financial incentives such as infrastructure development (e.g., charging/fueling stations in the neighborhood and at the workplace) can also increase people's intention to use AVs, in similar ways as it is for EVs [68, 69]. In addition, the deployment of AVs can start at places where the charging infrastructure is easily accessible given that AVs are also very likely to be electric. *Fourth*, promoting AVs ridesourcing services to the targeted population can be done with the assistance of financial incentives (e.g., discount, coupons, and toll waivers) and reoccurring incentives like the access to high-occupancy vehicle (HOV) lanes. *Fifth*, the finding that public transit riders also perceive high value of AVs should remind city planners and policy makers that a sustainable transportation system should not turn transit riders and people using active mode into pure AV users but to promote green travel with the aid of AVs (e.g., as a solution for the first- and last-mile problem) but it also points to the need for autonomous electric buses [70, 71].

Drawing on theories from behavior science, this study establishes a conceptual model to investigate the direct and indirect effects of a wide variety of observable background factors on public intentions to adopt AVs (buying or sharing) with a mediator perceived usefulness. The proposed conceptual model can help pinpoint how background factors like socioeconomic status affect behavioral intention via its antecedent cognitive construct more accurately in the mental process of intention formation. The practical discoveries can assist policymakers in making more efficient interventions to change people's attitudes towards AVs.

2.6.2 Limitations and Future Work

The conceptual determinants of intention to adopt AVs are definitely more than just perceived usefulness. Perceived safety/risk [44], perceived behavioral control, subjective norm [41], perceived privacy, and trust in AV performance, manufacturers and regulations [46] are worthy of consideration. However, without related survey questions, these latent constructs cannot be measured and integrated in our proposed model. Survey agencies can design a questionnaire to capture individuals' perceptions and attitudes to AVs from different perspectives. Questions like "Driverless cars generally will be ____ compared with most drivers on the road" with answers "(a) much safer (b) safer (c) a little safer (d) somewhat more dangerous (e) more dangerous (f) much more dangerous" can be used to measure the perceived risk of riding an AV [40]. Trust in AVs can be measured based on the level of agreement with statements such as "self-driving cars are reliable/dependable." [41] Conducting a well-designed questionnaire to measure these psychometric concepts is left as a future work. Nevertheless, the general structure of our presented conceptual model can be adopted to accommodate the addition of latent constructs. It is noteworthy that the validity of the attitudinal variables (i.e., perceived usefulness and behavioral intention) cannot be assessed due to the nature of stated responses under hypothetical situations where actual experience with AVs is lacking. In addition, the causal relationship between perceived usefulness and intention may be a two-way causal arrow that is best tested over time using longitudinal surveys [72]. Jing et al. [73] reach the same conclusion after performing review of studies on AVs and found no longitudinal data collection about AVs.

The household mobility indicators and built environmental factors can only coarsely represent mobility and environment. For example, the use of active mode (i.e., walk and bike), the frequency of different travel modes, the number of daily trips, the access to grocery stores and public transit, the road network density, the finer residential location information (e.g., at census tract or block group level) are absent from the data and also cannot be obtained or derived otherwise. The inclusion of these variables in our model could provide a more complete view of the relationships among variables. One recommendation for future studies is to add more detailed measurement of the environmental correlates of travel behavior and geocoding major places of interest and residences of respondents.

The sample used in this study can be under-represented for certain types of households, particularly as zero-car households, low-income households and households with kids. The results and findings should be treated with caution in view of data representativeness (although we use many explanatory variables to control for this). Furthermore, as a region with a big diverse population, vehicle ownership, and technology advancement, California is unique in terms of its local transportation and cultural contexts, the findings based in California might not be readily generalizable. The inclusion of and comparison with samples from other regions around the world can help deepen our understanding of intentions to adopt AVs through results comparison, which enables the discovery of commonality shared by different samples and the heterogeneity that varies by geography.

Chapter 3

Change of Attitudes towards Autonomous Vehicles Over Time

[1] **Abstract**. A growing number of research attempts has been made to enhance our knowledge about the characteristics of the potential early Autonomous Vehicle (AV) adopters. However, little is known about whether the public attitudes towards AVs change over time and how. With a multiyear cross-sectional travel survey data of the Puget Sound Region that encompasses the Seattle metropolitan area, we analyzed the fractions of population with various levels of interest and concerns regarding AVs. A two-part model combining a binary logit model and a partial proportional odds model was utilized to investigate the change of individuals' positions on AVs over time, controlling for their socio-demographic characteristics, travel behavior characteristics, and built environment attributes. We find that the percentage of population unfamiliar with AVs has declined over the years, which is probably due to a greater exposure to the infor-

[1] The content of this chapter is an revised version of a published article: Xiao, J., & Goulias, K. G. (2021). How public interest and concerns about autonomous vehicles change over time: A study of repeated cross-sectional travel survey data of the Puget Sound Region in the Northwest United States. *Transportation Research Part C: Emerging Technologies, 133,* 103446. `https://doi.org/10.1016/j.trc.2021.103446`

mation about AVs. All other variables being equal, individuals' interest in AVs has not changed over time while their concerns have increased across time. The findings suggest that information campaigns or educational programs that introduce the advantages of AV adoption with a focus on the safety aspects of AVs could potentially alter public attitudes, which could help achieve greater market penetration.

3.1 Introduction

Autonomous Vehicles (AVs) are considered a disruptive technology. When adopted widely, fully automated vehicles hold the promise to transform road transportation systems, urban dynamics, social wellbeing, and the environment. The past decades have seen a growing interest in AVs in academia, reflected by the increasing number of scientific publications. According to Gandia et al. [3], the number of publications on AVs has boosted from 140 in 1997 to 1,856 in 2017 using the Thomson Reuters' Web of Science (WoS) database. The average growth rate of publications on AVs was 39% over the analyzed periods (i.e., 1969-2018), which was much higher compared to the average science growth rate of 8-9%. In the growing body of literature, various advantages of AVs are assessed, including new mobility options for the disabled, senior, and children, more effective traffic flow and reduced traffic congestion [12, 13], and more open space freed from parking [74, 16, 75, 17, 76]. Adoption of AVs could also dramatically reduce traffic accidents and mortality rates [77, 18, 19], alleviate the pressure from long commutes [11], increase utility of in-vehicle time [20, 78], and reduce fuel use and lower greenhouse gas (GHGs) emissions [21, 79, 80]. On the flip side, the appeal of AVs could introduce additional (long) trips and possibly make people live further from cities, exacerbating the already deleterious impacts of urban sprawl [11, 23], which results in increased infrastructure costs and taxes, intensified segregation and inequity, more energy use, environmental degradation, and biodiversity and habitat loss [24, 25].

Before AVs actually take off, how the technology will change transportation networks and urban form remains largely uncertain. The potential impacts of AV adoptions on travel demand, road capacities, land use, and the environment are found to be inconclusive in literature. For instance, specifying several scenarios of varying connected–automated vehicle (CAV) market penetration rates and travel time valuation, Auld et al. [81] examined the changes of travel behavior, activity patterns and congestion level in the Chicago metropolitan region using activity-based travel demand models. They found that vehicle miles traveled (VMT) can increase 18% and 59% when penetration rates reach 20% and 75%, respectively, for the high value of travel time (VOTT) cases (with the caveat that travelers using CAV technologies are randomly assigned in that study). With various scenarios and assumptions in literature, the change of VMT is found to vary from -20% to +79% [81, 82, 83]. According to Zhang and Guhathakurta [75], shared AVs (SAVs) could reduce parking space by 4.5% in Atlanta at 5% market penetration level. Meanwhile, Kondor et al. [74] suggested that an increase of less that 2% VMT can help reduce parking needs by up to 50% when adopting AVs. Using an agent-based simulation model, Zhang and Wang [76] estimated that the parking demand will decrease by over 20% after 2030 for the optimal scenario of AV adoption. As for the environmental impacts of AVs, the reduction of GHG emissions is found to vary substantially among studies [21, 79, 80]. The discrepancies in existing research partly result from the different assumptions of AV market adoption and preferences for the options of privately-owned AV (PAV) or SAV. Therefore, to identify the potential AV adopters and how they will adopt the technologies are critical to the assessment of AVs' impacts.

Scientific endeavors on AV market identification are enormous. Individuals' demographic, socioeconomic, activity-travel characteristics and personality traits are commonly used to depict AV adaptors' profiles. For example, young men are more likely to be interested in adopting AVs [28, 29, 31, 84, 32, 37]. Well-educated people are also found to have greater propensity for AVs [36, 29, 31, 37]. Individuals who have diverse activity schedules and use different travel modes also reveal greater interest in AVs [85, 35]. Moreover, tech-savviness and green lifestyle appear to be positively correlated with the predisposition to AV technologies [29, 31]. While these personal characteristics are critical in identifying the AV population segment, Wang Akar [37] showed that people's attitudes towards AVs does not stay the same over time. However, little is known about whether and how public acceptance changes over time. Thus, to fill this research gap, we pose the following research questions:

1. How do public interest and concerns towards AV change over time?
2. Do individuals become more interested in adopting AV and less concerned over time when controlling for socio-demographic characteristics, travel behavior characteristics, and built environment attributes?

In this paper, we answer the research questions using repeated cross-sectional Puget Sound Region Household Travel Survey data in 2015, 2017, and 2019. The change of attitudes is first examined to represent the over 2 million regional population at the aggregate level. Then, a two-part model combining a binary logit model and a partial proportional model investigates the change of individuals' positions on AVs, accounting for their socio-demographic characteristics, activity-travel behavior characteristics, and built environment attributes. The results can provide empirical support for making realistic assessments of potential AV impacts. The findings also shed light on achieving better AV deployment and market penetration through added policy development and informed decision-making in transportation and city designs.

The remainder of this paper is organized as follows. Section 3.2 introduces work related to substantive research questions and research methods. Section 3.3 describes the data used in this study and presents descriptive statistics of the databases. Methodology is introduced in Section 3.4 and followed by results in Section 3.5. Discussion and conclusions are presented in Section 3.6.

3.2 Related Work

3.2.1 Public Acceptance of AVs

Prior to AV's entrance to the market, conducting surveys is the main approach to measure public acceptance and preferences as well as the determinants (Becker Axhausen, 2017). However, both the measures of acceptance and their corresponding explanatory variables vary substantially across research articles.

Acceptance Indicators

Commonly used direct measures of acceptance of AV adoption include intention to use/purchase [63, 86, 87], willingness to pay (WTP) [36, 64, 34], and mode choice for PAV, SAV, and conventional vehicles in stated preference (SP) surveys [88, 85, 31]. For instance, to understand people's intention to purchase an AV, a question "I would consider purchasing a vehicle that is fully self-driving, (for example, the vehicle drives itself)" was asked in the 2017 California Vehicle Survey [89], with responses being "agree", "neither agree or disagree", and "disagree". Despite being simple and straightforward, this type of questions may fail to capture the different dimensions of attitudes and perceptions people have towards AVs. To account for that, researchers often ask more specific questions (usually a Likert-type) in the survey and use (confirmatory) factor analysis to extract people's opinions from different perspectives. One example is to measure behavior intention (BI), which is a latent construct derived from three survey items regarding different use of AV [90]. Similar approaches are also found in many other studies [91, 92, 45, 46].

Determinants of Acceptance

Variables that are correlated with public acceptance and opinions are mainly of three types: people's demographics factors, mobility behavior factors, and psychological factors [93]. Yet, the conclusions in the literature vary by sample, measure, geography, and method; some are even found to be contradictory.

In terms of socio-demographics determinants, some scholars [28, 31, 37] stated that age was negatively associated with AV adoption. But, it was observed to be positively correlated with the intention to use, according to Rödel et al [86]. While men was found be to less concerned with the use of AVs [29, 94, 84, 32], Bansal et al. [36] reported that gender had no significant relationship with the intention to use. High education attainment is found to have a positive effect on AV acceptance consistently [36, 29, 31, 94, 37]. Meanwhile, the impact of income on attitudes varies. Lavieri et al. [29] and Shabanpour et al. [65] showed a positive correlation between income and interest in adopting AV. Conversely, negative and nonsignificant correlations were also noted by Nair et al. [95] and Wang and Arker [37], respectively. Urban dwellers in high density neighborhoods are also more disposed to AV technologies [36, 29, 94, 37].

A variety of travel behavior characteristics are also linked to the attitudes and acceptance of AVs. People with car crash experience [36, 65] and carsharing/ridesharing experience [85, 29, 37] usually perceive more utilities of (S)AV. Longer distance/time traveled [64, 96], higher diversity in transportation modes and activity time allocation patterns [85, 35] also increase the interest in and willingness to pay for AVs. Transport disadvantaged population (e.g., disabled) and people who cannot drive in certain situations (e.g., non-licensed, drunk, fatigued, inattentive, etc.) exhibit a higher level of intention to use AVs [14, 97].

Technology savviness is repeatedly recognized as one of the psychological determinants that positively affects AV adoption intention [36, 98, 29, 99, 34]. Nevertheless, the joy of driving adversely influences the likelihood of using AVs [98, 99, 34]. Other psychological factors positively associated with AV usage include environmental awareness (green travel pattern, green lifestyle, or environmental concern) [98, 29, 31, 99] and value of time [98]. Based on behavior theories, researchers have extensively investigated behavior intention (of adopting AVs) with its theoretical antecedents such as perceived usefulness, perceived benefits, perceived risk, subjective norm (social influence), and trust using techniques such as structural equation modeling [91, 92, 100, 101, 99, 46, 90].

Although the study on AV user identification is extensive, the understanding of how public attitudes to AV change over time is still limiting. This research aims to bridge this knowledge gap by examining the change of people's interest and concerns to AV using a repeated cross-sectional regional survey that spans six years, taking their socio-economic and travel behavior characteristics into account.

3.2.2 Models for Partially Ordered Survey Responses

No-opinion options like "don't know" (DK herein) are commonly offered explicitly in questionnaires to encourage people to admit their absence of attitudes, beliefs, or opinions, rather than forcing them to make committed responses. It is presumable that these noncommittal options could improve measurement and data quality by minimizing the responses lacking validity and reliability [102]. Various approaches are developed to analyze partially ordered survey responses that consist of ordinal choices (e.g., "strongly disagreed" to "strongly agreed" Likert-type scale responses) and an additional DK option.

One of the approaches is simply treating the responses as nominal by ignoring the partial ordering of the responses. Nominal data analysis such as multinomial logit regressions are usually performed. This, however, may lead to unwanted information loss and unnecessary reductions in statistical power. Moreover, models like multinomial logit regressions are not as parsimonious as cumulative logit models, which are commonly used in ordinal data analysis. Another approach is to treat DK responses as missing data and apply ordered categorical data analysis to the remaining data. However, data removal, if based on wrong presumptions (e.g., DK samples are randomly distributed), could lead to biased sample and thus incorrect conclusions pertaining to the substantive research questions being studied (e.g., erroneous magnitude and direction of the coefficients) [102]. Research in survey methodology has been done on the correlations between sociodemographic variables and DKs but the conclusions vary substantially across studies. For example, some suggested that females tend to give DK responses while others stated differently [102]. Krosnick et al. [103] reported a negative correlation between education attainment and DKs when other studies showed the opposite.

