12-2022

A Study of Readiness for Transportation Electrification and Automation Focusing on Safety and Future Adoption

Steve Lee
The University of Tennessee, Knoxville, dlee99@vols.utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Steve Lee entitled "A Study of Readiness for Transportation Electrification and Automation Focusing on Safety and Future Adoption." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Asad J. Khattak, Major Professor

We have read this dissertation and recommend its acceptance:

Christopher R. Cherry, Jerry D. Everett, Haileab Hilafu

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

A Study of Readiness for Transportation Electrification and Automation Focusing on Safety and Future Adoption

A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Steve Lee

December 2022

Acknowledgments

Thank God for always being with me and loving me.

I deeply appreciate my academic advisor, Dr. Asad Khattak for his wonderful guidance throughout my PhD course. I also appreciate my PhD committee, Dr. Chris Cherry, Dr. Jerry Everett, and Dr. Haileab Hilafu for their insightful feedback on my research. Thank you to my colleagues who have worked together at Room 311.

I appreciate my parents and younger brother, Craig, for always being on my side. Thank you to my relatives and friends in the United States, Canada, and South Korea. Thank you to my grandpa and grandma in Heaven for raising me with love.

Abstract

Transportation electrification and automation are growing societal trends and considered promising pathways to enhance the safety, mobility, efficiency, and sustainability of the surface transportation system. At this early stage of transportation electrification and automation, one of the most critical issues is whether and to what extent people are willing to adopt electric vehicle (EV) and automated vehicle (AV) technologies in the future. Another critical issue, especially concerning transportation automation, is how to thoroughly ensure the safety of automated driving performance to resolve safety concerns about AVs, which is one of the key challenges to AV adoption. In this regard, the dissertation aims to provide new knowledge and deep insights regarding the readiness for transportation electrification and automation in terms of safety and future adoption by investigating how different types of travelers are willing to embrace EV and AV technologies and what safety-related challenges the automated driving systems are facing. First, the dissertation systematically analyzes how individuals become inclined to use AV-based travel options and adopt alternative fuel vehicles (AFVs). For this, an “AV inclination index” is developed to quantify individual travelers’ inclination toward AV-based travel options encompassing owning an AV, using AV ride-hailing services, and using Shared AV (SAV) ride-hailing services. Importantly, the dissertation reveals a meaningful relationship between the “AV inclination index” and AFV adoption. Considering that the commercial sector has the potential to adopt a considerable amount of EVs in the future, the dissertation explores commercial light-duty fleet owners’ intention to adopt different types of EVs. Paying attention to early adopters’ experiences and perspectives, the dissertation investigates BEV owners’ satisfaction and willingness to repurchase a BEV in the future. Given that the safety of AVs is one of the critical factors associated with individual travelers’ willingness to use AVs in the future, the dissertation performs an exhaustive analysis of crashes involving AVs tested on public roads to provide a better understanding of AV safety performance. Based on the findings from each chapter, the dissertation provides the vehicle and transportation industries, engineers, planners, and policymakers with practical implications for a smooth transition to transportation electrification and automation.

Keywords:
Electric Vehicle Adoption, Automated Vehicle Adoption, Automated Vehicle Safety Assessment

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

The surface transportation system has created a variety of issues including traffic congestion, crashes, emissions, and energy issues, most of which directly compromise the quality of life (*1-3*). In this context, transportation electrification and automation are growing societal trends and considered promising pathways to improve the safety, efficiency, mobility, and sustainability of the surface transportation system. Alternative Fuel Vehicles (AFVs) such as Electric Vehicles (EVs) and Fuel Cell Vehicles (FCVs) are expected to help improve fuel economy and reduce emissions depending on the type of refueling and charging (*3-5*). Automated Vehicles (AVs) are expected to help enhance traffic safety by removing human errors, while connections among AVs are expected to help improve traffic flow (*6-7*). Moreover, AVs will provide people with disabilities and the elderly with additional travel options, which is expected to improve mobility and equity (*6*).

Currently, EVs are in the early stage of diffusion (*3-8-9*). Meanwhile, low-level automation technologies (Levels 1 and 2) such as lane-keeping assistance and adaptive cruise control are commercially available for vehicles, while high-level technologies are in development and assessment for conditional, high and full automation (Levels 3-5) (*6*). At this early stage of transportation electrification and automation, one of the most critical issues is whether and to what extent people are willing to adopt EV and AV technologies in the future. The surface transportation system would be required to have appropriate traffic operation and transportation planning strategies depending on the penetration rate of EVs and AVs on the road as well as the needs of EV and AV users. Another critical issue especially concerning transportation automation is how to thoroughly ensure the safety of automated driving performance to resolve safety concerns about AVs, which has been identified to be one of the key challenges to adoption of high-level (Levels 4-5) AVs in the future (*10-13*). Based on previous studies, the consumer adoption rate of high-level AVs will be highly dependent on whether uncertainties in AV safety performance can be sufficiently resolved, which requires a clear understanding of AV safety performance (*10-13*). According to a recent study with a nation-wide survey in the United States, for example, 40 percent of people have a negative perception of the safety of high-level AVs, which is expected to limit the market penetration of high-level AVs to 15 percent in the long run if this issue remains on the same level (*13*).

In this regard, the dissertation aims to provide new knowledge and deep insights regarding the readiness for transportation electrification and automation in terms of safety and future adoption by investigating how different types of travelers are going to embrace EV and AV technologies in the future and what specific safety-related challenges the automated driving systems are facing. To be specific, **Chapter 2** attempts to systematically analyze how individuals become inclined to use AV-based travel options as well as adopt AFVs including EVs. For this, an "AV inclination index" is developed to quantify individual inclination toward AV-based travel options encompassing owning an AV, using AV ride-hailing services, and using Shared AV (SAV) ride-hailing services. Importantly, this chapter examines the relationship between the "AV inclination index" and AFV adoption. Considering that the commercial sector has the potential to adopt a considerable amount of EVs in the future, **Chapter 3** explores whether and to what extent commercial light-duty fleet owners are willing to adopt different types of EVs such as Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles (BEVs), and Fuel Cell Electric Vehicles (FCEVs). Paying attention to early adopters' experiences and perspectives, **Chapter 4** investigates the satisfaction of BEV owners and their willingness to repurchase a BEV in the future. Given the findings from the literature that the perception of AV safety is one of the key factors associated with individual willingness to use AVs in the future, **Chapter 5** aims to provide a better understanding of AV safety performance (*10-13*). This chapter attempts to exhaustively analyze recent crashes involving Level 2 and Level 3 AVs to figure out the interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes.

The key **research questions** in the dissertation are as follows.

- How inclined are AFV owners to use AV-based travel options?
- What makes commercial light-duty fleet owners willing or unwilling to adopt different types of EVs (i.e., PHEVs, BEVs, and FCEVs) in the future?
- What makes current BEV owners satisfied and willing to repurchase a BEV in the future?
- What do AVs tell us about their safety performance when they fail on the road?

The key **contributions (intellectual merits)** of the dissertation are as follows.

- Develop an index to quantify individual inclination toward AV-based travel options.
- Systematically identify the relationship between AFV adoption and inclination toward AV-based travel options.
- Provide deep insights into barriers to and opportunities for EV diffusion from the commercial sector's and individual BEV owners' perspectives.
- Help better understand AV safety performance through an exhaustive analysis of recent crashes involving Levels 2-3 AVs.

The key **impacts** of the dissertation are as follows.

- The dissertation will help keep the surface transportation system prepared with appropriate plans and strategies by considering how individual residents will embrace vehicle electrification and automation.
- By referring to the findings from the dissertation, the EV industry, planners, and policymakers could figure out specific barriers for the commercial sector to adopt different types of EVs such as the hauling capacity of PHEVs, the range of BEVs, and the cost of installing fueling equipment for FCEVs. They can be encouraged to make an effort to lower the specific barriers.
- The dissertation will provide the BEV industry, planners, engineers, and policymakers with useful feedback from early adopters of BEVs on the opportunities for BEV diffusion. By referring to the findings, especially, they can make an effort for synergetic connections with low-level vehicle automation and the provision of real-time information to support early adopters.
- The findings from the AV crash investigation can be a reference for the safety assessment of Levels 4-5 AVs as well as for future operations of mixed traffic. Notably, the key factors identified in the dissertation can be included in the development of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication technologies.

Figure 1.1 and **Figure 1.2** visualize the overall conceptual framework and a summary of the dissertation, respectively. The main goal of the dissertation is to provide new knowledge and deep insights regarding the readiness for transportation electrification and automation in terms of safety and future adoption by investigating how different types of travelers are going to embrace EV and AV technologies in the future and what safety-related challenges the automated vehicles are facing. From individual residents' perspectives, **Chapter 2** explores how AFV and AV adoptions can be affected by the experience in shared mobility as well as how AV adoptions can be affected by the experience in AFVs. By scrutinizing a stated preference (SP) survey within a path-analytic framework with rigorous statistical modeling analysis, this chapter reveals that individual inclination toward AV-based travel options has a positive relationship with the experience in AFVs and shared ride-hailing services. From commercial light-duty fleet owners' perspectives, **Chapter 3** investigates the key barriers to and opportunities for the diffusion of different types of EVs. By analyzing a stated preference (SP) survey with rigorous statistical modeling analysis, this chapter identifies the limited hauling capacity of PHEVs, the limited range of BEVs, and the cost of installing fueling equipment for FCEVs as the key barriers, while identifying collaboration with the healthcare and social assistance, transportation and warehousing, and professional, scientific, and technical services industries as the key opportunities for EV diffusion. From early adopters' perspectives, **Chapter 4** explores what makes BEV owners satisfied and willing to repurchase a BEV in the future. By inspecting a stated preference (SP) survey within a path-analytic framework with rigorous statistical modeling analysis, this chapter reveals that BEV re-adoptions can be significantly supported by low-level vehicle automation features and providing real-time information for BEV users. From automated vehicles' perspectives, **Chapter 5** investigates the specific safety-related challenges AVs are facing. By analyzing a comprehensive dataset from multiple types of data sources within a path-analytic framework with rigorous statistical modeling analysis, this chapter reveals edge cases for AVs tested on actual roads, including roadway, vehicle, and human-related factors.

Chapter 2. How Inclined Are Alternative Fuel Vehicles to Use Automated Vehicle-Based Travel Options?

At the early stage of vehicle electrification and automation, one of the most critical issues is whether and to what extent individuals are willing to embrace them. Especially, this chapter aims to explore how inclined Alternative Fuel Vehicle (AFV) owners are to use high-level AV-based travel options (Levels 4-5), including owning an AV and using AV and Shared AV (SAV) ride-hailing services. Using a path-analytic framework with data from a survey of adult residents in California (N=4,248), this chapter explores the relationship between AFV adoption and inclination toward AV-based travel options and how they are associated with other relevant factors. Importantly, this chapter develops an "AV inclination index" to quantify individual travelers' inclination toward AV-based travel options. By providing comprehensive insights into how individuals will embrace vehicle electrification and automation, this chapter supports the movement toward improving surface transportation systems with appropriate strategies.