The third method is to combine DK with other responses like omitted and neutral responses or to treat DK as a scale midpoint if there is none already. The questions worthy of consideration are 1) whether or not DK and the scale midpoint such as neutral have the same psychological meaning, 2) if the combined measurement can be regarded as a meaningful response, and 3) would people choose neutral rather than DK if they had this option or the other way around. The “neutral” option allows the expression of a neutral opinion, similar to “neither agree nor disagree”. It is commonly included in surveys so respondents are not forced to choose either a disagreement or agreement option. However, studies show neutral has been (mis)interpreted and used as “undecided”, “need more information ”, “no opinion”, “don’t care”, “not applicable” [104]. On the other hand, DK is often interpreted as the lack of necessary knowledge, information, and/or experience with which to form an attitude [103]. Although interpreted differently, both neutral and DK are also found to be indicative of ambivalence, no attitudes or nonexistent cognitive states [102]. While there is no conclusive interpretation of DK and neutral responses conceptually, analyzing the joint responses as if they had similar distribution and reflected the same underlying construct could induce an averaging pooling effect, which can conceivably lead to inaccurate or even inverse estimation of the coefficients [102].

In this study, we use the fourth approach: a two-part model consisting of 1) a binary logit model for DKs versus all the other categories combined and 2) a partial proportional odds model for the ordinal Likert-type responses. Rather than deleting DK responses as in the second method, the binary logit model inspects whether a systematic difference exists between DK sample and the remaining sample, which helps to avoid biased estimation. The ordinal model retains the order of the responses rather than ignoring it in the multinomial logit model used in the first approach. In addition, our proposed solution avoids the potential misinterpretation of DK that may occur in the third approach. In interpreting the binary logit model for DKs, we follow Krosnick et al. [103] and treat DK responses as proxies of the multidimensional construct called consumer "savvy" in the marketing literature [105].

3.3 Data

This study uses the 2015, 2017, and 2019 cross-sectional Puget Sound Regional Travel Surveys. The Puget Sound Regional Council (PSRC) four-county region is a coastal area of the Pacific Northwest in the U.S. state of Washington, including the Seattle metropolitan area. It is made up of King, Kitsap, Pierce, and Snohomish counties, including 82 cities and towns with a population of about 4 million persons in 1.5 million households. The three consecutive biennial-basis surveys collected person- and household-level socio-demographic, geographic, activity-travel, and attitudinal information from residents throughout the PSRC region between April and June of 2015, 2017, and 2019. The multiyear data collection effort is to maintain and update the household travel behavior data of the Puget Sound region, allowing for transportation demand management, land-use modeling, and trend analysis over time [106].

3.3.1 Interest and Concerns Regarding AVs

The multiyear cross-sectional travel surveys collected attitudinal information about the level of interest and concerns that individuals had regarding AV technology. Specifically, all survey respondents no less than 18 years old were asked about the following four questions:

1. What is your level of interest in owning an autonomous car?
2. What is your level of interest in participating in an autonomous car-share system for daily travel?
3. How concerned are you about system and vehicle security in an autonomous car?
4. How concerned are you about autonomous cars' ability to react to the environment (e.g., other cars, bicyclists, pedestrians)?

The six possible responses to these questions are *very interested/concerned*, *somewhat interested/concerned*, *neutral*, *somewhat uninterested/unconcerned*, *not at all interested/concerned*, and *don't know*. We construct four attitudinal variables, i.e., *interest in owning an AV*, *interest in an AV carshare system*, *concerns about AV vehicle security*, and *concerns about AV react capability*, from the responses to the above questions as the dependent variables of this study to capture people's attitudes towards AV technology from different angles.

We excluded respondents under 18 years and adult respondents whose answers were filled in by someone else. Ultimately, the multiyear sample available for this study contained 12,882 individuals and 8,593 households. Particularly, there were 3,604 individuals and 2,415 households in 2015, 4,696 individuals and 3,154 households in 2017, and 4,582 individuals and 3,024 households in 2019. The sample size of different levels of interest and concerns related to AV technology is shown in Table 3.1.

Table 3.1: Sample size of different levels of interest and concerns related to AV technology

	Interest in owning an AV			**Interest in an AV carshare system**			**Concerns about AV vehicle security**			**Concerns about AV react capability**		
Response	2015	2017	2019	2015	2017	2019	2015	2017	2019	2015	2017	2019
Very	404	764	655	369	719	646	1,189	1,727	1,641	1,742	2,386	2,336
Somewhat	489	808	805	454	890	870	955	1,310	1,321	804	1,152	1,178
Neutral	420	676	656	437	678	633	567	695	644	325	427	380
Somewhat not	214	347	394	220	346	414	182	309	357	116	201	260
Not at all	1,696	1,795	1,801	1,759	1,753	1,793	313	367	346	237	271	231
Don't know	381	306	271	365	310	226	398	288	273	380	259	197
Total	3,604	4,696	4,582	3,604	4,696	4,582	3,604	4,696	4,582	3,604	4,696	4,582

3.3.2 Definitions of Sample Characteristics

The sample's characteristics were grouped into four broad categories: individual's socio-demographic characteristics, household characteristics, individual's activity-travel characteristics, and built environment around the residence of respondents (at census tract level). The descriptive statistics of these characteristics are presented in Table 3.2.

Table 3.2: Descriptive statistics of the sample's characteristics

	2015	**2017**	**2019**	**Population**
Individual's Socio-demographic Characteristics				
Individuals	n = 3,604	n = 4,696	n = 4,582	n = 3,139,115
Population (sample with expansion weights)	2,431,839	2,536,831	2,871,756	
Gender				
Male	2,002 (55.55%)	2,258 (48.08%)	2,175 (47.47%)	1,566,703 (49.91%)
Not Male	1,602 (44.45%)	2,438 (51.92%)	2,407 (52.53%)	1,572,412 (50.09%)
Age				
18 – 24	148 (4.11%)	290 (6.18%)	232 (5.06%)	608,579 (19.39%)
25 – 34	665 (18.45%)	1,480 (31.52%)	1,368 (29.86%)	652,120 (20.77%)
35 – 44	595 (16.51%)	1,004 (21.38%)	956 (20.86%)	554,013 (17.65%)
45 – 54	561 (15.57%)	609 (12.97%)	630 (13.75%)	523,570 (16.68%)
55 – 64	772 (21.42%)	596 (12.69%)	614 (13.40%)	329,830 (10.51%)
65+	863 (23.95%)	717 (15.27%)	782 (17.07%)	471,003 (15.00%)
Bachelor's degree or higher	2,337 (64.84%)	3,516 (74.87%)	3,298 (71.98%)	1,225,654 (39.04%)
Worker	2,190 (60.77%)	3,358 (71.51%)	3,337 (72.83%)	2,132,760 (67.94%)
Student	233 (6.47%)	394 (8.39%)	331 (7.22%)	-
Household Characteristics				
Households	n = 2,415	n = 3,154	n = 3,024	n = 1,603,060
Household size				
1	929 (38.47%)	1,249 (39.60%)	1,284 (42.46%)	433,371 (27.03%)
2	950 (39.34%)	1,300 (41.22%)	1,180 (39.02%)	558,233 (34.82%)
3	281 (11.64%)	323 (10.24%)	297 (9.82%)	256,066 (15.97%)
4+	255 (10.56%)	282 (8.94%)	263 (8.70%)	355,390 (22.17%)
Household income				
Under $25,000	338 (14.00%)	339 (10.75%)	277 (9.16%)	195,612 (12.2%)
$25,000-$49,999	476 (19.71%)	470 (14.90%)	435 (14.38%)	687,956 (42.92%)
$50,000-$74,999	366 (15.16%)	466 (14.77%)	463 (15.31%)	250,206 (15.61%)
$75,000-$99,999	334 (13.83%)	402 (12.75%)	414 (13.69%)	253,782 (15.83%)
$100,000 or more	741 (30.68%)	1,246 (39.51%)	1,248 (41.27%)	215,504 (13.44%)
Prefer not to answer	160 (6.63%)	231 (7.32%)	187 (6.18%)	-
Household lifecycle				
Household size = 1, Householder under age 35	147 (6.09%)	428 (13.57%)	395 (13.06%)	-
Household size = 1, Householder age 35 – 64	492 (20.37%)	585 (18.55%)	605 (20.01%)	-
Household size = 1, Householder age 65+	290 (12.01%)	236 (7.48%)	284 (9.39%)	-
Household includes children under 5	196 (8.12%)	262 (8.31%)	241 (7.97%)	-

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Table 3.2 – continued from previous page

		2015	2017	2019	Population
Household includes children age 5 – 17		238 (9.86%)	265 (8.40%)	237 (7.84%)	-
Household size > 1, Householder under age 35		214 (8.86%)	565 (17.91%)	461 (15.24%)	-
Household size > 1, Householder age 35 – 64		506 (20.95%)	557 (17.66%)	525 (17.36%)	-
Household size > 1, Householder age 65+		332 (13.75%)	256 (8.12%)	276 (9.13%)	-
Household vehicle count					
0		301 (12.46%)	508 (16.11%)	568 (18.78%)	126,902 (7.92%)
1		997 (41.28%)	1,527 (48.41%)	1,434 (47.42%)	499,321 (31.15%)
2		811 (33.58%)	881 (27.93%)	773 (25.56%)	605,226 (37.75%)
3+		306 (12.67%)	238 (7.55%)	249 (8.23%)	371,611 (23.18%)
Residential type					
Apartment/condo		846 (35.03%)	1,717 (54.44%)	1,580 (52.25%)	187,220 (11.68%)
Multi-family house		219 (9.07%)	403 (12.78%)	310 (10.25%)	168,420 (10.51%)
Single-family house		1,313 (54.37%)	995 (31.55%)	1,096 (36.24%)	954,438 (59.54%)
Others		37 (1.53%)	39 (1.24%)	38 (1.26%)	292,982 (18.28%)
Individual's Activity-Travel Characteristics					
Telecommute		746 (20.70%)	1,588 (33.82%)	1,724 (37.63%)	132,685 (4.23%)
Commute		1,977 (54.86%)	3,020 (64.31%)	3,010 (65.69%)	2,000,075 (63.71%)
Commute mode (for commuters)					
Drive alone		1,100 (55.64%)	1,485 (49.19%)	1,330 (44.19%)	1,442,429 (72.12%)
Carpool		142 (7.18%)	223 (7.39%)	197 (6.54%)	209,551 (10.48%)
Active mode (bike/walk)		156 (7.89%)	279 (9.24%)	373 (12.39%)	110,520 (5.53%)
Transit		412 (20.84%)	828 (27.43%)	831 (27.61%)	212,290 (10.61%)
Others		167 (8.45%)	204 (6.76%)	279 (9.27%)	25,285 (1.26%)
Use alternative fuel vehicles		187 (5.19%)	310 (6.60%)	365 (7.97%)	-
Transit as a travel mode		2,363 (65.57%)	3,478 (74.06%)	3,177 (69.34%)	-
Bike as a travel mode		1,263 (35.04%)	1,866 (39.74%)	1,408 (30.73%)	-
Walk as a travel mode		3,200 (88.79%)	4,285 (91.25%)	3,640 (79.44%)	-
Rideshare as a travel mode (derived for 2015)		300 (8.32%)	-	-	-
Rideshare as a travel mode (2017 & 2019)		-	782 (16.65%)	630 (13.75%)	-
Carshare as a travel mode (derived for 2015)		499 (13.85%)	-	-	-
Carshare as a travel mode (2017 & 2019)		-	2,250 (47.91%)	2,174 (47.45%)	-
Built Environment for Residence (Census Tract Level)					
Transportation index					
Very low		377 (10.46%)	206 (4.39%)	420 (9.17%)	804,904 (19.46%)
Low		536 (14.87%)	279 (5.94%)	548 (11.96%)	832,246 (20.12%)
Moderate		643 (17.84%)	288 (6.13%)	361 (7.88%)	840,171 (20.31%)
High		669 (18.56%)	753 (16.03%)	378 (8.25%)	819,112 (19.8%)
Very high		1,379 (38.26%)	3,170 (67.50%)	2,875 (62.75%)	840,772 (20.32%)
Density (continuous)					
Population density (people/acre)	Min.	0.007	0.017	0.007	0.000
	Mean	14.012	18.605	20.028	8.387
	S.D.	15.997	17.838	18.660	9.396
	Max.	92.570	92.570	92.570	92.570
Employment density (jobs/acre)	Min.	0.006	0.014	0.006	0.000
	Mean	12.452	16.883	18.303	7.049
	S.D.	15.648	17.556	18.380	8.913
	Max.	89.177	89.177	89.177	89.177
Accessibility (continuous)					
Jobs within 30 minutes auto travel time (normalized)	Min.	0.003	0.003	0.003	0.003

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Table 3.2 – continued from previous page

		2015	2017	2019	Population
	Mean	0.452	0.608	0.589	0.338
	S.D.	0.294	0.270	0.316	0.248
	Max.	1.000	1.000	1.000	1.000
Jobs within 45 minutes transit travel time (normalized)	Min.	0.000	0.000	0.000	0.000
	Mean	0.292	0.444	0.460	0.166
	S.D.	0.300	0.298	0.329	0.236
	Max.	1.000	1.000	1.000	1.000

Note: only the percentages of "true" category of binary variables are shown in the table. Population statistics are retrieved from the ACS 2015-2019 5-year estimates. ACS 1-year estimates for 2015, 2017, and 2019 are not shown in the table since the change in percentage of population is minor over time; the absolute percentage difference between 1-year and 5-year estimates are all less than 1 %. Both sample and population contains only individuals aged 18 years and over.

Some variables were directly from the survey and are self-explanatory, whereas some were derived from survey responses and supplementary data sources. The definitions of these characteristics are introduced as follows. The variable *household lifecycle* is a categorical variable defined as a combination of the presence of children (ages 0-4 or ages 5-17), number of adults (1 or 2+), and householder age (under 35, 35-64, or 65 or older) by the survey company Resource Systems Group, Inc. (RSG) [107]. According to the U.S. Census Bureau [2], householder is the "reference person" to whom the relationship of all other household members, if any, is recorded in surveys. Usually it refers to the person or one of the people in whose name the housing unit is owned or rented (maintained). The householder may be either the husband or the wife if the house is jointly owned or rented by a married couple. *Residential type* is a categorical variable with four possible values: single-family house, multi-family house, apartment/condo, and others, which contains mobile home, trailer, dorm or institutional housing, boat, RV, van, etc. given the small sample size of these categories. *Use alternative fuel vehicles* is a binary variable derived based on whether or not the vehicle's fuel type is an alternative fuel (to the gasoline or diesel) such as hybrid, electric, flex fuel, or biofuel. *Commute and telecommute* are also binary variables and equal to 1 if a worker has ever commuted and telecommuted

[2] The definition of householder is retrieved from `https://www.census.gov/programs-surveys/cps/technical-documentation/subject-definitions.html#householder`.