- To be presented at the Transportation Research Board 102nd Annual Meeting

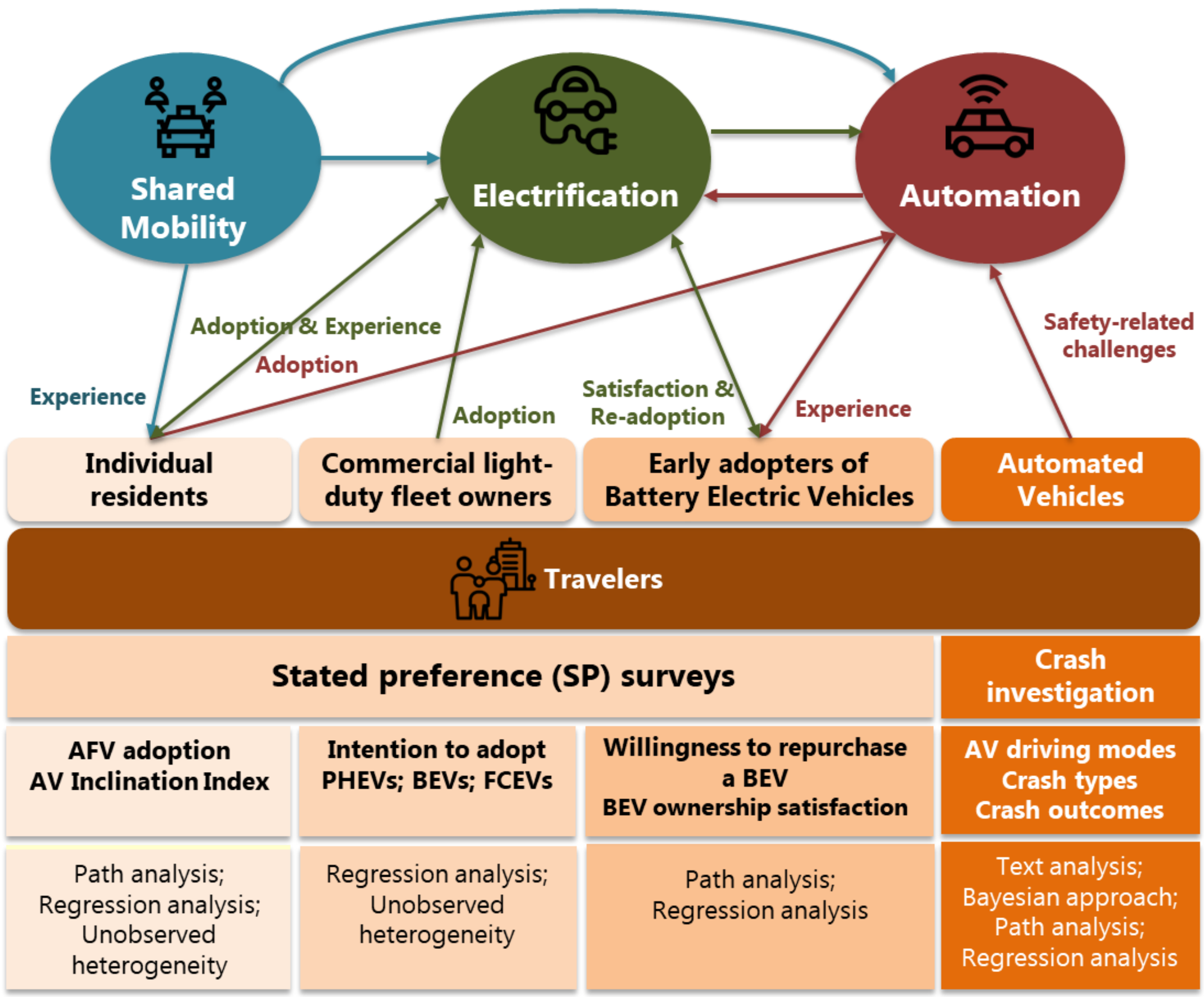


Figure 1.1 The Overall Conceptual Framework

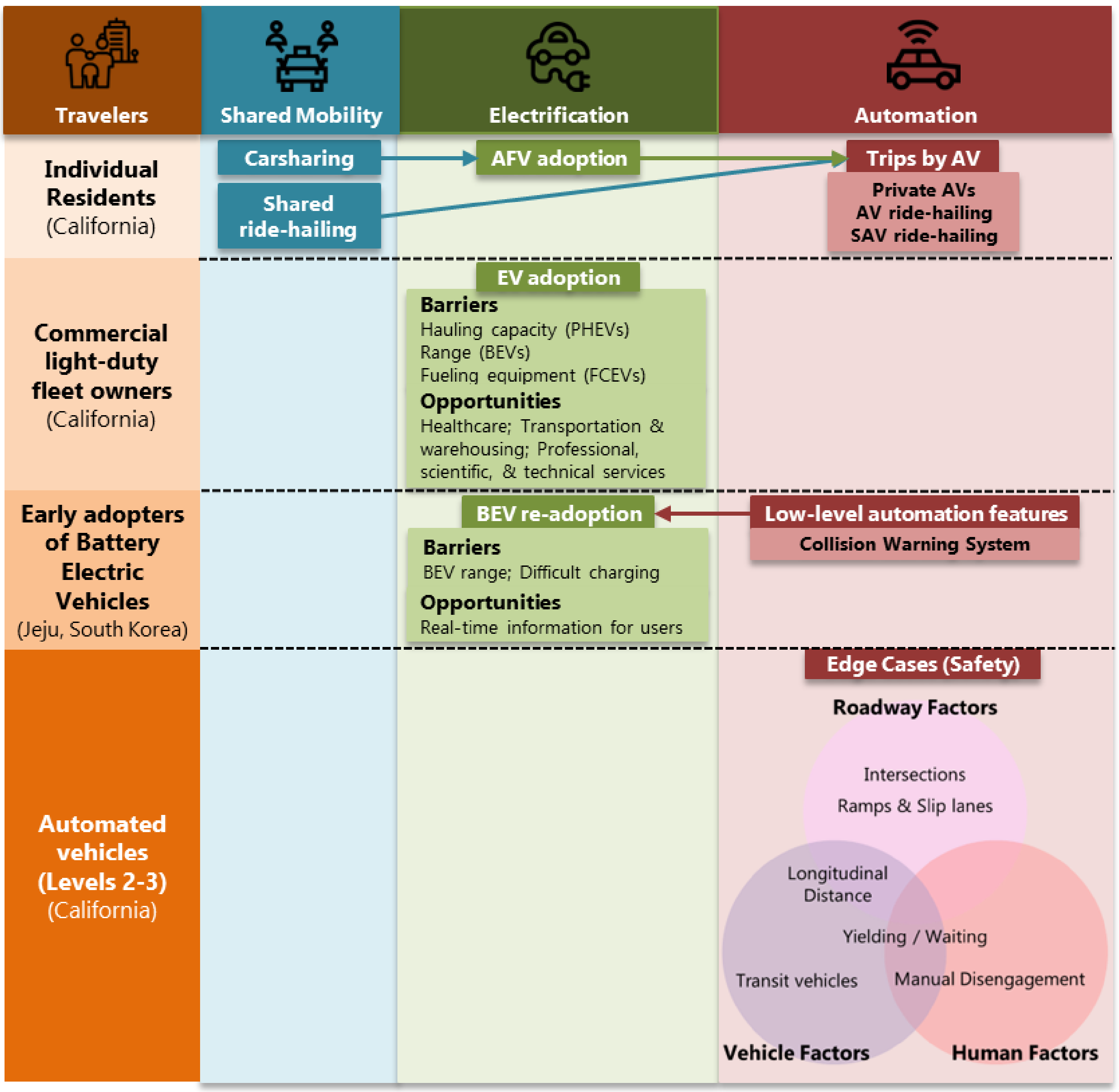


Figure 1.2 A Summary of Dissertation

Chapter 3. Adoption of Different Types of Electric Vehicles: Are Commercial Light-Duty Fleet Owners Interested?

Focusing on commercial light-duty vehicles, this chapter explores whether and to what extent the commercial sector is interested in different types of EVs, such as Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles (BEVs), and Fuel Cell Electric Vehicles (FCEVs). This chapter harnesses data from the 2019 California Vehicle Survey (N=2,301), which surveyed a wide range of commercial light-duty fleet owners. After descriptive analysis, rigorous statistical regression models are estimated to explain the relationships between the intention of EV adoption and company characteristics as well as specific concerns about EVs, while addressing unobserved heterogeneity. The findings from this chapter will provide transportation planners, policymakers, and the EV industry with valuable insights into critical challenges to vehicle electrification from the commercial sector's perspectives.

- Presented at the Transportation Research Board 101st Annual Meeting (*14*)
- Submitted to the International Journal of Sustainable Transportation

Chapter 4. How Many Battery Electric Vehicle Owners Will Repurchase a Similar Vehicle?

Will current Battery Electric Vehicle (BEV) owners repurchase such vehicles in the future? This chapter sheds light on this question by harnessing data from a carefully designed survey of BEV owners in Jeju, South Korea (N=1,094), implemented in December 2018. The survey has valuable information about user contexts and perceptions of BEVs from their BEV use. Based on the vehicle models reported in the survey, vehicle features are estimated to extract objective information that helps better explain EV ownership satisfaction and willingness to repurchase a BEV in the future. A rigorous path-analytic framework is developed to quantify the direct and indirect impacts of key factors on willingness to repurchase a BEV in the future, while exploring potential unobserved heterogeneity. This in-depth case study provides meaningful insights into what aspects of vehicle electrification should be improved from the BEV owners' perspectives, while helping planners, engineers, and policymakers in the transportation field make informed decisions about EV infrastructure.

- Presented at the Transportation Research Board 101st Annual Meeting (*15*)
- Submitted to the International Journal of Sustainable Transportation

Chapter 5. Advancing Investigation of Automated Vehicle Crashes Using Text Analytics of Narratives and Bayesian Analysis

This chapter investigates AV safety performance conducting a thorough analysis of recent AV crash data. Based on 148 AV collision reports from California in 2019 and 2020, this chapter extracts key variables from crash records, crash locations, and, importantly, a text analysis of crash narratives reported by AV manufacturers. Using a path-analytic framework with the frequentist and Bayesian approaches, this chapter explores the interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes. The risk factors identified in this chapter can be considered in AV safety assessment scenarios as well as in future operations of mixed traffic. Further, this chapter provides the implication that AV crash narrative data can be leveraged to improve knowledge of AV safety in mixed traffic.

- To be presented at the Transportation Research Board 102nd Annual Meeting
- Submitted to the journal of Accident Analysis and Prevention

Chapter 2. How Inclined Are Alternative Fuel Vehicle Owners to Use Automated Vehicle-Based Travel Options?

A version of this chapter has been accepted by Transportation Research Board (TRB) for presentation at TRB 102nd Annual Meeting in Jan. 2023.

Lee, S., Ahmad, N., and Khattak, A. How Inclined Are Alternative Fuel Vehicle Owners to Use Automated Vehicle-Based Travel Options? Transportation Research Board 102nd Annual Meeting 2023 (No.23-02063)

ABSTRACT

Vehicle electrification and automation are growing societal trends and promising pathways to deal with the issues generated by the surface transportation system, including crashes, congestion, emissions, and energy consumption. Alternative fuel vehicles (AFVs), including electric vehicles (EVs), are in their early stage of diffusion, while high-level automated vehicle (AV) technologies are in development and assessment. At this early stage of vehicle electrification and automation, one of the most critical issues is whether and to what extent individuals are willing to embrace them. Especially, this study aims to explore how inclined AFV owners are to use high-level AV-based travel options (Levels 4-5), including owning an AV and using AV and Shared AV (SAV) ride-hailing services. Using a path-analytic framework with data from a survey of residents in California (N=4,248), this study explores the relationship between AFV adoption and inclination toward AV-based travel options and how they are associated with other relevant factors. Importantly, this study develops an “AV inclination index.” Results reveal that 5.8% of respondents have owned or leased an AFV, while the average "AV inclination index" score is 2.38 on a scale of 0 to 7. Notably, the index score is found to be positively associated with AFV adoption, depending on subpopulations. Further, the index score has a positive relationship with using shared ride-hailing services. Other detailed relationships are elaborated. By providing comprehensive insights into how individuals will embrace vehicle electrification and automation, this study supports the movement toward improving surface transportation systems using appropriate strategies.

Keywords: Alternative Fuel Vehicle Adoption, Automated Vehicle Adoption, Automated Ride-Hailing Services

INTRODUCTION

The surface transportation system has created many issues, including traffic congestion, crashes, emissions, and energy issues, which directly compromise the quality of life. For instance, it is reported that people in the United States lose 97 hours a year on average due to traffic congestion, which costs them $1,348 a year per driver (*1*). According to Fatality Analysis Reporting System (FARS), crashes result in more than 30,000 fatalities annually in the United States, while there has been little reduction in the annual number (*2*). Besides, 28.7 percent of greenhouse gas emissions by the economic sector are from the transportation sector as of 2019 (*3*). When it comes to energy use, the transportation sector spends 2.2 times as much energy as the residential sector (*3*).

In this context, vehicle electrification and automation are growing societal trends and are considered promising pathways to deal with the issues generated by the surface transportation system. Alternative fuel vehicles (AFVs) such as battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs) are expected to help improve fuel economy and reduce emissions depending on the type of refueling and charging (*4-5*). According to the U.S. Department of Energy, the average BEV emits 3,932 pounds of CO_2 equivalent annually, whereas the average gasoline vehicle emits 11,435 pounds of CO_2 equivalent (*3*). Concerning fuel economy, as of 2020, the average BEV range is estimated to be 240 (mile/battery), while the average BEV is 3.54 times more efficient than the average vehicle with internal combustion engines (*3*). Meanwhile, Automated Vehicles (AVs) are expected to help enhance traffic safety by removing human errors, while connections among AVs are expected to help enhance traffic flow (*6-7*). Moreover, AVs will provide people with disabilities and seniors with additional travel options, which is expected to improve mobility and equity (*6*).

Currently, AFVs are in the early stage of diffusion. In the United States, the annual number of HEV sales has increased from 17 in 1999 to 400,746 in 2019, while the annual number of BEV and PHEV sales has increased from 17,763 in 2011 to 326,644 in 2019 (*3*). The annual FCEV sales in the United States increased from 4 in 2012 to 3,341 in 2021 (*8*). Nonetheless, AFVs are still taking a small portion of the vehicle market, given that BEVs, HEVs, and PHEVs take 4.1 percent of the light vehicle market as of 2019 (*9*). In California, it was reported that 19-21% of PHEV and BEV adopters stopped owning their EVs between 2015 and 2019 (*16*). Meanwhile, vehicle automaton is in development and assessment within the automation levels consisting of momentary driver assistance (Level 0), driver assistance (Level 1), additional assistance (Level 2), conditional automation (Level 3), high automation (Level 4), and full automation (Level 5) (*6-7-17*). Currently, automation technologies for Levels 1 and 2, such as lane-keeping assistance and adaptive cruise control, are commercially available for vehicles, while those technologies for Level 3 and higher levels are in development and assessment (*6*).

At this early stage of vehicle electrification and automation, one of the most critical issues is whether and to what extent individuals are willing to adopt AFV and AV technologies in the future. In this regard, it is worthy to deeply investigate who is currently adopting AFVs and who is willing to choose AV-based travel options. Especially, this study aims to explore how inclined AFV owners are to use high-level AV-based travel options (Levels 4-5), including owning an AV, using AV ride-hailing services, and using Shared AV (SAV) ride-hailing services. Using a path-analytic systems framework, this study investigates the relationship between AFV adoption and inclination toward AV-based travel options and how they are associated with other relevant factors. For the first step, this study analyzes how AFV ownership is affected by household characteristics, experience with different travel modes, and accessibility to AFV-related infrastructure. For the second step, this study develops an "AV inclination index" integrating individual preferences for different AV-based travel options, e.g., purchasing an AV, using AV ride-hailing services, and using SAV ride-hailing services. For the final step, this study analyzes how the AV inclination index is associated with ownership of AFVs, household characteristics, perceptions of AVs, and experience with different travel modes.

LITERATURE REVIEW

Concerning vehicle electrification, survey research has been performed to investigate AFV ownership and individual intention to adopt an AFV in the future. According to a previous study, AFVs are expected to take 69.7-78.6% of market shares in Germany in the long run (*18*). AFV ownership was found to be influenced by socio-demographic characteristics, behavioral factors, and AFV-related infrastructure and policies. For instance, it had a positive relationship with household income, education level, females, living in urban areas, having neighbors owning an AFV, using online shopping delivery, access to alternative fuel stations, and state-level incentives, while having a negative relationship with age (*19-21*). Meanwhile, individual intention to adopt an AFV in the future was found to have a positive relationship with education level, frequency of urban trips, access to chargers at home, and positive perceptions of AFVs, while having a negative relationship with age (*18-22*).

Regarding vehicle automation, there have also been efforts to explore individual willingness to adopt vehicles with high-level automation features in the future. According to a previous study, a nationwide adoption rate of Level 4 light-duty AVs in the United States would reach around 25% by 2045 with conservative assumptions (*23*). Individual willingness to adopt an AV was found to be affected by socio-demographic characteristics. For instance, it was found that individual willingness to purchase an AV had a positive relationship with household size, income level, males, not owning a vehicle, not having a driver's license, technology savviness, physical conditions prohibiting driving, and living in the downtown area while having a negative relationship with age and owning more than one vehicle (*10-24-28*). In addition, psychological factors, including perceptions of AV technologies, were found to influence individual willingness to adopt an AV. For example, individual willingness to purchase an AV had a positive relationship with positive perceptions of safety benefits of an AV and the utility of automated features, while having a negative relationship with enjoying driving and concerns about the cost of technology, liability, losing control of the vehicle, and unreliable technologies (*11-27-28*). Moreover, individual willingness to purchase an AV was found to be affected by behavioral characteristics. For instance, it had a positive relationship with frequent car purchases, not commuting, and commute time, while having a negative relationship with daily travel time (*24-26*). Besides, personal experience with a crash and exposure to a vehicle with automated features were found to have an impact on individual willingness to own an AV (*25-26*).

There have also been efforts to explore individual willingness to use AV and SAV ride-hailing services. Individual preference for SAVs was found to be influenced by socio-demographic characteristics and behavioral factors. For example, it was found to have a positive relationship with distance from the workplace, proximity to grocery stores, driving alone for commute, frequent use of public transit, and experience with a crash while having a negative relationship with daily travel distance (*12-23-29*). Meanwhile, individual willingness to use AV ride-hailing services was found to have a positive relationship with infrequent use of public transit while having a negative relationship with age (*29*).

Although previous studies have attempted to figure out individual preferences for a specific option with AV technologies in the future, there is a paucity of research to comprehensively cover different types of AV-based travel options. Considering that vehicle automation will provide multiple travel options, such as not owning an AV but using AV ride-hailing services or SAV ride-hailing services, this study develops an "AV inclination index" to quantify individuals' general inclination toward AV-based travel options. The idea behind the "AV inclination index" is that, as a person becomes more inclined to "every" AV-based travel option, a higher proportion of his or her trips will be made by AV regardless he or she owns an AV. In other words, when every travel option is available, a person with a higher AV inclination index is more likely to make a trip by AV than someone with a lower inclination index. Besides, although a previous study attempted to explore relationships between willingness to purchase an AV, EV ownership, and participation in car-sharing programs, there is a paucity of research to connect AFV adoption to general inclination toward vehicle automation (*30*). To fill the gap, this study attempts to systematically explain individual inclination toward AV-based travel options by relating it to individual experience in owning an AFV and experience with different travel modes as well as individual perceptions of AVs.

METHODOLOGY

Conceptual Framework

As visualized in **Figure 2.1**, this study applies a path-analytic systems framework to systematically investigate individual inclination toward AV-based travel options in connection with AFV ownership. In the first stage of the path analysis, the experience in owning or leasing an AFV is explained by household characteristics, experience with different travel modes, and access to charging spots. In the second stage, an "AV inclination index" is developed to integrate individual willingness to own an AV, use AV ride-hailing services, and use SAV ride-hailing services. The AV inclination index is analyzed with regard to household characteristics, experience with different travel modes, opinions about AVs, and experience in owning or leasing an AFV. Relying on the variables available from the data, this study considers PHEVs, BEVs, and FCVs as AFVs. HEVs are not included in the analysis, considering that they do not require charging infrastructure.

Data

This study harnesses part of the data from the "2019 California Vehicle Survey" conducted by the California Energy Commission (*31*). The data has been released by the National Renewable Energy Laboratory, United States Department of Energy (*31*). The "2019 California Vehicle Survey" consists of two categories of surveys, the commercial survey and the residential survey (*31*). This study uses data from the residential survey with a sample of 4,248 respondents in California. The survey interviewed residents of California to collect information on individual and household characteristics, vehicle ownership, travel behaviors, opinions about AVs, and willingness to use different AV-based travel options. (*31*). As shown in **Table 2.1**, the survey sample is well representative of the general population of California in terms of residency by county and annual household income, although it somewhat under-represents low-income people and over-represents older adults (*32-34*). It should be noted that the results of this study should be interpreted within the context of California. Considering that young people are expected to be more favorable of new technologies, for example, the AV inclination index and the percentage of those people with experience in AFVs might have been partially underestimated. On the other hand, considering that low-income people are expected to have fewer opportunities for new technologies, the AV inclination index and the percentage of those people with experience in AFVs might have been partially overestimated.

Analysis Methods

Binary Probit Regression

Considering the binary nature of the experience in owning or leasing an AFV with the outcomes, yes and no, a binary Probit model is applied to explain its relationship with explanatory variables relevant to household characteristics, experience with different travel modes, and access to charging spots (*35*). Details regarding mathematical forms of binary Probit models can be seen in the following reference: (*35*). Additionally, this study explores the evidence of unobserved heterogeneity by applying a random-parameter binary Probit model (*36-37*). For this, it is assumed that the impact of an explanatory variable on the experience in owning or leasing an AFV might vary from person to person (*36-37*). Details regarding the theoretical background of random-parameter models can be seen in the following references: (*36-37*).