(i.e., work from home, making use of the internet, email, and the telephone) regardless of frequency and 0 otherwise. The two variables are not mutually exclusive since some people can have a hybrid work model combining office and remote work. *Commute mode*, the answer to the question of usual mode to work, is reclassified to five main modes: drive alone, carpool, transit, active mode (walk bike), and others (including the mode of ferry, water taxi, airplane, helicopter, scooter, e-scooter, motorcycle/moped, skateboard given the small sample size). *Transit/bike/walk/carshare/rideshare* as a travel mode are also binary variables and equal to 1 if the individual has ever used this mode for daily activities regardless of frequency and 0 otherwise. Noticing that *carshare/rideshare as a travel mode* are separated for 2015 and for 2017 and 2019. The reason is that there were no survey questions on the frequency of general carshare/rideshare services usage in 2015 like there were for 2017 and 2019. However, questions on the frequency of using specific carshare/rideshare services, including Zipcar, Car2go, RelayRides, Lyft, UberX, Pronto, were asked in 2015. These questions were then aggregated to create *carshare/rideshare as a travel mode* for the sample in 2015. One can see a substantial gap between the percentages of using carshare/rideshare services of 2015 and those of 2017 and 2019 due to the nature of the data.

Built environment attributes are found to be associated with people's travel behavior with accessibility to opportunities historically taking a central role in explaining behavior [108]. Indicators of accessibility are generally intended to capture the density and diversity of potential opportunities for people's activities measured as a continuous field that changes over space and time [109]. Most measures of accessibility and reach of opportunities are centered around places where people spend most of their time in a day such as home and work locations [110, 111, 112, 113].

In this study, five measures were used to describe the built environment of the respondents' residence at census tract level encompassing the entire PSRC region. Two density measures including *population density* and *employment density* (counts/acre) were obtained from the ACS 2015-2019 five-year estimates. The *number of jobs within 30 minutes auto travel time* and*within 45 minutes transit travel time* were two indices from PSRC [3] to describe the job accessibility by automobile and public transit. Both accessibility measures were normalized by the maximums due to their large magnitudes. The *transportation index* produced by PSRC [106] is a synthetic indicator that assesses mobility and transportation for commuters based on four indicators, including average commute cost by driving, percentage of area within a quarter mile of transit stops, cost of average transit fare, and percentage of commuters who walk to work. The index is categorical and has five levels from very low, low, moderate, high to very high. This index is very high in places such as the waterfront of Seattle and Bellevue that are also the business places in this region.

3.3.3 Sample Representativeness

The survey sample was drawn randomly from each sampling stratum (defined using block groups and American Community Survey, ACS, data) to cover the PSRC region using address-based sampling method, yet discrepancies between targeted sample rates and actual response rates results in oversampling and nonresponse biases. Using the ACS 2015-2019 5-year estimates as a proxy for the regional population, we observe variations between the survey data and the population. In particular, male individuals were oversampled in 2015 and under-sampled in 2017 and 2019. Young adults aged 18 to 24 were underrepresented in all three surveys. Seniors were overrepresented in 2015 while the prime working age population (aged 25 to 44) were overrepresented in 2017 and 2019. All three surveys overrepresented people with bachelor's degrees or higher, telecommuters,

[3] Accessibility measures are obtained from `https://public.tableau.com/profile/psrc.data#!/vizhome/Accesstojobs/Jobs`.

and commuters using car-independent modes (e.g., transit, walking, cycling, ferry, etc.), especially in 2017 and 2019. Small-size, high-income, zero-vehicle households living in apartments/condos rather than single-family houses were also oversampled, especially for the 2017 and 2019 surveys. Households from census tracts with high population and employment density as well as high transportation index and accessibility to job opportunities were also overrepresented, particularly in 2017 and 2019.

Using expansion weights could help reduce sampling biases and improve the representativeness of survey data, enabling analysis and inference about population at large. The expansion weights developed by RSG [107, 114, 106] were computed based on the sampling rate of each sampling stratum and adjusted by aligning selected person- and household- demographics (e.g., gender, age, household size and income) with external data targets from ACS Public Use Microdata Areas (PUMAs) data. The sum of the resulting expansion weights reflects the total population of the survey region. In this study, the population represented by the sample using expansion weights is approximately 2.43 million persons in 2015, 2.53 million persons in 2017, and 2.87 million persons in 2019 (exact numbers are in row 3 of Table 3.2). Noticing that the population here was a little underestimated as a result of data cleaning and filtering (e.g., the exclusion of respondents who did not answer the attitudinal questions about AVs).

3.4 Methodology

3.4.1 Public Attitudes Over Time

To answer the first research question, the percentage of population at each level of interest and concerns for the four attitudinal variables were calculated. As the sample only covered a fraction of the population in the region and the sample profiles were not the same across years, the percentage of the sample at each level of interest and concerns may not be directly comparable. Thus, to make sensible comparisons for the population at large, the aforementioned expansion weights were used when computing the percentages to account for sampling biases and to improve the representativeness of the data.

3.4.2 Individuals' Attitudes Over Time

Despite that understanding of our first research question is important and informative, it is not clear how the attitudes change by population segments. To answer the second research question, this section introduces the method to correlate individual's interest in and concerns about AVs with time, controlling for a set of explanatory variables, which can be broadly classified into four categories: individual's socio-demographic characteristics, household's socio-demographic characteristics, individual's travel behavior characteristics, and build environment attributes of residence.

The multiyear survey collected cross-sectional observations in 2015, 2017, and 2019. It means that the individuals were randomly sampled for each year, making panel data analysis inappropriate. Pooling the repeated cross-sectional observations from multiple years together as if they were one big random sample makes more sense. Time effect was assessed through time dummy variables to see if there were any structural change of the attitudes not captured by the explanatory variables used in this study.

As previously stated, the attitudinal response variables used in this study have six possible values: *very*, *somewhat*, *neutral*, *somewhat not*, *not at all (interested/concerned)*, and DK. The variables are partially ordered as a mixture of ordinal and nominal values. The presence of DKs poses great difficulties in analyzing the data since it is not clear where DKs should be positioned in the Likert-type scale from *very* to *not at all*, and therefore models for ordinal data are inapplicable here.

A two-part model is proposed in this paper to accommodate the partially ordered data. It consists of a binary logit model for DKs versus all the other categories combined (i.e., very, somewhat, neutral, somewhat not, not at all) and an ordinal categorical model for the Likert-type portion of the data.

Let Y denote a binary variable of whether the response is DK or not and $\mathbf{x} = (x_1, x_2, \ldots, x_p)'$ denote the explanatory variables. We define the binary logit model as

$$\begin{aligned} \text{logit}[P(Y = DK|\mathbf{x})] &= \log[\frac{P(Y = DK|\mathbf{x})}{1 - P(Y = DK|\mathbf{x})}] \\ &= \alpha + \delta_{2017} d_{2017} + \delta_{2019} d_{2019} + \boldsymbol{\beta}'\mathbf{x} \end{aligned} \tag{3.1}$$

where α is the intercept, $\boldsymbol{\beta}$ is a $p \times 1$ vector describing the effects of $\mathbf{x}$ on the log odds of response in category j or below. Both d_{2017} and d_{2019} are time indicator variables defined as follows.

$$d_k = \begin{cases} 1 & \text{if the observation is collected in year k} \\ 0 & \text{otherwise} \end{cases}$$

In practice, binary models with logit link and probit link fit data almost equally [115]. Binary logit model is chosen in this study for its simple odds ratio interpretation.

Let Y denote an ordered attitudinal response variable with 5 categories. The categories are in ascending order from *not at all* (category 1) to *very* (category 5). Let $\pi_j = P(Y = j|\mathbf{x}), j = 1, \ldots, 5$, denote the conditional probability of a response equal to category j given the explanatory variables $\mathbf{x} = (x_1, x_2, \ldots, x_p)'$. We first introduce the general form of cumulative logit model as follows.

$$\text{logit}[P(Y \leq j|\mathbf{x})] = \log[\frac{P(Y \leq j|\mathbf{x})}{1 - P(Y \leq j|\mathbf{x})}] = \alpha_j + \boldsymbol{\beta}'\mathbf{x}, j = 1, \ldots, 4 \tag{3.2}$$

where $P(Y \leq j) = \pi_1 + \cdots + \pi_j, j = 1, \ldots, 4$ is the cumulative probability of the outcome category j. Models for cumulative probabilities do not use the final category since $(P(Y \leq 5|\mathbf{x})) = 1$, therefore, $1 - P(Y \leq 5|\mathbf{x}) = 0$.

This is a parsimonious model with only one parameter for each covariate compared to models such as baseline-category logit models for nominal responses that have separate parameters for each logit [115]. As a consequence, the interpretation of the effects of explanatory variables are also easier. For two values x_1 and x_2 of an explanatory variable x when all else being equal, the odds ratio comparing the cumulative probabilities is

$$\frac{P(Y \leq j|x_2)/P(Y > j|x_2)}{P(Y \leq j|x_1)/P(Y > j|x_1)}$$

The odds ratio, $e^{\beta}(x_2 - x_1)$, is proportional to the distance between the x values. In particular, for $x_2 - x_1 = 1$, the odds of response below any given category multiply by e^{β} for each unit increase in x. A noteworthy feature of this model is that the same proportionality constant applies for each cumulative logit. In other words, the effects of β on x does not change with category j. With the proportional odds assumption, this model is also called proportional odds model.

The generalized proportional odds model allows the effects on explanatory variables to differ for the different cumulative logits by replacing β with β_j in Equation 3.2. However, the proportional odds assumption does not hold anymore and the model has more parameters like the multinomial logit model. In between the two models is the partial proportional odds model [116], in which the odds proportionality holds for some explanatory variables but not for others. The partial proportional odds model used in this study is defined as follows.

$$\begin{aligned}\operatorname{logit}[P(Y \leq j|\mathbf{u},\mathbf{v})] &= \log[\frac{P(Y \leq j|\mathbf{u},\mathbf{v})}{1 - P(Y \leq j|\mathbf{u},\mathbf{v})}] \\ &= \alpha_j + \delta_{2017}d_{2017} + \delta_{2019}d_{2019} + \boldsymbol{\beta}'\mathbf{u} + \boldsymbol{\gamma}'\mathbf{v} \qquad (3.3)\\ j = 1, \ldots, 4 &\end{aligned}$$

where $\mathbf{u}$ denotes the predictors with a proportional odds structure whereas v are the ones without $(\mathbf{x} = \mathbf{u}, \mathbf{v})$. The model reduces to an ordinary proportional odds model when $\mathbf{u} = \mathbf{x}$, and becomes a generalized ordinary proportional odds model when $\mathbf{v} = \mathbf{x}$. For a predictor x_k having proportional odds, the parameter β_k has the ordinary cumulative log odds ratio interpretation that holds for each of the cumulative probabilities. For a predictor x_k not having proportional odds, β_k is the log odds ratio only for the first cumulative probability.

The global proportional odds assumption can be tested by a likelihood-ratio test, which requires the maximization of likelihood functions from both the proportional odds model (with proportional odds) and the generalized proportional odds model (without proportional odds). The likelihood-ratio test could fail when a convergence problem presents in obtaining the maximum likelihood estimates for the full set of parameters in the generalized proportional odds model. Score test is an alternative to test the assumption since it only requires likelihood function maximized under the null hypothesis of proportionality (Peterson Harrell, 1990). If the global proportional odds assumption is violated, the likelihood-ratio test can be used for each one of the predictors whose coefficients for different logits are significantly different in both statistical and practical terms.

3.5 Results and Discussion

3.5.1 Public Attitudes Change Over Time

Applying expansion weights to the sample, people's attitudes towards AVs at different levels of interest and concerns in 2015, 2017, and 2019 are visualized and contrasted in Figure 3.1. Overall, the sample-represented population (2.5-2.8 millions in the region over the years) has a nonpositive attitude towards AVs given the high proportion of people being uninterested in adopting AV, and yet being concerned about AV technology.

AV has gained popularity gradually over the years. Although approximately half of the population was indifferent to owning an AV, the percentage of the population having a positive attitude (i.e., at least somewhat interested) was continuously growing from 26.5% in 2015, to 27.9% in 2017 and 29.6% in 2019. It is noteworthy that the growth was mainly from the somewhat interested group given the slight decline in the percentage of the very interested group. Similar trend of increased population can also be observed for the interest in participating in an AV carshare system for daily travel. However, what's notable is that an AV carshare system was in general less favored compared to owning an AV, which can be seen from both the relatively lower fraction of being interested and the higher percentage of being uninterested in all three survey years.

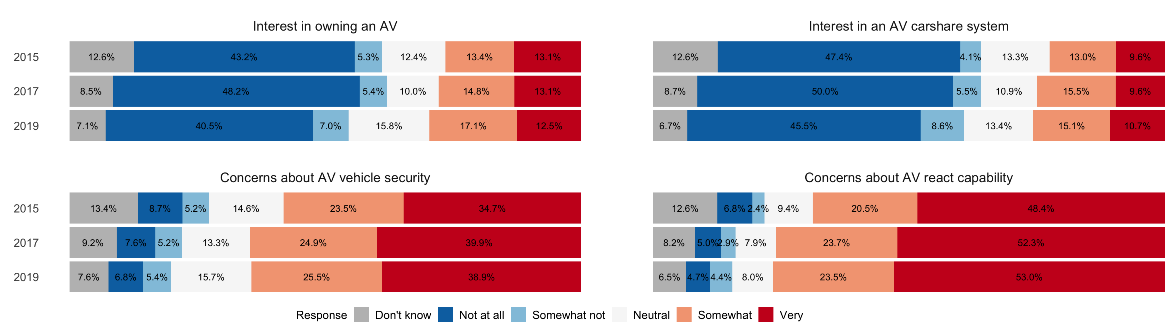

Figure 3.1: Percentage of weighted sample's responses to the four questions about AVs

Overall, the public has become even more concerned than they already were in 2015. The population that was at least somewhat concerned about AV technologies has increased over time both in terms of vehicle and system security and the ability to react to the environment. Meanwhile, the fraction of people that was not concerned at all has declined. However, AV's ability to react to the environment appeared to be a greater concern to the public than the security issue since the concerned portion was constantly higher (68.9%-76.5% vs 58.2% - 64.4%) and together the unconcerned proportion was lower (6.88% - 7.65% vs 7.87%-9.20%) over time. It is noticeable that the fractions of people answering don't know (DK) to all four AV questions have declined consistently over the years (by around 6% from 2015 to 2019), indicating that the public has become more informed about AVs. Presumably the reason is that the public has been exposed to more information about AV technology from news articles, reports, research papers, and auto industry advertisements, etc. in recent years. Empirically, the decline of DK proportion was not associated with an increase in the percentage of neutral, supporting our presumption that DK and neutral are conceptually different and cannot be combined.

In sum, the population has become more informed and educated about AV technology, progressively growing its interest as well as concerns with respect to the adoption of AVs. Nevertheless, the results should be treated with caution because the sample represented population underrepresented the actual population due to data filtering as explained in Section 3.3.1.

3.5.2 Modeling Results

While Figure 3.1 presents a general view of the public attitudes towards AVs at an aggregate level, it is the modeling results in this section through which we gain a detailed understanding of how the attitudes has changed over time at the individual level.

Binary Logit Model Results

To understand whether or not there is a systematic difference between survey respondents who answered DK versus those who did not, and if the odds of DK responses changed over time, binary logit models were built and estimated for the four attitudinal questions, respectively. We began modeling with all the individual and household socio-demographic and activity-travel characteristics, built environment attributes, along with the time dummy variables. Nonsignificant variables at 0.05 level were excluded from our final model specification and estimation through backward elimination in stepwise regression. The estimates of the four binary logit models are shown in Table 3.3. All the coefficients in the table are statistically significant at the 0.05 level.

The model results suggest that the odds of responding DK in expressing one's interest and concerns to AVs have significantly decreased over time, which is consistent with our finding in the previous section. More precisely, the odds of DK responses decreased by 30% - 40% in 2017 and 44% - 60% in 2019 compared to 2015 when controlling for all other variables. The greater decline in 2019 than 2017 implies that the decrease continued with time. Presumably the time dummy variables are associated with the public's greater exposure to AV related information over time, reflecting the exogenous effect that is not captured in the observed variables. Providing people with more information and knowledge on AVs may help shift their attitudes to AVs.

In addition to the time effect, the personal and household socio-demographics also exhibit correlations with the responses. As expected, workers with higher education attainment from middle-income households are less likely to respond DK to questions regarding the interest and concerns towards AVs than persons with lower education attainment. This population probably keeps up with the latest information and knowledge about advanced technologies, and are so-called technology-oriented [29]. This finding is also consistent with literature that people with higher education attainment are less likely to respond DK in questionnaires [103]. Yet, as the number of workers increases in households, people are more likely to answer DKs to these questions. Certain characteristics are found to affect the responses to concerns-related questions. For instance, young people between 25-44 years old are less likely to reply DKs compared to seniors of 65 and above. This is also true for people in households with more vehicles. Household life cycle also exerts different effects on answering DK depending on the questions. Compared to families with senior householders, households with children between 5-17 years old are less likely to take a clear position on owning an AV whereas single persons less than 35 years old are the opposite. Younger households are more likely to have explicit attitudes to AV carsharing and concerns about AV technology.

Individual's travel behavior characteristics also present associations with their knowledge about AVs. Active mode (i.e., walk and bike) travelers and public transit riders are less likely to answer DKs. People using alternative fuel vehicles tend not to answer DK to express their attitudes to their concerns about AV's ability to react to the environment. It is possible that people who use alternative fuel vehicles are also more tech-oriented and more knowledgeable about new technologies, and therefore more likely express their level of concerns regarding AV react capability. Workers' opinions on AV also vary with commute and telecommute frequency. Compared to non-telecommuters, telecommuters with high frequency (i.e., at least 5 days per week) are more likely to express their thoughts on owning an AV and also to answer DKs to the concerns-related questions. The opposite is true for the occasional telecommuters as they are less likely to express their attitudes to owning an AV and also to reply DK to the concerns-related questions. Compared to commuters with high frequency (at least 5 days per week), people who commute 1-4 days per week appear to take a stance on questions about the sharing and concerns of AVs when irregular commuters (less than 1 day per week) are the opposite, although it is not clear why this might be the case.

A variety of built environment attributes including population and employment density, accessibility to job opportunities by auto and transit, and transportation index, were also considered in the model specification. However, none of them were found to be significant in its correlation with the odds of responding DKs in any of four attitudinal variables. This means there is spatial homogeneity in the DK patterns of responses.

Table 3.3: Results of the Four Binary Logit Models

	Interest in owning an AV		**Interest in an AV carshare system**		**Concerns about AV vehicle security**		**Concerns about AV react capability**	
	Base: responses other than Don't know							
	Coef.	OR	Coef.	OR	Coef.	OR	Coef.	OR
Intercept	-1.164	0.312	-1.183	0.306	-0.652	0.521	-0.596	0.551
Time (base: 2015)								
2017	-0.402	0.669	-0.363	0.696	-0.467	0.627	-0.521	0.594
2019	-0.575	0.563	-0.737	0.479	-0.632	0.531	-0.931	0.394
Individual's Socio-demographic Characteristics								
Age 25-44 (base: 65+)	-	-	-	-	-0.333	0.717	-0.283	0.753
Individuals with Bachelor's degree and above	-0.205	0.815	-0.156	0.856	-	-	-0.234	0.791
Worker	-0.442	0.643	-0.553	0.576	-0.524	0.592	-0.461	0.631
Household Characteristics								
Number of workers in the household	0.169	1.184	0.26	1.297	0.226	1.254	0.275	1.316
Household income $25,000 and above (base: under $25,000)	-0.402	0.669	-0.35	0.704	-0.325	0.723	-0.33	0.719
Household lifecycle (base: household size ¿ 1, Householder age 65+)								
Household includes children age 5-17	0.447	1.564	-	-	-	-	-	-
Household size = 1, Householder under age 35	-0.421	0.657	-	-	-0.737	0.478	-0.772	0.462
Household size = 1, Householder age 65+	-	-	-0.355	0.701	-	-	-	-
Household size ¿ 1, Householder age 35 – 64	-	-	-0.185	0.831	-	-	-	-
Number of vehicles in the household	-	-	-	-	-0.090	0.914	-0.096	0.909
Individual's Activity-Travel Characteristics								
Use alternative fuel vehicles	-	-	-	-	-	-	-0.599	0.549
Telecommute frequency (base: never)								
Telecommute frequency at least 5 days per week	-0.389	0.678	-	-	0.366	1.442	0.482	1.620
Telecommute frequency less than 5 days per week	0.322	1.38	-0.467	0.627	-0.585	0.557	-0.703	0.495
Commute frequency (base: at least 5 days per week)								
Commute frequency 1 – 4 days per week	-0.247	0.781	0.358	1.43	0.400	1.491	0.346	1.413
Commute frequency less than 1 day per week	-	-	-1.315	0.268	-	-	-1.060	0.346
Transit as a travel mode	-0.247	0.781	-0.32	0.726	-0.466	0.627	-0.400	0.670
Bike as a travel mode	-0.331	0.718	-0.262	0.769	-0.230	0.794	-0.332	0.717
Walk as a travel mode	-0.233	0.793	-0.265	0.767	-0.593	0.553	-0.628	0.533
Model Goodness-of-fit								
McFadden pseudo R^2	0.045		0.045		0.068		0.087	
Cox and Snell (ML) pseudo R^2	0.023		0.022		0.036		0.041	
Cragg-Uhler (Nagelkerke) pseudo R^2	0.057		0.057		0.087		0.108	
Likelihood ratio	304.66		292.79		467.35		539.87	
Degree of freedom	14		14		15		17	
p-value of likelihood ratio test	<0.001		<0.001					
multicolumn2l<0.001 <0.001								
AIC	6547.4		6268.1		6391.8		5685.5	
Number of observations	12,882		12,882		12,882		12,882	

Note: Coef. = coefficient; OR = Odds Ratio; AIC = Akaike information criterion. Only coefficients with p ¡ 0.05 are shown in the table.

Partial Proportional Odds for Ordered Responses

To understand how the degree of interest and concerns regarding AV has changed over time, (partial) proportional odds models with cumulative logit link were specified and estimated for the four attitudinal variables. The complete model estimation results are shown in Table 3.4 and Table 3.5. Insignificant variables at the 0.05 level were excluded from the final model specification and estimation except for the time dummy variables, which were the interest of our study and retained regardless of statistical significance. Odds ratios were also calculated for ease of interpretation. When the proportional odds property holds, the odds ratios (i.e., the exponentiated value of the coefficient) is the ratio of the odds of being less interested/concerned (either "not at all interested" versus "somewhat not interested and above" or "neutral" versus "at least somewhat interested") in the presence of a particular event and the odds in the absence of that event. An odds ratio that is less than 1 (negative coefficient) suggests that the odds of being less interested/concerned decreases (i.e., the odds of being more interested/concerned increases) as a result of a one-unit increase in a continuous explanatory variable or the presence of an indicator variable. An odds ratio greater than 1 is the opposite.

Effects on the Interest

Among individual socio-demographic characteristics, people's age and gender, as well as education attainment are associated with their positions on both owning and sharing AVs. Young people appear to be more interested in adopting AVs in any form with those between 18-24 years old showing the greatest interest. Men also express a greater level of interest in AV technologies and services compared to women. It is worthy of mention that the coefficients of male differ across various cumulative logit, which is referred to as *asymmetrical effects* [117]. The interpretation is that the smaller odds ratios (more negative coefficients) in the more interested end of the spectrum suggest that males are more likely to be (strongly) interested in using AVs. Students (18+ years old) and people with Bachelor's degrees and above also tend to take a more positive attitude to AVs. The findings are consistent with previous studies [36, 29, 84, 32]. Furthermore, we find that non-workers and people with more than one job seem to be more averse to AV technology than people with one job.

As for household characteristics, people in a wealthy household (with an annual income of $100,000 or more) tend to express inclinations for owning and sharing an AV. Younger households are also more positively disposed to the different uses of AVs. Compared to people who live in apartments/condos, people living in mobile homes, trailers, dorms or institutional housings, boats, RVs, vans, etc. show greater reluctance in both owing and sharing AVs overall whereas single-family households are more reluctant to own an AV. This most likely captures people's different lifestyles and/or the location of the residence with respect to the built environment that are not captured by the explanatory variables used in our models. In the case of participating in an AV carshare system, a greater level of interest is found to be associated with more adults in a household, a smaller household size, and a smaller number of vehicles in a household.

Activity-travel characteristics also play an important role in developing individual interest in AV adoption. While public transit riders, rideshare service users, and alternative fuel vehicle users generally have greater interest in both private and shared AVs, cyclists and carshare service users also show propensity in AV carsharing mainly. It is intuitive that people who have used carshare service are also likely to use AV carshare service. Walkers, however, seem to be less interested in AVs. It is possible that traveling by public transit, bike and/or alternative fuel vehicles are indicative of a latent construct of green lifestyle [29], which can contribute to the increased interest in AV technology. Another plausible explanation is that people using diverse travel modes are also more receptive to various AV services. This explanation is also supported by findings by Krueger et al. [85]. Commuting behaviors are also found to be significantly associated with AV usage. It appears that AVs receive more favor from telecommuters with frequent telecommuters being the most favorable. The use of telecommuting might also be an indicator of tech-savviness. Yet, commuters exhibit greater resistance to adoption of AVs than noncommuters. Moreover, commuters who use active modes (walk/bike) and public transit for commuting exhibit a lack of interest in privately-owned AVs compared to auto commuters. The coefficients are also statistically significant and different from each other across cumulative logits. The larger coefficients in the "very interested" end of the continuum show that these people are very unlikely to show strong interest in privately-owned AVs. It is probable that people who commute by public transit or active modes are not car owners and are not interested in having a car in general, therefore, lacking interest in private AVs. Similar to this study, Wang Akar [37] examined factors that affect commuters' interest in commuting either using an AV alone or using a SAV with others (carpool) using the 2015 and 2017 data. Although their study focused on AVs' application in commuting, our discoveries concerning the activity-travel patterns are quite consistent.

With regard to the built environment attributes, people who live in a higher transportation index region lean towards owning and sharing AVs. One plausible explanation is that urban areas with high transportation index offer people with diverse travel modes, which in turn helps people develop a more open minded view to new mobility options like AVs. The positive association between urbaneness and interest in AV is also found in AV literature [36, 29, 37]. However, employment density and accessibility to job opportunities by automobiles are shown to have an adverse impact on owning AVs. Neither time dummy variable reveals a significant association with individual interest. This means that while controlling for all the observed variables, people's interest in AV adoption does not change over time. Similar finding that no significant difference between the level of interest in commuting alone using an AV for commuters in 2015 and 2017 was also noted by Wang Akar [37]. They also found that commuters' interest in commuting using a SAV decreased in 2017. In the previous section, the fraction of the population that embraces AVs is found to increase over time. While it seems to contradict the findings here, the model results indicate change in attitude is due to change in the variable we use as determinants and not due to unobserved temporal effects. This may also indicate that some people who respond DKs are not significantly different from people who are interested in AVs after getting more informed.

Table 3.4: Partial Proportional Odds Model Results for the Interest in AVs

	Interest in owning an AV		**Interest in an AV carshare system**	
	Coef.	OR	Coef.	OR
Cutoff points				
Not at all | Somewhat not	0.762	2.142	1.350	3.857
Somewhat not | Neutral	1.137	3.118	1.785	5.960
Neutral | Somewhat	1.851	6.368	2.552	12.838
Somewhat | Very	2.933	18.792	3.821	45.655
Time (base: 2015)				
2017	0.013a	1.013 [a]	0.013 [a]	1.013 [a]
2019	0.024a	1.024 [a]	0.009 [a]	1.009 [a]
Individual's Socio-demographic Characteristics				
Male (Not at all | Somewhat not)	-0.259	0.772	-0.216	0.806
Male (Somewhat not | Neutral)	-0.303	0.739	-0.277	0.758
Male (Neutral | Somewhat)	-0.372	0.690	-0.339	0.712
Male (Somewhat | Very)	-0.349	0.705	-0.410	0.664
Age (base: 65+)				
18 – 24	-1.143	0.319	-0.798	0.450
25 – 34	-0.923	0.397	-0.712	0.491
35 – 44	-0.889	0.411	-0.672	0.510
45 – 54	-0.591	0.554	-0.384	0.681
55 – 64	-0.276	0.759	-	-
Bachelor's degree and above	-0.102	0.903	-0.126	0.881
Student	-0.186	0.830	-0.234	0.792
Job count (base: one job)				
No job	0.244	1.276	0.208	1.231
More than one jobs	0.233	1.262	-	-
Household Characteristics				
Household size	-	-	0.117	1.124

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Table 3.4 – continued from previous page