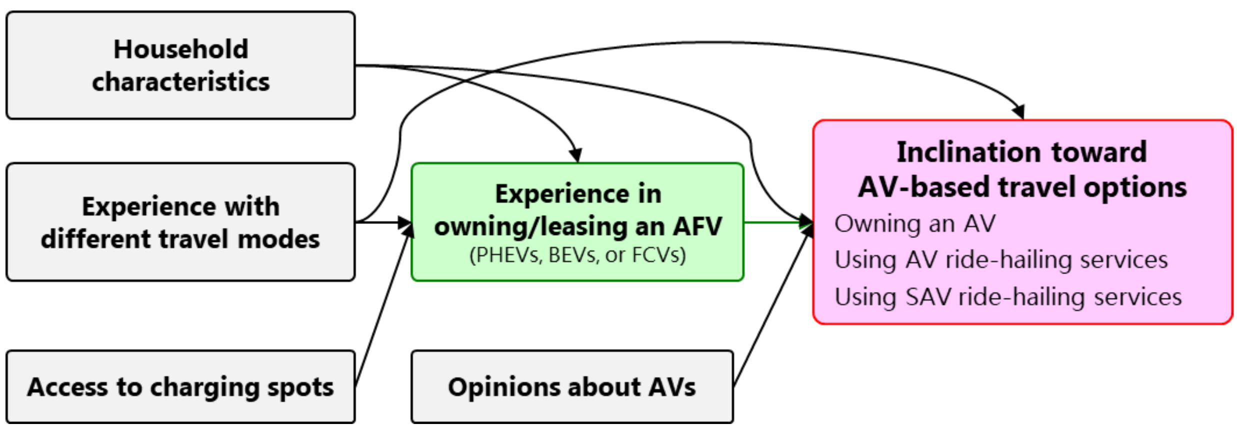


Figure 2.1 Conceptual Framework

Table 2.1 Survey Sample Characteristics (Residents in California)

Sample Characteristics (N=4,248 adult residents)	**Survey (2019)**	**General Population of CA (2019)**
Annual household income (%)		
Less than $9,999	1.4	4.6
$10,000 to $24,999	5.5	10.3
$25,000 to $34,999	5.2	6.8
$35,000 to $49,999	8.3	9.9
$50,000 to $74,999	14.1	15.3
$75,000 to $99,999	14.5	12.5
$100,000 to $149,999	18.3	17.4
$150,000 to $199,999	10.1	9.4
$200,000 or more	13.7	13.7
Prefer not to answer	8.8	0.0
Age Group (%)		
18-34	12.4	31.7
35-64	52.9	49.2
65 and over	34.7	19.1
Residency by county (%)		
Los Angeles County	23.0	25.4
Orange County	10.1	8.0
San Diego County	9.1	8.4
Santa Clara County	6.3	4.9
Alameda County	5.8	4.2
Riverside County	5.1	6.3
Sacramento County	4.4	3.9
San Bernardino County	4.2	5.5
Contra Costa County	3.1	2.9
Other	28.8	30.4

Notes:
For missing values in “annual household income,” mode imputation was performed according to the distribution.
For statistical modeling analysis, “annual household income” was converted to a continuous variable.

Development of AV inclination index
This study develops an "AV inclination index" to quantify individual inclination toward AV-based travel options. This index consists of individual willingness to own an AV with a 3-point scale (0, 1, and 2), willingness to use AV ride-hailing services with a 3-point scale (0, 1, and 2), and willingness to use SAV ride-hailing services with a 4-point scale (0, 1, 2, and 3). Accordingly, the AV inclination index has eight scores from 0 to 7.

Finite-Mixture Poisson Regression
According to the distribution of the AV inclination index scores, this study applies a Poisson model to explain the relationship between the index and explanatory variables relevant to household characteristics, experience with different travel modes, opinions about AVs, and experience in owning or leasing an AFV (*35*). Details regarding mathematical forms of Poisson models can be seen in the following reference: (*35*). To capture unobserved subpopulations within the sample regarding the AV inclination index, this study applies a finite-mixture Poisson model (*38*). Details regarding the theoretical background of finite mixture models can be seen in the following reference: (*38*).

RESULTS AND DISCUSSION

Key Statistics

Based on data from the residential survey, descriptive statistics of key variables are summarized in **Table 2.2**. Importantly, statistics show the information on the experience in owning or leasing an AFV. It is revealed that 5.8 percent of respondents have owned or leased an AFV. In detail, 3.5 percent of respondents have owned or leased a PHEV, while 2.7 percent have owned or leased a BEV. Besides, 1.5 percent of respondents have owned or leased an FCV.

Concerning AV adoption, 9.0 percent of respondents answered that they would purchase an AV as soon as possible, while 46.1 percent said they would try not to purchase an AV. The remaining 45.0 percent answered that they would purchase an AV only after they are widely used. When it comes to AV ride-hailing services, 8.8 percent of respondents answered that they would use AV ride-hailing services and remove at least one household vehicle, while 43.3 percent said that they would not use AV ride-hailing services while keeping their household vehicles. The remaining 47.9 percent answered that they would use AV ride-hailing services whenever needed while keeping their household vehicles. Regarding SAV ride-hailing services, 66.9 percent of respondents somewhat or strongly agreed that they would "not" use them, while 33.1 percent somewhat or strongly disagreed with that statement.

Regarding household characteristics, the average number of household members and vehicles was 2.29 and 1.89, respectively. The average household income was 115.70 (USD in thousands). Meanwhile, it was revealed that 15.7 percent of households had solar panels.

Moreover, statistics show information on access to charging infrastructure for AFVs. Concerning PHEVs and BEVs, 71.7 percent of respondents have access to at least one EV charging spot in their local area. When it comes to FCVs, 16.3 percent of respondents have access to Hydrogen refueling stations in their local area.

Besides, statistics show information on individual experiences with different travel modes in their local area. It is revealed that 19.7 percent of respondents use shared ride-hailing services, while 52.5 percent do not use them, although they are available. Meanwhile, 2.3 percent of respondents use carsharing, while 39.2 percent do not use it, although it is available.

Table 2.2 Key Statistics of the Residential Survey (N=4,248)

Variable	Freq/Mean	%/S.D.	Min.	Max.
Experience in owning or leasing an AFV (PHEVs, BEVs, or FCVs)	246	5.8	0	1
Experience in owning or leasing a PHEV (1/0)	148	3.5	0	1
Experience in owning or leasing a BEV (1/0)	116	2.7	0	1
Experience in owning or leasing an FCV (1/0)	64	1.5	0	1
Willingness to adopt an AV				
0: My household would try to avoid purchasing an AV.	1,957	46.1	0	1
1: My household would purchase an AV only after they are widely used.	1,910	45.0	0	1
2: My household would purchase an AV as soon as possible.	381	9.0	0	1
Willingness to use AV ride-hailing services				
0: My household would not use it, while keeping household vehicles.	1,840	43.3	0	1
1: My household would use it, while keeping household vehicles.	2,033	47.9	0	1
2: My household would use it, while removing at least one household vehicle.	375	8.8	0	1
Willingness to use SAV ride-hailing services				
I would not use SAV ride-hailing services. ** reversely scored				
3: Strongly disagree	445	10.5	0	1
2: Somewhat disagree	959	22.6	0	1
1: Somewhat agree	1,384	32.6	0	1
0: Strongly agree	1,460	34.4	0	1
Household characteristics				
Household size *	2.29	1.21	1	16
Number of vehicles in household *	1.89	1.02	0	8
Annual household income (USD in thousands) *	115.70	75.54	5	300
Possession of solar panels (1/0)	667	15.7	0	1
Access to EV charging spots in the local area				
No	460	10.8	0	1
One place	423	10.0	0	1
A few places	1,480	34.8	0	1
Several places	1,144	26.9	0	1
Not sure	741	17.4	0	1
Access to Hydrogen fueling stations in the local area				
No	3,556	83.7	0	1
Yes	692	16.3	0	1

Notes: * indicates that the variable is continuous.

Table 2.2 (Continued)

Variable	Freq/Mean	%/S.D.	Min.	Max.
Experience with different travel modes				
Experience with **"Shared ride-hailing"** (e.g., UberPool and LyftLine)				
Not familiar with it	829	19.5	0	1
Not available in the local area	353	8.3	0	1
Available, but not using it	2,231	52.5	0	1
Available, and using it	835	19.7	0	1
Experience with **"Carsharing"** (e.g., Car2Go and ZipCar)				
Not familiar with it	1,538	36.2	0	1
Not available in the local area	946	22.3	0	1
Available, but not using it	1,665	39.2	0	1
Available, and using it	99	2.3	0	1
Opinion about AVs: Willingness to accept longer travel times				
I would accept longer travel times for safety. (4-point scale)				
0: Strongly disagree	1,008	23.7	0	1
1: Somewhat disagree	980	23.1	0	1
2: Somewhat agree	1,558	36.7	0	1
3: Strongly agree	702	16.5	0	1
Opinion about AVs: Willingness to work more in an AV				
I would work more in the AV. (4-point scale)				
0: Strongly disagree	1,954	46.0	0	1
1: Somewhat disagree	1,216	28.6	0	1
2: Somewhat agree	844	19.9	0	1
3: Strongly agree	234	5.5	0	1
Opinion about AVs: Willingness to pick up (or drop off) a child by AV				
I would allow an AV without a driver to pick up (or drop off) my child. (4-point scale)				
0: Strongly disagree	2,594	61.1	0	1
1: Somewhat disagree	812	19.1	0	1
2: Somewhat agree	623	14.7	0	1
3: Strongly agree	219	5.2	0	1
Opinion about AVs: Anticipation of traveling more often				
AVs would enable me to travel more often. (4-point scale)				
0; Strongly disagree	1,201	28.3	0	1
1: Somewhat disagree	822	19.4	0	1
2: Somewhat agree	1,495	35.2	0	1
3: Strongly agree	730	17.2	0	1

Furthermore, statistics show information on individual opinions about AVs. Notably, only 19.8 percent of respondents were somewhat or strongly willing to pick up or drop off their children by an AV without a driver. This indicates that a vast majority of residents might not fully trust the safety of AVs. In addition, it is revealed that 53.2 percent of respondents were somewhat or strongly willing to accept longer travel times for safety when they use an AV. While 25.4 percent of respondents were somewhat or strongly willing to work more in the AV, 74.6 percent were somewhat or strongly unwilling to do so. Meanwhile, 52.4 percent of respondents thought that AVs would enable them to travel more often.

Analysis and Discussion

Experience in owning or leasing an AFV

As summarized in **Table 2.3**, a binary Probit model (Model 1A) was estimated to figure out how the experience inn owning or leasing an AFV can be explained by household characteristics, experience with different travel modes, and access to charging infrastructure for AFVs. Regarding the goodness of fit, McFadden's R squared of the model is 0.192. The model has the Akaike's Information Criteria (AIC) value of 1539.91 and the Bayesian Information Criteria (BIC) value of 1609.80. No evidence was found for unobserved heterogeneity in the sample, given that no explanatory variables were found to have random parameters. This study considers a coefficient meaningful to interpret when its p-value is lower than 0.1.