	Interest in owning an AV		Interest in an AV carshare system	
	Coef.	OR	Coef.	OR
Number of adults in the household	-	-	-0.148	0.863
Household lifecycle (base: household size > 1, Householder age 65+)				
Household includes children under 5	-0.292	0.747	-0.902	0.406
Household includes children age 5 – 17	-	-	-0.598	0.550
Household size = 1, Householder under age 35	-0.380	0.684	-0.797	0.450
Household size > 1, Householder age 35 – 64	-	-	-0.485	0.616
Household size = 1, Householder age 35 – 64	-	-	-0.491	0.612
Household size > 1, Householder under age 35	-0.533	0.587	-0.964	0.381
Household income $100,000 or more (base: under $25,000)	-0.245	0.783	-0.206	0.814
Residential type (base: apartment/condo)				
Residential Type: Single-family house	0.159	1.172	-	-
Residential Type: Others	0.612	1.845	0.501	1.650
Number of vehicles in the household	-	-	0.113	1.120
Individual's Activity-Travel Characteristics				
Commute mode (base: drive alone)				
Active mode (bike/walk) (Not at all | Somewhat not)	0.096 [a]	1.101 [a]	-	-
Active mode (bike/walk) (Somewhat not | Neutral)	0.268	1.307	-	-
Active mode (bike/walk) (Neutral | Somewhat)	0.339	1.404	-	-
Active mode (bike/walk) (Somewhat | Very)	0.377	1.458	-	-
Transit (Not at all | Somewhat not)	0.208	1.232	-	-
Transit (Somewhat not | Neutral)	0.262	1.299	-	-
Transit (Neutral | Somewhat)	0.347	1.415	-	-
Transit (Somewhat | Very)	0.383	1.466	-	-
Commute	0.233	1.262	0.253	1.288
Telecommute frequency (base: never)				
Telecommute frequency at least 5 days per week	-0.429	0.651	-0.326	0.722
Telecommute frequency 1 – 5 days per week	-0.368	0.692	-0.445	0.641
Telecommute frequency less than 1 day week	-0.235	0.790	-0.308	0.735
Use alternative fuel vehicles	-0.470	0.625	-0.344	0.709
Transit as a travel mode	-0.109	0.896	-0.256	0.775
Bike as a travel mode	-	-	-0.100	0.905
Walk as a travel mode	0.134	1.143	0.130	1.139
Rideshare as a travel mode (derived for 2015)	-0.339	0.712	-0.237	0.789
Rideshare as a travel mode (2017 & 2019)	-0.288	0.750	-0.404	0.668
Carshare as a travel mode (derived for 2015)	-	-	-0.529	0.589
Carshare as a travel mode (2017 & 2019)	-	-	-0.330	0.719
Built Environment for Residence				
Employment density	0.004	1.004	-	-
Jobs within 30 minutes auto travel time (normalized)	0.272	1.313	-	-
Transportation index (base: very low)				
Low	-0.211	0.810	-0.211	0.809
Moderate	-0.337	0.714	-0.408	0.665

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Table 3.4 – continued from previous page

	Interest in owning an AV		Interest in an AV carshare system	
	Coef.	OR	Coef.	OR
High	-0.493	0.611	-0.430	0.651
Very high	-0.415	0.661	-0.384	0.681
Model Goodness-of-fit				
McFadden pseudo R^2		0.052		0.079
Cox and Snell (ML) pseudo R^2		0.141		0.206
Cragg-Uhler (Nagelkerke) pseudo R^2		0.150		0.217
Likelihood ratio		1704.1		2574.2
Degree of freedom		44		40
p-value of likelihood ratio test		<0.001		<0.001
AIC		30932.4		30127.03
Number of observations		11,175		11,175

Note: Coef. = coefficient; OR = Odds Ratio; AIC = Akaike information criterion. a: p > 0.1.

Effects on the Concerns

We turn now to the two attitudinal questions about concerns. There was a significant decline in the odds of being less concerned about AVs over time, as the results suggest. In particular, the odds of being less concerned decreased by 10% - 18% in 2017 and 2019 compared to 2015 when all else being equal. This is consistent with our findings in the aggregate analysis and also findings by Wang Akar [118]. Being more exposed to information about AVs may explain people's growing concerns about AVs over time. Although AVs are expected to be safer than human drivers given that 94% of serious crashes are due to human error [119], people still develop more fear over time. It implies that proper education on the advantages of AVs is of great importance in alleviating public concerns.

In regards to socio-demographic characteristics, age and gender are significant in their associations with concerns about AV vehicle security and react capability. Males show lower levels of concern than their counterparts. The concerns also grow as age goes up, which can be seen from the decreased odds ratios of being less concerned. The odds of being less concerned are about 2 times for people between 18-24 years old than they are for seniors of 65 years old and older. Workers are also less likely to be concerned compared to non-workers. Students, on the other hand, tend to have more worries than non-students. Education attainment is not significant in explaining the level of concerns. Increased number of vehicles a household owns appears to also intensify people's concerns about AVs. However, households with more adults exhibit less disquietudes regarding AV's ability to react to the environment. Affluent households with more than 100k annual income are also less worried about AV vehicle security.

With respect to travel behavior characteristics, commuters tend to express more concerns in general whereas telecommuters are less likely to be suspicious of the capability of AV to react to the environment. Compared to people who drive alone to work, those who commute by active travel modes, public transit, carpool, and others tend to be less worried about the capability of AV to react to the environment including other cars, bicyclists, pedestrians, etc. People who use alternative fuel vehicles are less concerned about vehicle security probably due to their trust in advanced technologies. Yet, people who use transit and/or walking as their travel modes seem to be more skeptical about AVs than those who do not.

The residential built environment attributes can also significantly explain the degree of concerns. Higher employment density is associated with less perceived risks regarding AVs. Places with a very low transportation index also contribute to the lower level of concerns perceived.

Table 3.5: Proportional Odds Model Results for the Concerns about AVs

	Concerns about AV vehicle security		**Concerns about AV react capability**	
	Coef.	OR	Coef.	OR
Cutoff points				
Not at all | Somewhat not	-2.446	0.087	-2.752	0.064
Somewhat not | Neutral	-1.742	0.175	-2.108	0.121
Neutral | Somewhat	-0.823	0.439	-1.365	0.255
Somewhat | Very	0.44	1.553	-0.129 [a]	0.879 [a]
Time (base: 2015)				
2017	-0.196	0.822	-0.11	0.896
2019	-0.2	0.818	-0.168	0.845
Individual's Socio-demographic Characteristics				
Male	0.157	1.17	0.181	1.198
Age (base: 65+)				
18 – 24	0.694	2.001	0.613	1.846
25 – 34	0.443	1.558	0.349	1.418
35 – 44	0.334	1.396	0.235	1.265
45 – 54	0.168	1.183	-	-
Worker	0.198	1.219	0.192	1.211
Student	-0.144	0.866	-0.181	0.835
Household Characteristics				
Number of adults in the household	-	-	0.162	1.176
Number of vehicles in the household	-0.047	0.954	-0.073	0.93
Household income $100,000 or more (base: under $25,000)	0.163	1.177	-	-
Individual's Travel Characteristics				
Telecommute	-	-	0.148	1.16
Commute	-0.151	0.86	-0.232	0.793
Commute mode (base: drive alone)				
Active mode (bike/walk)	-	-	0.197	1.217
Transit	-	-	0.123	1.131
Carpool	-	-	0.207	1.23
Others	0.17	1.186	0.203	1.225
Use alternative fuel vehicles	0.195	0.195	-	-
Transit as a travel mode	-	-	-0.138	0.871
Bike as a travel mode	0.097	1.102	-	-
Walk as a travel mode	-0.131	0.877	-0.278	0.757
Built Environment for Residence				
Employment density	0.006	1.006	0.004	1.004
Transportation index (base: very low)				
Low	-0.24	0.786	-0.204	0.816
Moderate	-0.185	0.831	-0.193	0.824
High	-0.177	0.838	-0.176	0.839
Very high	-0.226	0.798	-0.165	0.848
Model Goodness-of-fit				
McFadden pseudo R^2		0.010		0.011

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Table 3.5 – continued from previous page

	Concerns about AV vehicle security		**Concerns about AV react capability**	
	Coef.	OR	Coef.	OR
Cox and Snell (ML) pseudo R^2		0.027		0.026
Cragg-Uhler (Nagelkerke) pseudo R^2		0.028		0.029
Likelihood ratio		300.72		295.28
Degree of freedom		21		23
p-value of likelihood ratio test		< 0.001		< 0.001
AIC		31647.06		27235.65
Number of observations		11,175		11,175

Note: Coef. = coefficient; OR = Odds Ratio; AIC = Akaike information criterion. a: $p > 0.05$.

3.6 Discussion and Conclusions

Realistic and accurate evaluations of the potential influences of AVs on transportation systems and the environment can only be achieved based on an adequate understanding of the market penetration and customers preferences of various AV technologies and services. Although an increasing number of research efforts has been made to enhance our knowledge about what population segments could be the early AV passengers, few attempts are made to examine the change of public attitudes towards AVs over time. To close this knowledge gap, this paper investigates the change of people's interest and concerns towards AVs over time at aggregate and individual level using a multiyear cross-sectional Puget Sound Region Travel Study data in 2015, 2017, and 2019. Expansion weights are used to calculate the proportions of population with different levels of interest and concerns of AVs across survey years. The results show that there was a gradual growth of public interest in AVs as well as a rising concern from 2015 to 2019, accompanied by a continuing decrease in the fraction of the population unfamiliar with

AVs. Moreover, the two-part model results suggest that individuals become less likely to state don't know (DK) over time with their socio-demographic characteristics, travel characteristics and built environment being equal. In addition, individuals' interest in AVs have not changed over the years and the increased portion of interest in the population was a result of a declining population not having sufficient knowledge to answer the attitudinal questions about AVs. However, individuals' concerns about AVs have grown over the years after controlling for their variety of characteristics. Together with the decreasing proportion of people who do not express their opinion, they explain the greater percentage of concerns in the population. One policy implication is that public acceptance of AVs does change as a result of greater exposure to more information and knowledge about AVs over time; although negative comments on AVs seem to have bigger impacts in forming public attitudes. Information campaigns or educational programs that introduce the advantages of AV adoption with a focus on the safety aspects of AVs could potentially alter public attitudes, which could probably lead to a larger group of AV users.

The analysis of the various socio-demographic characteristics, travel behavior characteristics, and built environment attributes in this study could also provide useful insights to city planners and policy makers to attain a socially and environmentally desired outcome through policy development. Young well-educated male workers in wealthy households are more likely to be the early adopters of AVs given their stronger interest as well as being less concerned regarding AV technology than other population segments, which is consistent with previous studies using a subset of the data here and different statistical techniques [29, 37]. The policy implication is that the education campaigns, interventions and incentives should aim at target population segments such as elders, people with relatively low education attainment, and low- and mid-income households to change their attitudes and intention to use AVs. In terms of work arrangements, telecommuters tend to have a higher interest level and a lower concern level than non-telecommuters. The difference of tech-savviness between telecommuters and commuters might help explain their contrasting attitudes. Individuals' use of alternative fuel vehicles and public transit also show significant associations with a stronger inclination of adopting AVs, which might reveal their underlying environmental awareness. Transit riders' interest in adopting AV can be a concern of ridership decline, meanwhile, it could also be an opportunity to increase transit ridership by using AV for the first and last mile problem. Short-distance AV pass and price varying by distance range could be strategies to promote AV adoption for the first/last mile problem. People who use on-demand mobility services such as ridesharing and carsharing services show greater propensity to AV carsharing services, although their perceived risks are not found to be significantly less than others. Overall, people with more diverse travel modes tend to embrace the new mobility options enabled by AVs. People living in places of high mobility also tend to be more receptive to the technology. These findings could help in determining the areas for prior AV deployment.

As one of the first few attempts to examine public interests and concerns about AVs over time, this study has its limitations and can be expanded in different ways. Interactions between time dummy variables and other explanatory variables are not considered in this study and can be included in the future work to improve the goodness-of-fit of our model. Another direction is to study the latent psychological constructs that shape people's attitudes towards AVs and how they change over time. For instance, perceived usefulness/benefits is found to be positively associated with public attitudes to AVs [91, 101, 99]. Perceived safety and risk [92, 100, 46, 90], trust in AV performance, government and manufacturers [46, 90], perceived behavior control [91], social influence and subjective norm [92, 101] are also studied widely. The understanding of these latent variables could help validate the effectiveness of educational campaigns and policy interventions before and after they take place for greater AV penetration. Other built environment attributes such as land use mix, street connectivity, and intersection density would also lead to more comprehensive knowledge about the effect of neighborhood environment, contributing to more effective urban design to embrace AVs. For example, Wang and Akar [37] reported that people who live in mixed-use neighborhoods with high traffic signal density perceive less risk of adopting AVs than those who do not. Finally, the COVID-19 pandemic has changed the world in many ways, including how people travel and do activities. It would be of great interest to see how the pandemic has changed public attitudes to the alternative means of transportation facilitated by AVs as some early reports claim for passenger and goods movement [120, 121].

Chapter 4

Attitudes and Travel Behavior Patterns

[1] **Abstract**. The key to Autonomous Vehicles (AVs) successful penetration of markets lies in identifying specific needs that AVs satisfy for daily activity-travel participation of individuals. In this paper we explore whether and to what extent people's exhibited spatiotemporal activity-travel pat-terns correlate with their stated perceptions about self-driving cars. We investigate the travel diaries of 3,411 survey respondents who live in the Pu-get Sound region of the U.S. in 2017 using sequence analysis. In parallel, we apply hierarchical clustering to identify people's attitudes based on their stated interest and perception of risks about AVs. A multinomial regression model is built to examine the correlations between AV attitude clusters and daily activity-travel patterns. Statistically significant correlations are then identified. The model results suggest that people exhibiting different activity-travel behavior patterns also express distinct attitudes towards

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the uses of AVs. The model shows that people who travel to work during the day are more likely to be positive to AVs. In particular, the group traveling to work later than the regular 8-to-5 schedule shows stronger interest and less concerns to AVs, which can be partially explained by the diverse activities they do throughout the day, the variety of travel modes they use and presumably more schedule flexibility they need than the public transportation system offers.

4.1 Introduction

We consider autonomous vehicles to be the highest level of autonomy/robotization, in which the car makes most if not all the moving decisions except selecting origin, destination, and timing of departure of a trip. In the specialist literature, these are called autonomous vehicles, automated vehicles, self-driving cars, driverless cars, and robocars and are all considered synonyms herein and called Autonomous Vehicles (AVs). AVs are considered a potentially disruptive and transformative mode of transportation also when combined with sharing; they reshape the landscape of the current transportation system and mobility services. The development of AVs has rapidly progressed due to a push to the market by technology companies and the automotive industry. The Society of Automotive Engineers (SAE) International [2] defines the 5 levels of autonomy. Automobiles at levels 2 and 3 with self-parking functions and advanced warning systems are already in the market. Although the reality of fully automated vehicles may seem distant, there is an increasing need to understand the impact of AVs on transportation systems and mobility services.

In the growing body of literature, various aspects of AVs are examined (mainly through simulations), including the positive and negative impact of AVs on our lives and environment. The advantages of adopting AVs are numerous, such as increased mobility options for everyone, especially for the disabled, drunk, inattentive, senior, and children to have better access and options to fit their transportation needs [14]; more effective traffic flow and reduced traffic congestion [17]; increased safety and declining traffic accidents and fatality rates [19], improved productivity and gains in pleasure while traveling in a car [122]; more smooth and comfortable and less stressful rides [14]; and lower greenhouse gas (GHGs) emissions [21]. The negative impact lies in the possible consequences resulting from safety, security, privacy, and liability related issues [14, 123].

While many studies have been focused on assessing the impact of AVs, public acceptance of AVs and its determinants have not been fully investigated. Evaluating public acceptance and assessing the type of services desired by markets are critical in the adoption of Autonomous Vehicles (AVs). The key to AV successful penetration of the market is to identify the best market segment for early adoption of the technology. A majority of research examines people's stated preference, acceptance, attitudes, and perceived risk towards AVs using (online) surveys, and correlates them to survey participants' sociodemographic traits such as age, gender, income, and education. Schoettle Sivak [84, 32] show that men are less concerned with adopting this new technology. Young respondents also exhibit less concerns [32] and more interest [86] in using AVs. In addition, people with high income are more interested in owning an AV [36].

Yet, few studies have attempted to examine the relationship between individuals' dispositions towards AVs and their observed daily activity-travel behavior (e.g., using survey participants' daily travel diaries), which could have enabled a better focus of the market niche(s). To fill this knowledge gap, we pose a central research question in this paper:

How do individuals' daily activity-travel patterns relate to their disposition to-wards the use of AVs?

To answer this question, we analyze the 3,411 responses to survey questions about the positive and negative dispositions toward self-driving cars from people living in the Puget Sound region of the United States based on the data from the 2017 Puget Sound Regional Household Travel Survey. We extract travel diary information from the same respondents to derive their daily activity patterns using sequence analysis and hierarchical clustering. We then investigate the association between daily activity-travel patterns and AV dispositions.

4.2 Data

The data used in this study comes from the 2017 Puget Sound Regional Household Travel Survey [114]. The Puget Sound Region in the Northwestern United States is the area that surrounds and includes the City of Seattle. The region encompasses the entire Puget Sound Regional Council (PSRC) four-county region, which includes King, Kitsap, Pierce, and Snohomish counties. The region including 82 cities and towns has a population of approximately four million persons (and approximately 1,548,788 households), with 730,000 in the City of Seattle, and the rest distributed throughout the region in smaller cities. The percent of persons in the labor force approaches 70%, and the median household income exceeds $75,000 per year. The region houses many aerospace and information technology companies, and it is the home of major education institutions. Seattle is also consistently found to be one of the most congested cities in the United States [124]. Therefore, this is an ideal AV market with knowledge and income to afford the most expensive car technology.

The PSRC Household Travel Survey, conducted between April and June 2017, collected information at the household and person levels, including socio-demographic (e.g., gender, age, education, employment), geographic (e.g., place of residence at census tract level) and vehicle ownership (e.g., car ownership and fuel type) information, and travel diaries from every respondent within households. In particular, the travel diaries consist of one-day weekday travel diaries from approximately 80% of participants and entire one-week travel diaries from the remaining 20% of participants. In each travel diary, respondents reported every trip they made, travel party, trip purposes, origin and destination type of places and timings, travel mode(s), trip costs and details associated with each mode, and other trip information.

This survey also contains twelve questions about interest and concerns regarding the use of AVs for participants above 18 years old. There are seven questions on the interest of various AV uses (e.g., use for commuting and short trips) and five questions on concerns of AV related issues like concerns on system safety and legal liability. The data provided by PSRC portal comprises survey results from 6,254 persons in 3,285 households. From these we select persons that answered the AV questions and the one-day diaries. There are 3,411 people who have traveled during 03:00AM on the survey day to 03:00AM on the following day.

4.3 Methodology

Our methodology includes three basic steps:

1. Identify groups of individuals that share similar daily activity-travel patterns by applying sequence analysis.

2. Identify groups of dispositions towards AVs from the questionnaire on the interest and concerns about AV utilizing clustering analysis for discrete data.

3. Investigate the correlations between daily activity-travel patterns and attitudes to-wards AVs using a Multinomial Logit regression model.

4.3.1 Identify Spatiotemporal Daily Activity-Travel Patterns

A sequence is a series of time periods at which a subject can move from one discrete "state" to another. Sequences have been used to describe individuals' activity-travel episodes [125]. They are efficient in capturing many details of the activities and travel, such as the ordering and duration of activities, and the transition from one to another. In this section, we derive daily activity-travel patterns using sequence analysis.

First, we construct individuals' daily activity-travel sequences using the one-day travel diary records from the 3,411 participants. For each record, we use the departure times and arrival times of trips, and the origin and destination trip purposes (can be a place or an activity) to create the sequence. The finest temporal resolution of all trips is 5 minutes. Therefore, we generate a sequence for each person as a series of 288 states for every 5 minutes of the survey day starting at 3:00 AM and ending the next day at 3:00 AM, where each state is an activity, place, or the state of traveling between places. The total eight states used in this study are Home, Work, School, Shopping, Drop off / Pickup (passengers), Travel, Mode Transfer, and Others. Examples of the daily activity-travel sequences are shown in Table 4.1.

To identify daily travel behavior patterns is to group activity-travel sequences that resemble each other. Sequence alignment is a technique developed to make one sequence the same as another. The operations applied to sequence alignment are substitution and indel (insertion, and deletion). Distance (dissimilarity) between two sequences is defined as the cost to align two sequences, i.e., the number of operations performed and sum of penalties accumulated in the alignment. Penalties for different operations can differ. There are usually many combinations of operations to achieve sequence alignment. In this study specifically, Optimal Matching (OM) edit distance is applied to measure the dissimilarity between sequences. It is defined as the minimal cost to transform one sequence to another. The penalty for substitution is derived from the transition rates between two states in the sequences, i.e., the conditional probability to switch from one state to another.

A 3,411-by-3,411 dissimilarity matrix is generated based on OM edit distance, where the cells represent pairwise dissimilarity between two activity-travel sequences in our sample. To identify a small number of groups of sequences that represent similar time-of-day activities and travel patterns in our sample, we use the agglomerative nesting (AGNES) clustering method [126] following McBride et al. [125]. Comparing to other clustering methods, AGNES has a few advantages: 1) the clustering result is stable; unlike AGNES, the cluster and its membership change with initialization in K-means; 2) the clusters are not as sensitive to extreme values as they are in K-means, which creates clusters based on the mean. Starting with the individual sequence, we group them into pairs based on the dissimilarity scores. Then, Ward distance [127] is used to lump together sub-clusters with smaller dissimilarity scores. We proceed until all observations are in one cluster. This process can be thought of as a tree (dendrogram) that starts with every sequence as an individual "leaf" and ends with one cluster as the "trunk." The optimal number of clusters is determined by the "elbow" method of within-cluster sum of squares (i.e., increasing the number of clusters does not improve the within cluster homogeneity much).

While the clusters capture the general daily activity-travel patterns, summary quantitative measures can be used to summarize the complexity of an activity-travel sequence, travel time budget in the daily activities, and within each sequence the variation of trip modes selected by each respondent. We first introduce Shannon Entropy as follows.

$$h(s) = h(\pi_1, \ldots, \pi_a) = -\sum_{i=1}^{a} \pi_i log(\pi_i) \tag{4.1}$$

Where s is a sequence, a is the number of possible states and π_i is the proportion of occurrences of the ith state in the considered sequence. The proportion of minutes allocated to each state over the course of the entire day and the number of distinct states drive the value of Entropy. For this measure, the number of state changes and the contiguity of states do not matter. It simply uses the proportion of total time spent in each state, regardless of the number of different episodes that time is spread over.

Complexity of a sequence is defined in Equation 4.2 [128]. It is a function of Entropy and the number of transitions in a sequence (where $l_d(s)$ is the distinct successive states in a sequence), normalized by the maximum theoretical entropy (h_{max}) and the maximal number of transitions, which is the length of the sequence minus one ($l(s) - 1$).

$$C(s) = \sqrt{\frac{l_d(s) - 1}{l(s) - 1} \frac{h(s)}{h_{max}}} \tag{4.2}$$

Complexity always has a value between 0 and 1, with zero corresponding to Entropy zero and no transitions (e.g., staying at a single place for the entire day of the observation). We use it to handle very long sequences, and it is based on the concept of Entropy and transitions between distinct states. The explanation follows McBride et al. [125, 129] closely. High complexity indicates more states and frequent changes of state. Complexity reaches the maximum of 1 only when a sequence has all possible states and changes its states in every time period. Therefore, people who do different activities will have more complex sequences. The sequence of Person 2 in Table 4.1 has the highest complexity since this person has more activities in terms of diversity and transitions.

Travel Time Ratio (TTR) [130] is an indicator to delineate trade-offs of people between travel and activity time. In this paper, TTR is defined as the total travel time in a day divided by the sum of the total time in activities outside home plus the total travel time in a day. It should be noted the daily patterns we derived here are for the persons that made at least one trip on the day of interview on weekdays. Large TTR sometimes is undesired because it implies that people spend more time travelling and less time on activities. It also suggests that the travel cost of the activities is high.

In travel behavior, it is also important to study the frequency with which a person switches travel means (called mode). One way to measure this switching is to use the Gini index that quantifies the daily variation of mode choices. In Equation 3, t is a sequence of daily trips, n is the total number of modes used, and p_i is the proportion of the ith mode in the considered sequence of mode choice.

$$Gini(t) = 1 - \sum_{i=1}^{n} p_i^2 \tag{4.3}$$

Gini takes values between 0 and 1. It is zero when only one type of mode is used for all the trips. Greater Gini coefficient indicates more types of modes are used in the daily trips. Person 5 in Table 4.1 has a Gini of 0, implying that this person uses only mode to travel throughout the survey day.

The three indicators depict the daily activity-travel behavior from different angles. Thus, they are computed for all 3,411 sequences in our sample. Table 4.1 shows examples of activity-travel sequences, their corresponding Complexity, TTR, and Gini indicators.

4.3.2 Extract Individual's Attitudes on AVs

Twelve questions about AVs were asked in the 2017 PSRC Household Travel Survey, including seven questions on the interest of AV uses and five questions on perceived risks of AV uses. These questions are preceded by a statement on AVs:

"Autonomous cars, also known as 'self-driving' or 'driverless' cars, are capable of responding to the environment and navigating without a driver controlling the vehicle. Advantages of autonomous car usage include the potential for reduced congestion,

Table 4.1: Example Activity-Travel Sequences, Complexity, TTR, and Gini Index

	Activity-Travel Sequence (State, Duration in minutes)	**C(s)**	**TTR**	**Gini**
1	(Home,415)-(Travel,10)-(Other,5)-(Travel,5)-(Shopping,35)-(Travel,10)-(Home,35)-(Travel,25)-(Other,190)-(Travel,20)-(Home,690)	.108	.233	.480
2	(Home,305)-(Travel,10)-(Other,175)-(Travel,10)-(Home,70)-(Travel,15)-(Other,35)-(Travel,20)-(Home,165)-(Travel,5)-(Shopping,10)-(Travel,5)-(Home,15)-(Travel,10)-(School,10)-(Travel,10)-(Home,570)	.142	.270	.375
3	(Home,300)-(Travel,10)-(Dropoff/Pickup,5)-(Travel,10)-(Home,215)-(Travel,25)-(Work,505)-(Travel,20)-(Home,350)	.106	.113	.750
4	(Home,600)-(Travel,30)-(Other,10)-(Travel,20)-(Other,90)-(Travel,15)-(Other,10)-(Travel,25)-(Other,110)-(Travel,35)-(Home,495)	.109	.362	.480
5	(Home,315)-(Travel,15)-(Others,70)-(Travel,10)-(Others,15)-(Travel,5)-(Others,5)-(Travel,5)-(shopping,30)-(Travel,15)-(Home,955)	.090	.294	.000
6	(Home,240)-(Travel,40)-(Dropoff/Pickup,20)-(Travel,75)-(Work,345)-(Travel,75)-(Dropoff/Pickup,5)-(Travel,55)-(Shopping,30)-(Travel,10)-(Home,545)	.138	.390	.480

increases in parking capacity, and faster travel times." [114]

What is your level of interest (AVinterest herein) in the following uses of autonomous cars? (with levels being *very interested*, *somewhat interested*, *neutral*, *somewhat uninterested*, *not at all interested*, and *don't know*)

1. Taking a taxi ride in an autonomous car with no driver present

2. Taking a taxi ride in an autonomous car with a back-up driver present

3. (If commutes) Commuting alone using an autonomous vehicle

4. (If commutes) Commuting with others (carpool) using a shared autonomous vehicle
5. Owning an autonomous car
6. Participating in an autonomous car-share system for daily travel
7. Riding in an autonomous car for a short trip to get to a vehicle (e.g., from airport terminal to parking lot)

How concerned (AVconcern herein) are you about the following potential issues related to autonomous cars? (with levels being *very concerned*, *somewhat concerned*, *neutral*, *somewhat unconcerned*, *not concerned at all*, and *don't know*)

1. Equipment and system safety
2. Legal liability for drivers or owners
3. System and vehicle security
4. Capability to react to the environment (other cars, bicyclists, pedestrians, etc.)
5. Performance in poor weather or other unexpected conditions

The overall survey results for all twelve questions from the 3,411 respondents is shown in Figure 4.1. As can be seen, less than one-fifth participants are very interested in the many uses of AVs. However, the degree varies by type. Riding in an AV for a short trip is the most favorable use among the seven different kinds, followed by commuting alone using an AV. It is possible that interest in using AVs is by people that have a type of schedule in a day for which an AV will serve them better than existing options. As for perception of risks, more than two-thirds of the respondents show concerns. The capability to react to the environment concerns most people.

Before proceeding with the clustering of AV responses, we need to check internal consistency of the AV interest and concerns using Cronbach's alpha and McDonald's omega that account for the strength of association between items [131]. The AVinterest items yield alpha = 0.95 and omega = 0.96 and the AVconcern items yield alpha=0.95 and omega=0.96. The high values of alpha and omega suggest substantial internal consistency and reveal homogeneity, meaning that a person that is positive towards an AV taxi is also positive towards ownership of an AV. However, no strong correlations between AVinterest items and AVconcern items are found, which means the two aspects of responses are close to orthogonal and capture different dimensions of attitudes.