According to Model 1A, notably, the experience in owning or leasing an AFV has a positive relationship with the experience with "Carsharing." Specifically, those who use carsharing are 13.02 percent more likely to have experience in owning or leasing an AFV, compared to those who are unfamiliar with it, according to the marginal effect (M.E.) in **Table 2.3**. This relationship can be understood in the sense that a person gets a chance to use different types of vehicles including AFVs when using carsharing, which can make the person more interested in AFVs. At the same time, those who do not use "Carsharing" are 1.94 percent more likely to have experience in owning or leasing an AFV than those who are unfamiliar with it. When it comes to access to charging infrastructure, expectedly, the experience in owning or leasing an AFV has a positive relationship with having access to EV charging spots and Hydrogen fueling stations in the local area, which is consistent with a previous study (*39*). For example, it is revealed that those who have access to several EV charging spots are 3.39 percent more likely to have experience in owning or leasing an AFV. Meanwhile, the experience in owning or leasing an AFV is also associated with household characteristics. As expected, it has a positive relationship with household size and the possession of solar panels. Specifically, having solar panels in the household is positively correlated with having experience in owning or leasing an AFV by 3.57 percent. This implies that those who have such eco-friendly equipment for electricity generation would become more likely to decide to adopt an AFV.

Development of "AV Inclination Index"

By integrating willingness to own an AV, use AV ride-hailing services, and use SAV ride-hailing services, the "AV inclination index" was developed to quantify individual inclination toward AV-based travel options. As shown in **Table 2.4** and **Figure 2.2**, the index has scores from 0 to 7. The higher an individual's score is, the more inclined the person is toward AV-based travel options. The average and standard deviation are 2.38 and 1.71, respectively. It is revealed that the highest proportion of respondents, 21.8%, had a score of 3, while 20.0 percent of respondents had a score of 0.

Table 2.3 Model 1A (Binary Probit): Experience in owning or leasing an AFV

Explanatory Variables	$\boldsymbol{\beta}$	**P-value**	**M.E.(%)**
Household Characteristics			
Household size	0.121	<0.001	1.15
Possession of solar panels	0.376	<0.001	3.57
Experience with "Carsharing"			
Not familiar with it	Base	Base	Base
Not available in the local area	0.123	0.224	1.04
Available, but not using it	0.215	0.014	1.94
Available, and using it	0.910	<0.001	13.02
Access to EV charging spots in the local area			
No	Base	Base	Base
One place	0.413	0.038	3.41
A few places	0.170	0.339	1.16
Several places	0.411	0.019	3.39
Not sure	0.451	0.013	3.83
Access to Hydrogen fueling stations (1/0)	0.978	<0.001	9.28
Constant	-2.741	<0.001	NA
Summary Statistics			
Sample Size (N)	4,248		
McFadden's Pseudo R^2	0.192		
AIC	1539.91		
BIC	1609.80		

Notes:
Coefficients (β's) with a p-value lower than 0.1 are considered meaningful.
M.E. (%) indicates the marginal effect of each variable on the chance (%) of having experience with an AFV.

Table 2.4 AV Inclination Index

AV Inclination Index	Frequency	Percentage (%)
0	850	20.0
1	588	13.8
2	713	16.8
3	926	21.8
4	691	16.3
5	359	8.5
6	106	2.5
7	15	0.4

Notes: This index was developed by combining:
(1) Willingness to own an AV (3-point scale: 0 to 2),
(2) Willingness to use AV ride-hailing services (3-point scale: 0 to 2), and
(3) Willingness to use SAV ride-hailing services (4-point scale: 0 to 3).

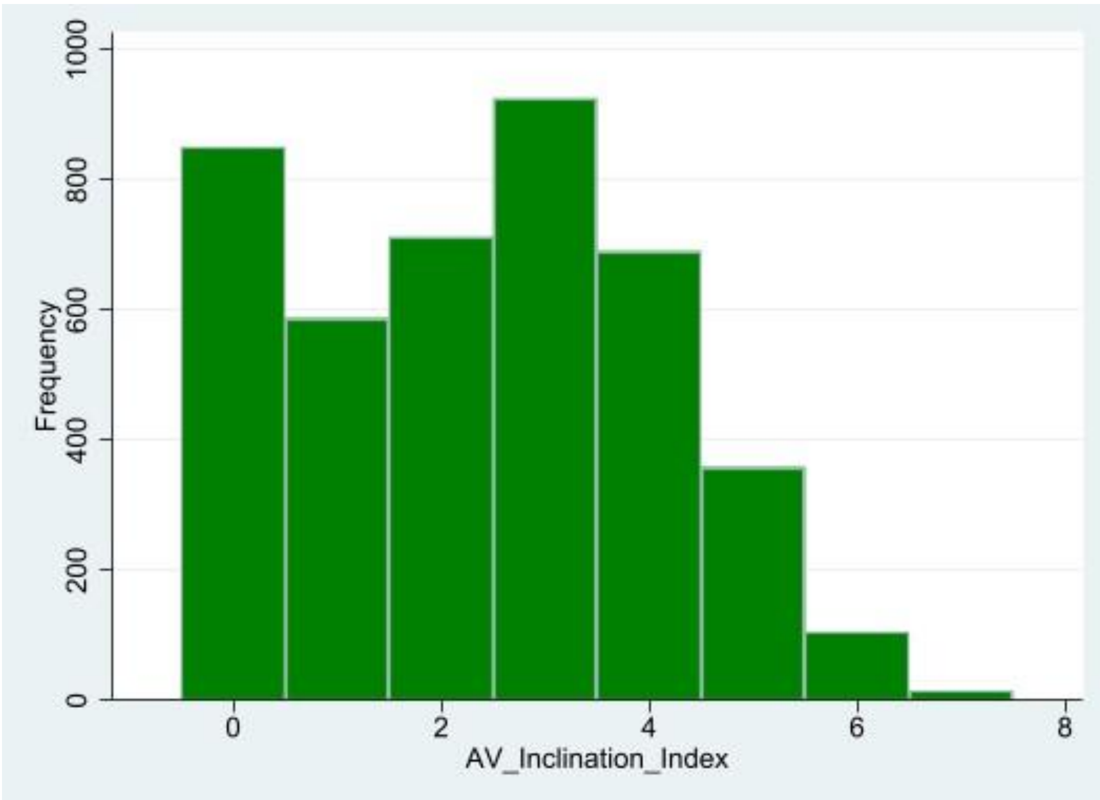


Figure 2.2 AV Inclination Index

Alternatives structures of AV Inclination Index

In this study, the AV inclination index was developed in a straightforward manner by keeping the original structure of the three variables, i.e., willingness to own an AV, willingness to use AV ride-hailing services, and willingness to use SAV ride-hailing services. However, the AV inclination index can be developed in various manners from different perspectives. When assuming that owning an AV represents a stronger inclination toward transportation automation than using AV ride-hailing services and SAV ride-hailing services, for instance, the willingness to own an AV can be weighted more than the willingness to use AV ride-hailing services and the willingness to use SAV ride-hailing services. The following is an example of the alternative structure of the AV inclination index that weighs the willingness to own an AV.

- Willingness to own an AV has scores of 0, 2, and 4.
- Willingness to use AV ride-hailing services has scores of 0, 1, 2.
- Willingness to use SAV ride-hailing services has scores of 0, 1, 2, and 3.
- AV inclination index has scores from 0 to 9.

Moreover, the AV inclination index can be developed with more sophisticated weighting methods. When assuming that using AV ride-hailing services represents a stronger inclination toward transportation automation than using SAV ride-hailing services while representing a weaker inclination than owning an AV, the willingness to use AV ride-hailing services can be weighted more than the willingness to use SAV ride-hailing services but less than owning an AV. From this perspective, the following is a simple example of a structure of the AV inclination index.

- Willingness to own an AV has scores of 0, 3, and 6.
- Willingness to use AV ride-hailing services has scores of 0, 2, and 4.
- Willingness to use SAV ride-hailing services has scores of 0, 1, 2, and 3.
- AV inclination index has scores from 0 to 13.

Future research may explore how to develop a reasonable structure for the AV inclination index. Concerning this item, the weighting methods should not be affected by researchers' personal bias or subjective judgment. In this regard, this study keeps the original structure of the variables in developing the AV inclination index.

AV Inclination Index and AFV experience

Regarding the AV inclination index, it was observed that those people with experience in owning or leasing an AFV (AFV experience =1) tended to have a higher inclination toward AV-based travel options, as shown in **Figure 2.3**. The average AV inclination index score of those people with AFV experience was 3.22, whereas the average of those people without AFV experience was 2.32. Especially, more than 20 percent of those people without AFV experience have a score of 0, whereas about 25 percent of those people without AFV experience have a score of 3. This observation indicates that the AV inclination index and AFV experience would have a statistically positive relationship. In modeling analysis, thus, the experience in owning or leasing an AFV was included as an explanatory variable for the AV inclination index.

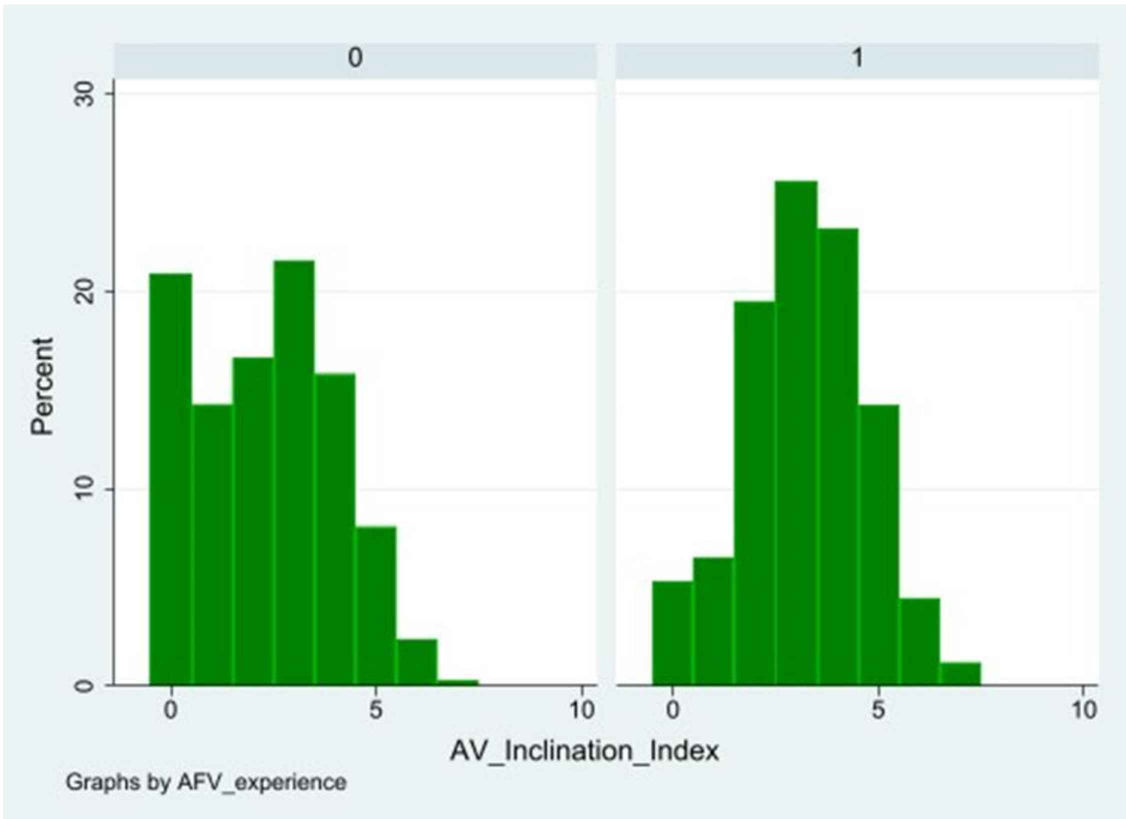


Figure 2.3 AV Inclination Index scores by the experience in owning or leasing an AFV

Inclination toward AV-based travel options

Considering the distribution of the AV inclination index scores, this study estimated a finite-mixture Poisson model to figure out how individual inclination toward AV-based travel options can be explained by household characteristics, experience with different travel modes, opinions about AVs, and experience in owning or leasing an AFV. As shown in **Table 2.5** and **Figure 2.4**, the sample was clustered into two subpopulations, Class 1 and Class 2, by the model. Specifically, 28.3 percent of respondents were expected to fall into Class 1, the mean score of which was estimated to be 1.648. The remaining 71.7 percent were expected to fall into Class 2, the mean score of which was estimated to be 2.668. The results of the finite-mixture Poisson model (Model 2) are summarized in **Table 2.6**. The model fits well with the data, given that McFadden's R^2 is 0.261.