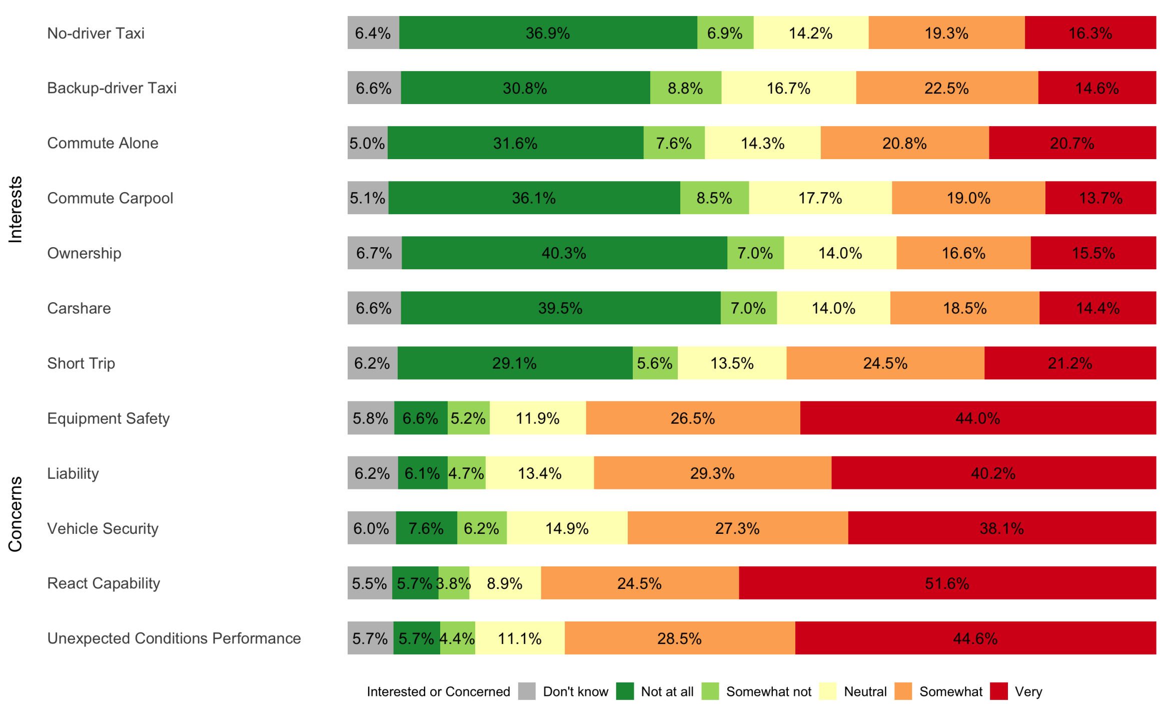

Figure 4.1: The figure shows the twelve AV questions responses results from the 3,411 respondents, except that questions 3 and 4 only apply to commuters, resulting in 2,254 responses for these two questions.

To extract the overall attitudes on AVs, we continue as follows. We first treat an individual's responses as a vector with length of twelve, since the twelve items in the questionnaire were developed as a group to discern people's views about autonomous vehicles from different perspectives, and therefore should be considered jointly. Each of the item responses is treated as a categorical variable that can draw values from the seven categories: *very*, *somewhat*, *neutral*, *somewhat*, *not at all*, *don't know*, and no answers (for the commuting variables not applicable for people that do not commute). Although the item response scale is a Likert-like scale, it includes the "don't know" and "no answer" categories, violating the original Likert design. Therefore, treating the answers as categorical variables with no order could avoid imposition of structure among "don't know" and "no answer". In this way, we also avoid imposing a rank order and making assumptions about the interval between answers. For instance, one person's responses of the twelve question is

not at all interested – somewhat uninterested – no answer – no answer – not at all interested – not at all interested – neutral – somewhat concerned – neutral – some-what concerned – very concerned – somewhat concerned

To group similar responses, we first create a dissimilarity matrix using Gower distance [132], which is designed for data coded as categories or mixed categorical and continuous. Then, we compute the within-cluster sum of squares using different numbers of clusters for AGNES clustering method. The optimal number of clusters is selected based on the "elbow" method of within-cluster sum of squares.

4.3.3 Cluster to Cluster Multinomial Logistic (MNL) Regression Model

We utilize a Multinomial Logistic regression model [133] to study the relationship between the patterns derived from daily activity-travel sequences and the clusters of attitudes to AVs in terms of interest and concerns.

4.4 Results and Findings

4.4.1 Five Spatiotemporal Daily Activity-Travel Patterns

Five clusters are identified in the travel diaries from the 3,411 respondents. Figure 4.2 shows these daily patterns with cluster names based on the daily travel pattern each cluster exhibits. The descriptive statistics of the Complexity, TTR, and Gini indicators for each cluster are shown in Table 4.2.

Figure 4.2: Five daily travel patterns in the 2017 Puget Sound Travel Survey

Run Errands Day Cluster has over one-third (n = 1,301; 38.1%) of the sample falling into this group. People having this daily pattern go out for some activities other than work and spend a substantial amount of time staying at home. The activities also happen relatively evenly across the day. It is notable that some respondents also have school activities for a portion of their day. The cluster has a low average Complexity indicator of 0.0894, showing that people's activity-travel pattern is relatively simple. Noticing that this pattern has the highest mean, median, and maximum TTR, which is consistent with our observation of a simple daily pattern. The maxi-mum TTR of 1 suggests that people in this group also have loop trips (i.e., trips that start and end at home such as going out for a jog or walking a dog).

Typical Work Day Cluster has 986 persons (28.9%) of the sample. This is the typical commuting pattern similar to other analysis for California [129], where people travel in the early morning to work, take a lunch break, return to work in the after-noon, and visit some other locations usually before going back home. High Complexity and low TTR are observed in this group due to the diverse activities through-out the day. The median of Gini being zero implies that more than half of the people in this cluster use only one mode (usually cars) to travel.

Late Work Day Cluster show the daily pattern of 898 (26.3%) people. Compared to people with a typical work day pattern, people in this pattern start working later and also finish later. It is worth noting that people in this group also have more time allocated to other activities than the Typical Work Day people. Another feature that differentiates them is Gini. Not only do they have more activities but also they travel using combinations of more modes. The mean, median and maximum of complexity of this cluster is consistently higher than all other groups, aligned with our inspections of more variation in activities.

Very Late Work Day Cluster is the least populous cluster with only 106 (3.1%) people. These people start work very late and have irregular schedules. Travel ac-counts for a small portion of the daily time use, which is also reflected in the low Complexity and Gini index.

Table 4.2: Descriptive Statistics of Complexity, TTR, and Gini of Each Daily Pattern

	Complexity				
	min	mean	std.	median	max
Run Errands Day	0.015	0.089	0.041	0.084	0.242
Typical Work Day	0.049	0.106	0.032	0.103	0.221
Late Work Day	0.041	0.113	0.035	0.11	0.246
Very Late Work Day	0.031	0.093	0.036	0.08	0.209
Mostly Out of Home Day	0	0.108	0.046	0.108	0.22

	TTR				
	min	mean	std.	median	max
Run Errands Day	0.009	0.391	0.196	0.365	1
Typical Work Day	0.017	0.15	0.075	0.139	0.583
Late Work Day	0.008	0.147	0.074	0.134	0.595
Very Late Work Day	0.004	0.166	0.12	0.15	0.681
Mostly Out of Home Day	0	0.245	0.235	0.165	1

	Gini				
	min	mean	std.	median	max
Run Errands Day	0	0.219	0.249	0	0.8
Typical Work Day	0	0.217	0.251	0	0.75
Late Work Day	0	0.249	0.254	0.278	0.75
Very Late Work Day	0	0.181	0.237	0	0.7
Mostly Out of Home Day	0	0.272	0.268	0.356	0.776

Mostly Out of Home Day Cluster includes people that spend considerable time in their second homes, hotels, camping grounds, and all other places that could not be assigned as the primary home location. Only 120 (3.5%) people belong to this group. Notable is that the mean and median Gini in this group is much higher than all the other four clusters, which is a reflection of traveling by combinations of modes. Overall low TTR suggests that they spend a large portion of their time on activities.

4.4.2 Individual Attitudes and Risk Perceptions on AVs

We extract five different attitude clusters from the answers to the twelve questions about AVs. The clusters are labeled as *Uninterested Concerned*, *Somewhat Interested Concerned*, *Neutral Neutral*, *Interested Unconcerned*, and *Uninterested Unconcerned.* This labeling was done from the visualization of the individual responses from all 3,411 people using a heatmap in Figure 4.3. The plotting order of the responses in the heatmap is not arbitrary but based on clusters; similar responses from the same cluster are plotted together. The responses forming the five aforementioned clusters are plot-ted from bottom to top. The colors (responses) within each cluster look homogeneous for each of the two aspects of the questions, showing that the clusters we identified indeed bring people with similar attitudes together.

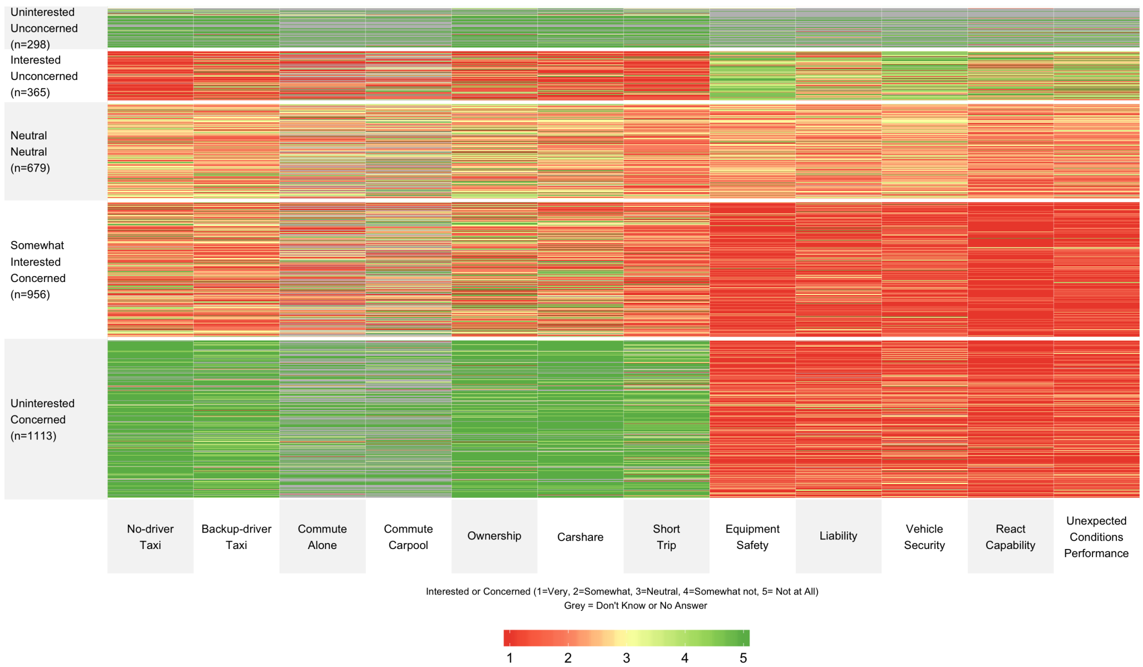

Figure 4.3: Heatmap of people's attitudes towards AVs. Each (very thin) horizontal line in the heatmap represents one respondent' answers to the twelve questions about AVs; each column (in x-axis direction) represents the answer to one of the twelve questions (the first seven columns shows the answers to the AVinterest questions and the last five columns show the AVconcern answers). People' responses (thin line) are plotted by clusters they belong to. The five groups of responses are separated by thick white lines, with the attitudes cluster labels shown on the left.

The clear distinction in clusters divides persons into "positive", "negative", and "uncertain" about autonomous cars for both interest and concerns. Approximately one third (n = 1,113, 32.6%) people show a negative attitude to AVs as they are uninterested and concerned about AVs. Three groups of participants express some interest in AVs with varying degrees as they are the *Somewhat Interested Concerned* (n = 956, 28.0%), the *Neutral Neutral* (n = 679, 19.9%), and the *Interested Unconcerned* (n = 365, 10.7%).

The remaining 8.9% (n = 298) are not interested or concerned.

4.4.3 MNL Modeling Results

The multinomial logit (MNL) regression model used to correlate peoples' AVs disposition includes the five daily patterns as dummy variables (the Run Errands Day cluster is set as the contrast), Complexity, TTR, and Gini index of each individual activity-travel sequence as explanatory variables. Using the *Uninterested Concerned* (the "negative" attitude category) as the reference category makes it easier to recognize variables that are associated with more "positive" attitudes in the results of MNL.

Results of the model are presented in Table 4.3, in which the coefficients take the form of odds ratio for ease of interpretation (all the variables are strongly correlated to the attitudes of AVs at a significant level of 0.05). An odds ratio shows how the change of odds of choosing one category (in the AV attitude variable) over another is associated with the change in the explanatory variable. If an odds ratio is greater than 1, it means the change in the explanatory variable increases the odds of choosing that category over the reference category. Inversely, the odds decrease when an odds ratio is less than 1. For instance, the odds ratio for the Late Work Day in the *Interested Unconcerned* category is 2.788, meaning that if a person exhibits the Late Work Day activity-travel pattern, the odds of this person being interested and unconcerned to AVs increase by 2.788.

With other factors controlled for, it is quite obvious that daily activity-travel patterns play a statistically significant role in people's attitudes to AVs. Compared to the Run Errands Day cluster, all other daily patterns have higher odds ratios of being more positive towards AVs. Specifically, the high odds ratios in the Typical Work Day and Late Work Day patterns are observed in the "positive" attitude categories (compared to the reference category *Uninterested Concerned*), i.e. the *Neutral Neutral* and *Interested*

Unconcerned. Both these groups exhibit a high Complexity index, indicating that people in these groups have more variety in their daily activities. Hence, the positive AV inclination is a reflection of people's strong demand for travel based on the high number of activities throughout their day. In particular, the odds ratios in the Late Work Day cluster is consistently the highest in all three "positive" categories. This is also explained by the high Gini index in this group, that is to say, they have more variation in their mode choices (not just cars) compared to, for example, the Typical Work Day cluster. Possibly the Late Work Day people are actively looking for alternatives to travel other than cars or public transit to avoid congestion and/or to complement the less frequent public transportation services after the regular peak periods.

It is also interesting to see that the odds ratio for people in the Very Late Work Day cluster is the highest as of 2.393 in the *Uninterested Unconcerned* category. Their low activity frequency (reflected in the low Complexity and Gini) and thus low demand for travelling might be a strong contributor to this attitude.

We note that the odds ratio for the Mostly Out of Home Day people in being very positive (*Interested Unconcerned* category) is specially high, which could partially be explained by their high Gini (the diversity in travel modes used for their daily activities and travel).

In summary, using daily activity-travel patterns to explain the negative or positive predispositions towards AVs helps us identify at least two market segments that will be the early adopters of AV technology. People with late work schedules are most likely to favor AVs. People in the Mostly Out of Home Day group is the second market segment. Measures such as Complexity and Gini capture the individual variation within each daily group. The key in all this is that AVs are preferred by people who have complex schedules and who use different modes to travel.

Table 4.3: Multinomial Logistic Regression of AV Attitudes and Daily Activity-Travel Patterns

	Dependent Variables (Reference: Uninterested Concerned)			
	Somewhat Interested Concerned	**Neutral Neutral**	**Interested Unconcerned**	**Uninterested Unconcerned**
Intercept	0.622 t = -3.366***	0.459 t = -4.837***	0.182 t = -8.173***	0.211 t = -7.596***
Typical Work Day	1.158 t = 1.110	1.425 t = 2.422**	1.552 t = 2.295**	1.409 t = 1.779*
Late Work Day	1.814 t = 4.325***	1.865 t = 4.058***	2.788 t = 5.345***	1.198 t = 0.830
Very Late Work Day	1.156 t = 0.530	0.782 t = -0.713	1.685 t = 1.423	2.374 t = 2.664***
Mostly Out of Home Day	1.572 t = 1.798*	1.405 t = 1.178	2.645 t = 3.085***	0.81 t = -0.459
Complexity $\geq$ 75% Quantile	0.801 t = -1.957*	0.966 t = -0.280	0.881 t = -0.842	0.647 t = -2.353**
TTR	0.836 t = -0.579	0.531 t = -1.727*	0.781 t = -0.540	2.015 t = 1.643
Gini	2.601 t = 4.926***	2.223 t = 3.715***	2.613 t = 3.631***	0.839 t = -0.596
Akaike Inf. Crit.	10,103.32	10,103.32	10,103.32	10,103.32

Note: *p<0.1; **p<0.05; ***p<0.01.
The coefficients are transformed to odds ratio for easy interpretation.