Within Class 2, notably, the AV inclination index has a positive relationship with the experience in owning or leasing an AFV. Specifically, when an individual has experience in owning or leasing an AFV, his or her AV inclination score is expected to be higher by 0.240. This implies that vehicle electrification and automation could have a synergetic connection where AFV adoptions boost not only AV adoptions but also the use of AV and SAV ride-hailing services in the future. It should be noted that there is a chance that, within Class 2, part of those respondents with the AFV experience had already been inclined to AV-based travel options before owning or leasing an AFV, which needs further investigation in future studies with appropriate datasets. Within Class 2, besides, the AV inclination index has a positive relationship with the willingness to work more in the AV. In detail, a unit increase in the willingness to work more in the AV is correlated with a higher AV inclination index by 0.117. Nonetheless, the relationship between these variables is not significant within Class 1, which reveals unobserved heterogeneity.

For both classes, the AV inclination index is found to have a positive relationship with annual household income, which is consistent with a previous study (*25*). According to the marginal effects (M.E.) in **Table 2.6**, a 1000-dollar increase in the annual household income is correlated with a higher score of the AV inclination index by 0.002. Likewise, for both classes, those who use shared ride-hailing services are more likely to be inclined toward AV-based travel options than those unfamiliar with shared ride-hailing services. Further, for both classes, the AV inclination index has a positive relationship with the willingness to accept longer travel times by AV, willingness to allow an AV without a driver to pick up or drop off a child, and anticipation of gaining options for frequent travel. For instance, as shown in **Table 2.6**, within Class 2, a unit increase in the willingness to allow an AV without a driver to pick up or drop off a child is positively correlated with a higher AV inclination index by 0.342. Within Class 1, for example, a unit increase in anticipation of traveling more often by AV is positively associated with a higher AV inclination index by 0.878. These results indicate that , for both classes, the anticipation of gaining options for frequent travel can be a significant motivation for choosing AV-based travel options in the future. Meanwhile, when an individual does not use carsharing, if available, his or her AV inclination index score would be higher by 0.391 within Class 1 and by 0.248 within Class 2 compared to when not familiar with carsharing. These results indicate that AV-based travel options could attract part of those who are currently reluctant to use carsharing. They can be significantly attracted by the fact that they do not have to drive in a high-level AV. On the other hand, within Class 1, the AV inclination index has a negative relationship with using carsharing. Specifically, within Class 1, when an individual uses carsharing, if available, his or her AV inclination index score would be lower by 0.577. This indicates that AV-based travel options would not attract part of those who are already using carsharing.

Table 2.5 Subpopulations with regard to AV Inclination Index

Class	Proportion (%)	Mean (Score)	p-value	95% Confidence Interval (Mean)	
				Lower	Upper
Class 1	28.3	1.648	<0.001	1.388	1.908
Class 2	71.7	2.668	<0.001	2.559	2.777

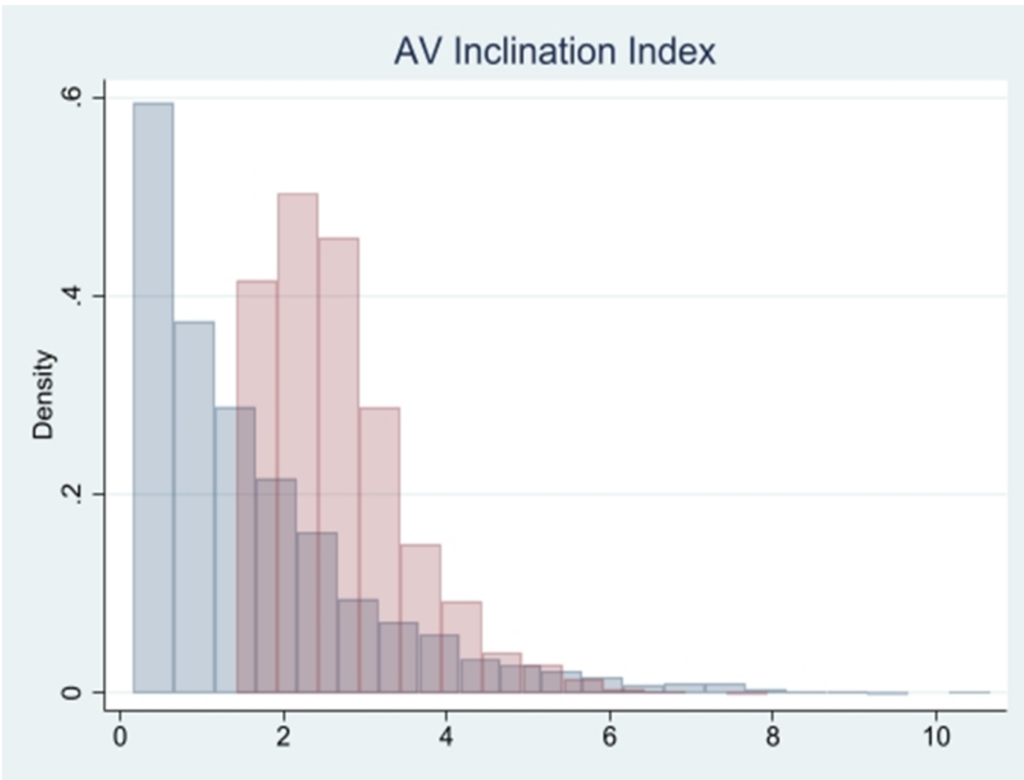


Figure 2.4 Prediction of AV Inclination Index by subpopulation

Table 2.6 Model 2 (Finite-Mixture Poisson): AV Inclination Index

Explanatory Variables	Class 1			Class 2		
	β	P-value	M.E.	β	P-value	M.E.
Household Characteristics						
Annual household income (USD in thousands)	0.002	0.007	0.002	0.001	<0.001	0.002
Experience with "Shared ride-hailing"						
Not familiar with it	Base	Base	Base	Base	Base	Base
Not available in the local area	0.155	0.556	0.209	0.022	0.736	0.058
Available, but not using it	0.273	0.148	0.390	-0.057	0.163	-0.147
Available, and using it	0.473	0.019	0.752	0.148	0.001	0.423
Experience with "Carsharing"						
Not familiar with it	Base	Base	Base	Base	Base	Base
Not available in the local area	0.170	0.198	0.267	0.048	0.232	0.126
Available, but not using it	0.240	0.033	0.391	0.093	0.006	0.248
Available, and using it	-0.511	0.042	-0.577	0.032	0.684	0.083
Experience in owning or leasing an AFV (1/0)	-0.089	0.591	-0.146	0.090	0.054	0.240
Opinions about AVs (4-point scale)						
I would accept longer travel times for safety.	0.241	0.001	0.396	0.129	<0.001	0.344
I would work more in the AV.	0.070	0.197	0.115	0.044	0.008	0.117
I would allow an AV without a driver to pick up (or drop off) my child.	0.126	0.015	0.207	0.128	<0.001	0.342
AVs would enable me to travel more often.	0.533	<0.001	0.878	0.043	0.016	0.115
Constant	-1.657	<0.001	NA	0.410	<0.001	NA
Summary Statistics						
Sample Size (N)	4,248					
McFadden's Pseudo R^2	0.261					
AIC	14,715.01					
BIC	14,886.57					

Notes:
Coefficients (β's) with a p-value lower than 0.1 are considered meaningful.
M.E. indicates the marginal effect of each explanatory variable on the AV inclination index score.

Path analysis

Based on Models 1A and 2, the path analysis results are summarized with marginal effects in **Figure 2.5** and **Table 2.7**. Throughout the path analysis, within Class 2, notably, the experience in owning or leasing an AFV is associated with a higher score of the AV inclination index by 0.240. On the other hand, within Class 1, the AV inclination index score does not have a statistically significant relationship with the experience in owning or leasing an AFV. Regarding the experience with different travel modes, using available "Carsharing" is associated with a higher chance of having experience in owning or leasing an AFV by 13.02%, which is indirectly correlated with a higher AV inclination index score by 0.031 within Class 2. At the same time, within Class 2, not using available "Carsharing" is directly associated with an increase in the score of the AV inclination index by 0.248. Using "Shared ride-hailing services" is directly associated with an increase in the AV inclination index score by 0.752 and 0.423 within Class 1 and Class 2, respectively.

Concerning AFV charging infrastructure, having access to EV charging spots in several places is correlated with a higher chance of owning or leasing an AFV by 3.39%, which is indirectly associated with a higher score of the AV inclination index by 0.008 within Class 2. Likewise, having access to Hydrogen fueling stations is associated with an increase in the chance of owning or leasing an AFV by 9.28%, which is correlated with a higher score of AV inclination index by 0.022 within Class 2. These results within the path-analytic framework imply that, as expected, travelers' inclination toward AV-based travel options would be indirectly associated with their exposure to AFV charging infrastructure in their local area.

When it comes to individual opinions about AVs, a unit increase in the willingness to accept longer travel times by AV is directly correlated with a higher AV inclination index score by 0.396 within Class 1 and 0.344 within Class 2, respectively. A unit increase in anticipation of traveling more often by AV is directly associated with a higher AV inclination index score by 0.878 within Class 1 and 0.115 within Class 2. Likewise, a unit increase in the willingness to pick up or drop off a child by AV without a driver is directly correlated with a higher AV inclination index score by 0.207 within Class 1 and 0.342 within Class 2. Besides, a unit increase in the willingness to work more in the AV is directly associated with a higher AV inclination index score by 0.117 within Class 2, whereas this relationship is not the case for Class 1. These results provide the evidence of unobserved heterogeneity in how individuals become inclined toward AV-based travel options.

Potential backward relationship

To explore the potential backward relationship from the AV inclination index to the AFV experience, as shown in **Table 2.8**, an additional binary Probit model (Model 1B) was estimated to figure out how the AFV experience can be affected by the AV inclination index. This model can be interpreted based on the assumption that the AV inclination index of those people with AFV experience was the same in the past before adopting an AFV. When applying this assumption, a unit increase in the AV inclination index is positively associated with the AFV experience by 0.73%. However, the assumption would not be the case. Now that the data has no information on the AV inclination index in the past, especially before adopting an AFV, the potential backward relationship from the inclination toward AV-based travel options to AFV experience requires further investigation in future studies with appropriate datasets such as panel surveys to keep track of individuals' travel behavior.

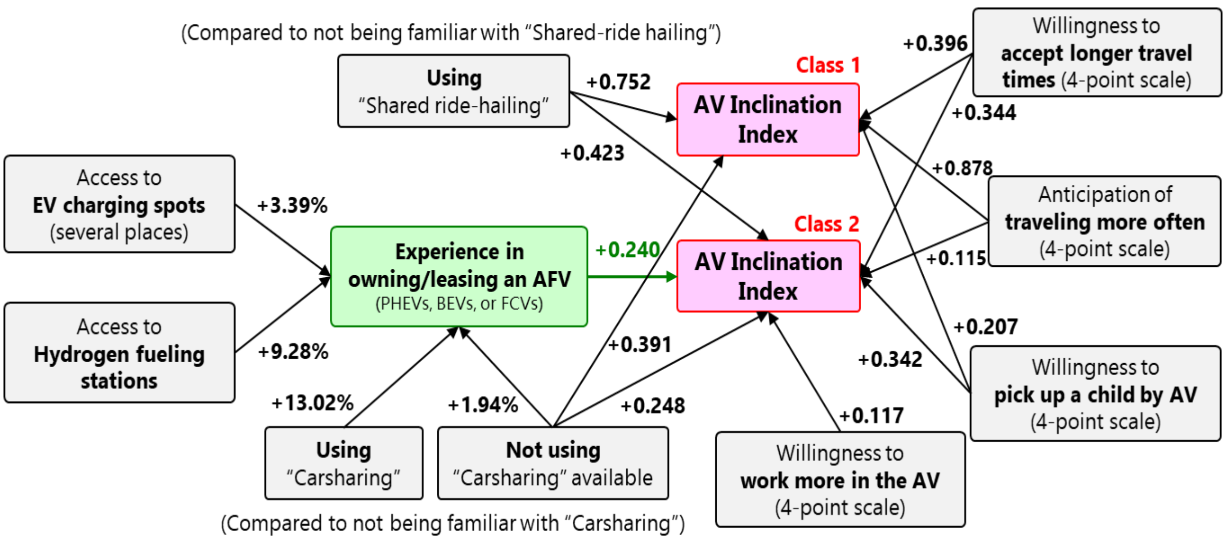


Figure 2.5 Key Results of Path Analysis

Table 2.7 Path Analysis Results with Marginal Effects

Explanatory Variables	M.E. on AFV experience (%)	M.E. on the AV inclination index score			
		Class 1	Class2		
		Direct	Direct	Indirect	Total
Household Characteristics					
Household size	1.15	---	---	0.003	0.003
Annual household income (USD in thousands)	---	0.002	0.002	---	0.002
Possession of solar panels	3.57	---	---	0.009	0.009
Experience with "Shared ride-hailing"					
Not familiar with it	Base	Base	Base	Base	Base
Not available in the local area	---	---	---	---	---
Available, but not using it	---	---	---	---	---
Available, and using it	---	0.752	0.423	---	0.423
Experience with "Carsharing"					
Not familiar with it	Base	Base	Base	Base	Base
Not available in the local area	---	---	---	---	---
Available, but not using it	1.94	0.391	0.248	0.005	0.252
Available, and using it	13.02	-0.577	---	0.031	0.031
Access to EV charging spots					
No	Base	Base	Base	Base	Base
One place	3.41	---	---	0.008	0.008
A few places	---	---	---	---	---
Several places	3.39	---	---	0.008	0.008
Not sure	3.83	---	---	0.009	0.009
Access to Hydrogen fueling stations	9.28	---	---	0.022	0.022
Opinions about AVs (4-point scale)					
I would accept longer travel times for safety.	---	0.396	0.344	---	0.344
I would work more in the AV.	---	---	0.117	---	0.117
I would allow an AV without a driver to pick up (or drop off) my child.	---	0.207	0.342	---	0.342
AVs would enable me to travel more often.	---	0.878	0.115	---	0.115

Notes:
--- indicates that it is not significant at the 10% level.
M.E. indicates the marginal effect of each explanatory variable.
For Class 2, the marginal effect of AFV experience on the AV inclination index score is 0.240.

Table 2.8 Model 1B (Binary Probit): Experience in owning or leasing an AFV

Explanatory Variables	β	P-value	M.E.(%)
Household Characteristics			
Household size	0.116	<0.001	1.09
Possession of solar panels	0.378	<0.001	3.56
Experience with "Carsharing"			
Not familiar with it	Base	Base	Base
Not available in the local area	0.103	0.310	0.88
Available, but not using it	0.184	0.037	1.65
Available, and using it	0.848	<0.001	11.79
Access to EV charging spots in the local area			
No	Base	Base	Base
One place	0.400	0.046	3.46
A few places	0.140	0.433	1.00
Several places	0.350	0.049	2.91
Not sure	0.374	0.041	3.17
Access to Hydrogen fueling stations (1/0)	0.942	<0.001	8.86
AV Inclination Index	0.078	<0.001	0.73
Constant	-2.864	<0.001	NA
Summary Statistics			
Sample Size (N)			4,248
McFadden's Pseudo R^2			0.199
AIC			1529.51
BIC			1605.76

Notes:
Coefficients (β's) with a p-value lower than 0.1 are considered meaningful.
M.E. (%) indicates the marginal effect of each variable on the chance (%) of having experience with an AFV.

Limitations

Now that the survey data is from a specific region, California, the results of this study should be interpreted within the context of California. Given that California is considered one of the EV-friendly states with policies to support transportation electrification, such as the Clean Vehicle Rebate Programs for individuals and businesses, part of the survey results could be different if a case study were performed in another region with different contexts (*40-41*). If a case study were conducted in another state or country with fewer policies to support AFV adoptions, the proportion of AFV owners would be lower than 5.8%. Likewise, the proportion of shared ride-hailing service users would be lower than 19.7% if a case study were conducted in another state or country with lower availability of that service. Accordingly, it is expected that the impact of those variables highly related to the regional contexts is less generalizable compared to those variables that are little related to the regional contexts. For example, the positive relationship between using carsharing and adopting an AFV might be weaker in other regions without an electric carsharing program than in California with an electric carsharing program, BlueLA, in Los Angeles (*42*). Future studies would be able to overcome this limitation by performing surveys in other states or countries to obtain more generalizable findings. Even though the AV inclination index developed in this study is capable of quantifying individuals' general inclination toward AV-based travel options, it does not capture different natures among AV-based travel options. Thus, separate models for three AV-based travel options are additionally estimated in the Appendix of this chapter. In future studies, it would be meaningful to conduct a deeper analysis of each AV-based travel option.

CONCLUSION

With survey data from California, this study investigated key relationships that include correlates of AFV adoption, what makes individuals inclined to AV-based travel options in the future, and how AFV adoption and inclination toward AV-based travel options are associated with each other. Currently, residents in California seem partially ready to embrace vehicle electrification and automation. Results reveal that 5.8 percent of respondents have owned or leased an AFV, while the average "AV inclination index" score is 2.38 on a scale of 0 to 7. Specifically, 53.9 percent of respondents are willing to purchase an AV in the future. While 56.7 percent of respondents are willing to use AV ride-hailing services, 33.1 percent are willing to use SAV ride-hailing services. Using a rigorous path-analytic systems framework, this study provides appropriate information that may be considered by transportation planners, engineers, and policymakers. Through insights into how likely individuals are willing to embrace vehicle electrification and automation, this study contributes to understanding emergent societal trends.

Importantly, individual experience in owning or leasing an AFV is correlated with vehicle automation, although this would not necessarily be the case for the entire population. Contributing factors for AFV adoptions include expansion of AFV charging infrastructure, exposure to shared travel modes such as carsharing, and experience with eco-friendly equipment such as solar panels. According to the path-analysis results, these factors would be indirectly associated with willingness to use AV-based travel options in the future. In this regard, efforts for successful vehicle electrification are expected to indirectly facilitate vehicle automation in the future. On the other hand, these relationships indicate that the diffusion of AV-based travel options can be disproportionate among travelers depending on whether a person has owned or leased an AFV when AFVs are not widely adopted. That is, those people with high exposure to AFVs are more likely to choose AV-based travel options in the future. For a smooth transition to transportation electrification and automation, in this regard, planners and policymakers should be prepared for potential variations in the demand for electrified and/or automated travel modes in the future by taking these relationships into account.

The results from this study suggest potential heterogeneity in general inclination toward AV-based travel options. Specifically, clustering the population into classes shows that, within a subpopulation (Class 2) with a higher mean score of AV inclination index, the proclivity toward AV-based travel options is positively correlated with the willingness to work in the AV, while this relationship is not significant within the other subpopulation (Class 1) with a lower mean score of AV inclination index. Likewise, the positive relationship between the AV inclination index score and the AFV experience is significant only within Class 2 with a higher mean score of AV inclination index.

This study reveals that individual experience with shared travel modes in the local area could be positively associated with adopting both AFV and AV technologies. Vehicle electrification and automation can be accelerated in the regions with high availability and quality of shared travel modes than in the regions with low availability and quality of those modes. However, this might result in disparities in the diffusion of AFVs and AV-based travel options among regions, which needs further investigation.

ACKNOWLEDGMENT

This chapter is based on data released by the National Renewable Energy Laboratory, United States Department of Energy (DOE) from the "2019 California Vehicle Survey" that was conducted by the California Energy Commission (www.nrel.gov/tsdc). Any opinions, findings, conclusions, or recommendations in this chapter are those of the authors and do not necessarily reflect the views of those organizations above.

APPENDIX

As shown in **Table 2.9**, separate Poisson models (Models 3A, 3B, and 3C) were estimated to further explore individual components of the AV inclination index, i.e., willingness to own an AV (3-point scale), willingness to use AV ride-hailing services (3-point scale), and willingness to use SAV ride-hailing services (4-point scale). The results are generally consistent with Model 2 for the AV inclination index, while a few relationships have some variations across the separate models. For example, the experience in owning or leasing an AFV is correlated with a higher willingness to own an AV by 0.145, while having a statistically insignificant relationship with the willingness to use AV ride-hailing services and the willingness to use SAV ride-hailing services. Besides, using shared ride-hailing services is associated with a higher willingness to use AV ride-hailing services and willingness to use SAV ride-hailing services by 0.092 and 0.390, respectively. On the other hand, its relationship with the willingness to own an AV is statistically insignificant. This indicates the inertia of using ride-hailing services. Furthermore, not using carsharing is correlated with a higher willingness to own an AV by 0.069 and a higher willingness to use SAV ride-hailing services by 0.196, whereas its relationship with the willingness to use AV ride-hailing services is statistically insignificant. Concerning opinions about AVs, the willingness to work more in the AV is associated with a higher willingness to own an AV by 0.070 and a higher willingness to use AV ride-hailing services by 0.049. This indicates that people tend to consider sharing an AV inappropriate for working in the AV.