4.5 Conclusion

In this study we analyze the 2017 PSRC Household Travel Survey data to study the association between people's daily activity-travel patterns and their attitudes to the use of AVs. Particularly, we identify five distinct daily activity-travel patterns using the travel diaries of 3,411 survey participants; they are the Typical Work Day, Late Work Day, Very Late Work Day, Run Errands Day, and Mostly Out of Home Day patterns. Daily activity-travel summary measures including Complexity, TTR, and Gini are also computed to characterize the individual's activity-travel sequence. We also extract five clusters of people who hold different attitudes to AVs, i.e., *Uninterested Concerned*, *Somewhat Interested Concerned*, *Neutral Neutral*, *Interested Unconcerned*, and *Uninterested Unconcerned*. A multinomial logistic regression model is built to examine the correlation between people's daily activity-travel patterns and their attitudes towards AVs. We find systematic differences in the positive and negative attitudes towards AVs that depend on the timing of travel decisions in a day and the variety of modes used. This means a more detailed pin-pointing of possible barriers people face in their daily scheduling choices will help AV develop solutions for niche markets.

Our study is the first of its kind in correlating daily patterns to AV positive and negative predispositions. In the next steps we plan to analyze the compositions of each cluster (daily patterns and AV interest/concerns) in terms of the social and demographic characteristics of respondents. We also plan to do this over time using repeated cross-sectional data from this region. One of the limitations in this analysis is also lack of correlating AV predispositions and use of other technologies by the respondents (e.g., ownership of electric cars or advanced computational technologies at home and work). In addition, car ownership and use decisions are often at the household level via within household negotiations and task allocation. Studying the AV disposition correlation within households is also left as a future task.

Chapter 5

Conclusions and Future Work

This last chapter concludes the dissertation. First, summary and key findings of this dissertation are highlighted. Then, the contributions of this study to theories, methodologies and practical applications are presented. Lastly, the limitations of the research are discussed and directions for future work are proposed.

5.1 Summary and Discussion

AVs hold the promise to profoundly alter the way people move around by providing a safer, faster, greener, more accessible and comfortable means of transportation. Yet, the benefits of AVs could also result in undesired consequences like urban sprawl. Before AVs actually take off, how the technology will change transportation networks and urban form is far from certainty. Therefore, it is very important to identify AV adopters and their travel behavior and activity time allocation patterns, in order to make more realistic and accurate evaluations of AV impacts on transportation systems and implications for urban planning. This will also help achieve better AV deployment and more informed decision-making and policy development in transportation and city designs.

Specifically, by leveraging the power of structural equation modeling, Chapter 2 shows that perceived usefulness is an important latent determinant of the intentions to use AVs and background factors such as demographics affect behavior intention both directly and indirectly through the mediator perceived usefulness. For example, less wealthy households exhibit lower intention to buy AVs than well off ones, even with the same level of perceived usefulness. Reducing financial barriers for low- and mid- income households through tax incentives, rebates and loan financing programs to make AVs more affordable could promote the possession of AVs to mimic similar strategies for EVs as a potential behavior-change intervention.

Using a multiyear cross-sectional travel survey, Chapter 3 reveals that public acceptance of AVs does change as a result of greater exposure to more information and knowledge about AVs over time. In particular, the population unfamiliar with AVs has declined over the years. Controlling for their socio-demographic characteristics, travel behavior characteristics, and built environment attributes, individuals' interest in AVs has not changed over time while their concerns have increased across time. Young well-educated male workers in wealthy households are the potential early adopters of AVs given their strong interest in AVs and less concerns.

Chapter 4 explores the relationship between individuals' spatiotemporal activity-travel patterns and their stated propensity to AVs. Using sequence analysis and clustering techniques, five distinct daily activity-travel patterns are identified. The statistical modeling results suggest that people exhibiting different activity-travel behavior patterns also express distinct attitudes towards the uses of AV: people who travel to work during the day are more likely to be positive to AVs; those who have various activities throughout the day and those who use diverse travel modes also perceive higher utility of AVs.

In sum, this dissertation advances our understanding of the niche market of AVs and its evolution over time and how the population will use AVs for their activity time allocation. The findings help create informed models for the adoption and market uptake of AVs. The discoveries also lay the foundation for AV impact assessment.

5.2 Research Contributions

The theoretical and practical contributions made by this dissertation are as follows.

Link the latent constructs with observable variables in behavior theories for AV adoption. The proposed conceptual model in Chapter 2 can help pinpoint how background factors like socioeconomic status affect behavioral intention via its antecedent cognitive construct more accurately in the mental process of intention formation. The findings extend our knowledge about AV user profile: young well-educated male workers in wealthy households are the potential early adopters. Persons with positive predispositions towards new technology and especially sustainable energy production (photovoltaic at home electricity) and electric cars are also the potential AV users. The practical discoveries can assist policymakers in making more efficient interventions to change people's attitudes towards AVs.

Enhance understanding of public attitudes evolution. The study in Chapter 3 uses a multiyear travel survey to examine the attitude adaptation across time when more information about AVs becomes available to the public. The discoveries can help predict AV market share under different scenarios and time frames. In addition, separating "don't know" responses from Likert-scale responses can be used to infer information exposure and knowledge trend, rather than discarding it as missing data.

Identify correlation between individuals' spatiotemporal activity-travel patterns and intention to adopt AV. Chapter 4 shows that people with certain activity-travel patterns have a stronger preference for AVs than others. The diversities in activity types and travel modes also correlate with the uses of AV. In terms of methodology, the pattern recognition combination of sequence analysis and latent cluster with MNL regression is the first analysis of this type in the literature and shows it has a great potential for other types of behavioral analysis. Using travel behavior pattern recognition also captures the spatial heterogeneity of accessibility to transport services and activity opportunities indirectly when detailed spatial descriptors are not available. In practice, it helps uncover the possible barriers people face in their daily scheduling choices and will help AV develop solutions for niche markets.

Lay the foundation for evaluating the impacts of AVs on transportation system and the environment. Although AVs are not available in the market for adoption, simulation provides us with an indispensable way to evaluate the implication of AVs in transportation systems, mobility services, and urban planning. Understanding by whom, when, and how AVs are used can help simulate the adoption behavior of synthetic population in the transportation network, for example, the percentage of total vehicles miles traveled (VMT) by AVs in the road network. Moreover, simulations of various AV adoption scenarios can assist policy makers and city planners in making more informed decisions to better AV deployment, attaining a socially and environmentally desired outcome.

5.3 Limitations and Future Work

Limitations of this research and possible research directions are provided below.

Validity of the attitudinal variables. The entire dissertation is based on stated responses under hypothetical situations in questionnaires to proxy people's attitudes about AVs. However, behavior intentions can be very different from actual behavior. Retrieving recent rideshare AV user data from companies like Waymo can help alleviate the problem, if data are made publicly available. Ideally, one could develop a naturalistic study in which households are provided with AVs replacing current household fleet vehicles and observe differences in use of vehicles before and after provisions of an AV.

Limited measures for the latent variables related to behavioral intention. Due to the lack of related survey questions, many latent constructs cannot be measured and integrated in our proposed model. Conducting a survey and creating a well-designed questionnaire to measure these psychometric concepts such as perceived behavioral control, perceived safety and risk, and subjective norm can deepen our understanding of behavioral intentions.

Household interaction. Vehicle ownership and use decisions are often at the household level via within household negotiations and task allocation. This dissertation focuses on AV adoption at individual level. Studying the AV disposition correlation within households can be extended as a future task.

Transportation and environmental implication This research identifies the potential AV adopters and their activity-travel patterns. By applying the model to the synthetic population and their travel demand, the impacts of AVs on transportation system can be quantified using metrics including percentage of VMT by AVs, percentage of vehicle replaced by AVs in terms of body type and fuel type and so on. Assuming AVs to be fully electric, the implication of AVs on the environment can also be estimated. For example, if an ICE vehicle is replaced by an AV, based on its body type, vintage, and annual mileage, the GHGs emissions reduced can be computed. Aggregating to population level, the total emission reduction can be calculated for the environment.

Lack of evaluation mechanism. There are still many oversimplified assumptions about how AV are used at different system levels, from vehicle level, transportation system level, to urban system and society level [80], and how the impacts are correlated among these these levels. Before AV's entry to the market, the actual impacts of AV cannot be observed. It is therefore very difficult to evaluate and compare the results that come out of different studies. Future research should strive for a more comprehensive and systematic approach to evaluate the implications of AV adoption.

Other aspects that affect the adoption of AVs. The advancement of technology and positive disposition does not guarantee the extensive use and adoption of AV. Privacy and liability issues, heterogeneous valuation of time, cost of operating an AV, and motion sickness are all important factors affecting the experience and long term use of AVs. The aforementioned naturalistic studies or provision of data collected by technology testing under way in the real world (e.g., autonomous vehicles deployment program [1]) can also help analyze these aspects.

[1]https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-deployment-program/

Appendix A

A.1 Supplementary Data

Table A.1 and A.2 present the descriptive statistics of the CVS 2019 data at person- and vehicle-level.

Table A.1: Person- (16+ years old) Descriptive Statistics (N=8,365)

Variable	**Category**	**Sample**	**Percent**
Gender	Male	4,002	47.84
	Female	4,268	51.02
	Others	12	0.14
	Prefer not to answer	83	0.99
Race	American Indian and Alaska Native	60	0.72
	Asian	1,339	16.01
	Black or African American	267	3.19
	Native Hawaiian and Other Pacific Islander	44	0.53
	White	5,331	63.73
	Two or more races	269	3.22
	Other specified	358	4.28
	Prefer not to answer	697	8.33
Hispanic or Latino		959	11.46
Bachelor's and above		4,743	56.7
Employed		4,927	58.9
Student		683	8.16
Licensed Driver		7,828	93.58
Drive Frequency	Frequently	5,642	67.45
	Sometimes	1,701	20.33
	Rarely	341	4.08
	Never	681	8.14
Transit rider		1,208	14.44
TNC user		1,162	13.89

Table A.2: Vehicle-level Descriptive Statistics (N=8,049)

Variable	Category	Sample	Percent
Year	1980-1989	258	3.21
	1990-1999	487	6.05
	2000-2009	2,506	31.13
	2010-2019	4,798	59.61
Fuel type	Gasoline	6,338	78.74
	Hybrid (gasoline)	587	7.29
	PHEV	220	2.73
	Diesel	118	1.47
	Full electric vehicle	333	4.14
	Hydrogen vehicle (FCEV)	306	3.8
	Ethanol flex fuel vehicle (E85 FFV)	140	1.74
	Natural gas vehicle	7	0.09
Vehicle type	Large vehicle	971	12.06
	Midsize vehicle	1,654	20.55
	Small vehicle	5,424	67.39
TNC vehicle		109	1.35
Delivery vehicle		92	1.14
Annual mileage		8,000 (4,025, 12,000) [1]	
Miles-per-gallon (MPG)		25 (20,30) [1]	

Note: 1 = Median (IQR).

Table A.3 presents the built environment attributes at the county level.

Table A.3: Built Environment Attributes at County-level

County	Public Transit Rider Percentage (%)	Telecommuter Percentage (%)	Average Commute Time (min.)	Employment Rate (%)
Alameda	16.88	6.45	34.33	63.94
Alpine	0.77	21.52	18.13	40.21
Amador	0.12	9.37	32.68	41.03
Butte	1.26	5.63	20.90	51.78
Calaveras	1.08	9.77	38.29	44.40
Colusa	0.15	4.19	25.69	59.63
Contra Costa	11.62	6.63	38.69	61.33
Del Norte	0.39	4.13	14.47	40.70
El Dorado	1.59	9.48	29.96	54.72
Fresno	1.17	4.55	23.08	55.61
Glenn	0.17	5.37	22.17	52.69
Humboldt	1.93	7.16	18.67	55.17
Imperial	0.98	4.56	22.10	44.73
Inyo	0.76	3.81	16.49	55.85
Kern	0.85	3.39	23.29	52.32
Kings	0.24	4.65	22.79	47.81
Lake	0.82	14.24	30.68	46.43
Lassen	0.33	6.34	20.63	32.31
Los Angeles	6.16	5.58	31.84	60.68
Madera	0.50	3.65	28.34	49.56
Marin	11.00	12.43	32.60	61.31
Mariposa	2.24	10.05	26.58	47.52
Mendocino	0.33	9.19	20.75	53.17
Merced	1.21	3.53	28.64	52.56
Modoc	0.00	13.76	16.14	40.15
Mono	22.58	5.56	15.08	69.55
Monterey	1.66	4.64	23.43	56.56
Napa	1.84	5.89	25.62	62.23
Nevada	0.41	13.64	25.48	52.22
Orange	2.07	6.38	28.04	62.48
Placer	1.20	9.93	27.85	57.59
Plumas	0.95	5.78	19.77	48.38
Riverside	1.32	5.36	33.97	55.21
Sacramento	2.64	6.28	27.80	58.62
San Benito	0.64	3.16	35.74	63.10
San Bernardino	1.46	5.15	31.59	55.67
San Diego	3.17	6.98	26.47	59.46
San Francisco	37.22	6.60	33.84	68.07
San Joaquin	1.74	4.10	34.23	55.65
San Luis Obispo	1.45	7.40	21.73	55.39

(Continued on next page)

Table A.3 – continued from previous page

County	Public Transit Rider Percentage (%)	Telecommuter Percentage (%)	Average Commute Time (min.)	Employment Rate (%)
San Mateo	11.63	5.28	29.28	66.26
Santa Barbara	3.20	6.26	20.47	59.87
Santa Clara	4.68	5.03	29.32	64.61
Santa Cruz	3.26	7.82	27.73	60.10
Shasta	0.62	5.89	20.52	51.20
Sierra	0.41	18.24	30.55	48.98
Siskiyou	0.26	9.56	18.37	46.30
Solano	3.34	4.50	33.18	58.48
Sonoma	1.96	7.42	25.56	62.11
Stanislaus	0.88	4.75	29.95	55.40
Sutter	0.78	4.70	27.50	52.93
Tehama	0.29	4.79	23.38	48.76
Trinity	1.62	17.38	21.56	41.31
Tulare	0.71	3.66	22.61	53.39
Tuolumne	0.59	5.93	26.94	45.66
Ventura	1.19	6.00	27.20	61.72
Yolo	4.45	5.98	23.97	56.38
Yuba	0.99	4.96	30.02	52.08

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