Table 2.9 Models 3A, 3B, and 3C (Poisson): Willingness to use AV-based travel options

Explanatory Variables	Model 3A: Willingness to own an AV			Model 3B: Willingness to use AV ride-hailing services			Model 3C: Willingness to use SAV ride-hailing services		
	β	P-value	M.E.	β	P-value	M.E.	β	P-value	M.E.
Household Characteristics									
Annual household income (USD in thousands)	0.002	<0.001	0.001	0.002	<0.001	0.001	<0.001	0.320	<0.001
Experience with "Shared ride-hailing"									
Not familiar with it	Base	Base	Base	Base	Base	Base	Base	Base	Base
Not available in the local area	0.025	0.782	0.015	0.017	0.846	0.011	0.041	0.547	0.043
Available, but not using it	0.020	0.744	0.012	0.054	0.351	0.034	-0.062	0.167	-0.062
Available, and using it	0.085	0.213	0.054	0.139	0.036	0.092	0.319	<0.001	0.390
Experience with "Carsharing"									
Not familiar with it	Base	Base	Base	Base	Base	Base	Base	Base	Base
Not available in the local area	0.090	0.121	0.055	0.076	0.175	0.050	0.077	0.082	0.080
Available, but not using it	0.111	0.026	0.069	0.054	0.267	0.035	0.179	<0.001	0.196
Available, and using it	0.053	0.634	0.032	-0.248	0.052	-0.139	-0.034	0.716	-0.033
Experience in owning or leasing an AFV (1/0)	0.231	0.001	0.145	0.074	0.304	0.049	-0.040	0.502	-0.044
Opinions about AVs (4-point scale)									
I would accept longer travel times for safety.	0.229	<0.001	0.144	0.181	<0.001	0.119	0.118	<0.001	0.128
I would work more in the AV.	0.111	<0.001	0.070	0.074	0.001	0.049	<0.001	0.980	-0.001
I would allow an AV without a driver to pick up (or drop off) my child.	0.170	<0.001	0.107	0.112	<0.001	0.074	0.132	<0.001	0.144
AVs would enable me to travel more often.	0.208	<0.001	0.131	0.182	<0.001	0.119	0.041	0.017	0.045
Constant	-1.800	<0.001	NA	-1.464	<0.001	NA	-0.413	<0.001	NA
Summary Statistics									
Sample Size (N)	4,248			4,248			4,248		
McFadden's Pseudo R^2	0.118			0.072			0.040		
AIC	7,391.93			7,860.12			10,958.34		
BIC	7,474.53			7,942.73			11,040.94		

Notes:
Coefficients (β's) with a p-value lower than 0.1 are considered meaningful.
M.E. indicates the marginal effect of each explanatory variable

Chapter 3. Adoption of Different Types of Electric Vehicles: Are Commercial Light-Duty Fleet Owners Interested?

A version of this chapter was originally submitted to and presented at the Transportation Research Board 101st Annual Meeting, and was submitted to the International Journal of Sustainable Transportation for publication:

Lee, S., Ahmad, N., and Khattak, A. (2022) Adoption of Electric Vehicles: Is the Commercial Transportation Sector Interested? Transportation Research Board 101st Annual Meeting 2022 (No.22-00449) (*14*).

Lee, S., Ahmad, N., and Khattak, A. Adoption of Different Types of Electric Vehicles: Are Commercial Light-Duty Fleet Owners Interested? Under-review in International Journal of Sustainable Transportation for publication.

ABSTRACT

Vehicle electrification is playing an increasingly important role in developing a sustainable transportation system by addressing energy and environmental issues. In addition to Electric Vehicle (EV) acquisition by individual drivers, fleet owners in the commercial sector also have the potential to adopt a considerable amount of EVs. Focusing on commercial light-duty vehicles weighing less than 10,000 pounds, this study explores whether and to what extent the commercial sector is interested in different types of EVs such as Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles (BEVs), and Fuel Cell Electric Vehicles (FCEVs). The study harnesses data from the 2019 California Vehicle Survey (N=2,301), which interviewed a wide range of commercial light-duty fleet owners. After descriptive analysis, rigorous statistical regression models are estimated to understand the relationships between the intention of EV adoption and company characteristics as well as specific concerns about EVs, while addressing unobserved heterogeneity. Results reveal that 60.9 percent of the companies are interested in adopting either HEVs, PHEVs, BEVs, or FCEVs. Companies in the "healthcare and social assistance," "transportation and warehousing," and "professional, scientific and technical services" industries are found to be more interested in adopting EVs. The key barriers to EV adoption by commercial light-duty fleet owners include the limited hauling capacity of PHEVs, the limited range of BEVs, and the cost of installing fueling equipment for FCEVs. The findings from this study will provide transportation planners, policymakers, and the EV industry with useful insights into barriers to and opportunities for vehicle electrification from the commercial sector's perspective.

Keywords: Electric Vehicle Adoption, Commercial Light-Duty Fleet Owners, Plug-in Hybrid Electric Vehicles, Battery Electric Vehicles, Fuel Cell Electric Vehicles

INTRODUCTION

Vehicle electrification is expected to play an increasingly important role in developing a sustainable transportation system by dealing with energy and environmental issues, a significant part of which is caused by surface transportation. Specifically, it is known that air quality could be improved by using electric vehicles (EVs) depending on the type of electricity source for EVs (*4-5*). According to a previous study, driving an EV can considerably reduce the pollution cost resulting from air pollutants such as Carbon Dioxide (CO_2) and Particulate Matter up to 10 (PM_{10}) compared to driving a conventional vehicle (*4*). In terms of fuel economy, besides, it is known that EVs are more efficient than those vehicles with a gasoline engine (*43-44*). Especially, truck electrification was found to have the potential to reduce energy consumption and costs of truck operations (*45*). With these hopeful expectations, EV adoption has been gradually increasing in the United States although it is in its early stage of diffusion. According to statistics, the annual sales of Plug-in Electric vehicles (PEVs) including Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs) in the United States have increased from 345 units in 2010 to 329,528 units in 2019 (*46*). Accordingly, the market share of PEVs is about 2 percent, and the cumulative sales since December 2010 are more than 1.45 million as of 2019 (*46*). Meanwhile, a study of EV diffusion in Portugal expected that the market share of EVs in Portugal would reach up to 10 percent by 2030 (*47*).

Concerning EV diffusion, it should be noted that EVs can be adopted not only by individual drivers but also by the commercial sector. Notably, the commercial sector has the potential of purchasing a huge amount of EVs considering that there are more than 140 million commercial vehicles in use which takes 53.7 percent of all vehicles in use in the United States as of 2015 (*48*). This implies that the pace of vehicle electrification would be quite dependent on how the commercial sector will be favorable to EVs. Another reason that EV adoption by the commercial sector in the future is especially important is that larger vehicles typically consume more fuel and emit more gasses into the atmosphere (*49-50*). That is, the impact of EV adoption by the commercial sector on the environment and energy would be more powerful than that by individual drivers. Meanwhile, vehicle electrification is currently in development with different types of EVs in terms of how they are powered and charged including Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles (BEVs), and Fuel Cell Electric Vehicles (FCEVs) (*51-52*). Thus, it is also worthy to look into the aspects of different types of EVs.

Focusing on commercial light-duty vehicles with less than 10,000 pounds of gross weight, this study aims to investigate what makes light-duty fleet owners in the commercial sector willing or unwilling to adopt different types of EVs in the future. The analysis is conducted by investigating their willingness to adopt different types of EVs while exploring potential unobserved heterogeneity in contributing factors. The findings from this study will offer deep insights into opportunities and barriers to vehicle electrification from the commercial sector's perspective, which will be a useful reference for transportation planners, policymakers, and the EV industry.

LITERATURE REVIEW

Types of Electric Vehicles

As this study covers different types of EVs, this section briefly introduces EV types as summarized in **Figure 3.1**. According to the United States Department of Energy (USDOE), BEVs, PHEVs, and HEVs can be colloquially called EVs (*51*). While BEVs are powered solely by electricity, PHEVs and HEVs are powered by both liquid fuels and electricity (*51*). The difference between PHEVs and HEVs is that PHEVs should be plugged into an electric power source to charge a battery as described in **Figure 3.2**, whereas HEV batteries are charged only by regenerative braking and not charged by plugging in (*51-53*). Besides, FCEVs are powered solely by electricity and fueled with hydrogen gas as described in **Figure 3.3** (*52*) (*54*). The common feature of HEVs, PHEVs, BEVs, and FCEVs is that they can be charged by regenerative braking (*51-52*). Meanwhile, PHEVs and BEVs can be grouped into Plug-in Electric Vehicles (PEVs) given that they are plugged into an EV charger (*51*).

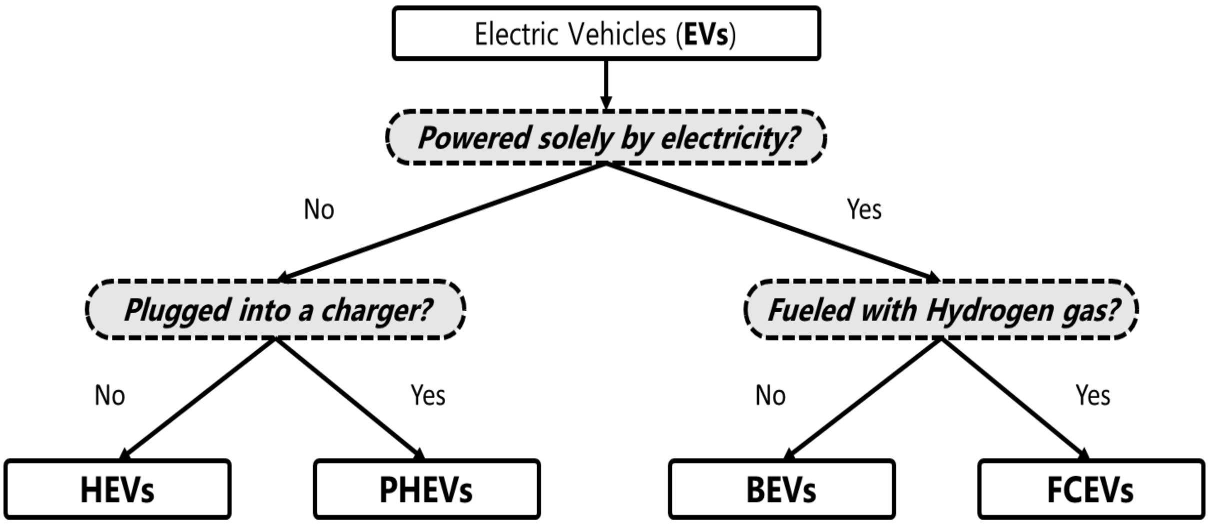


Figure 3.1 Type of Electric Vehicles

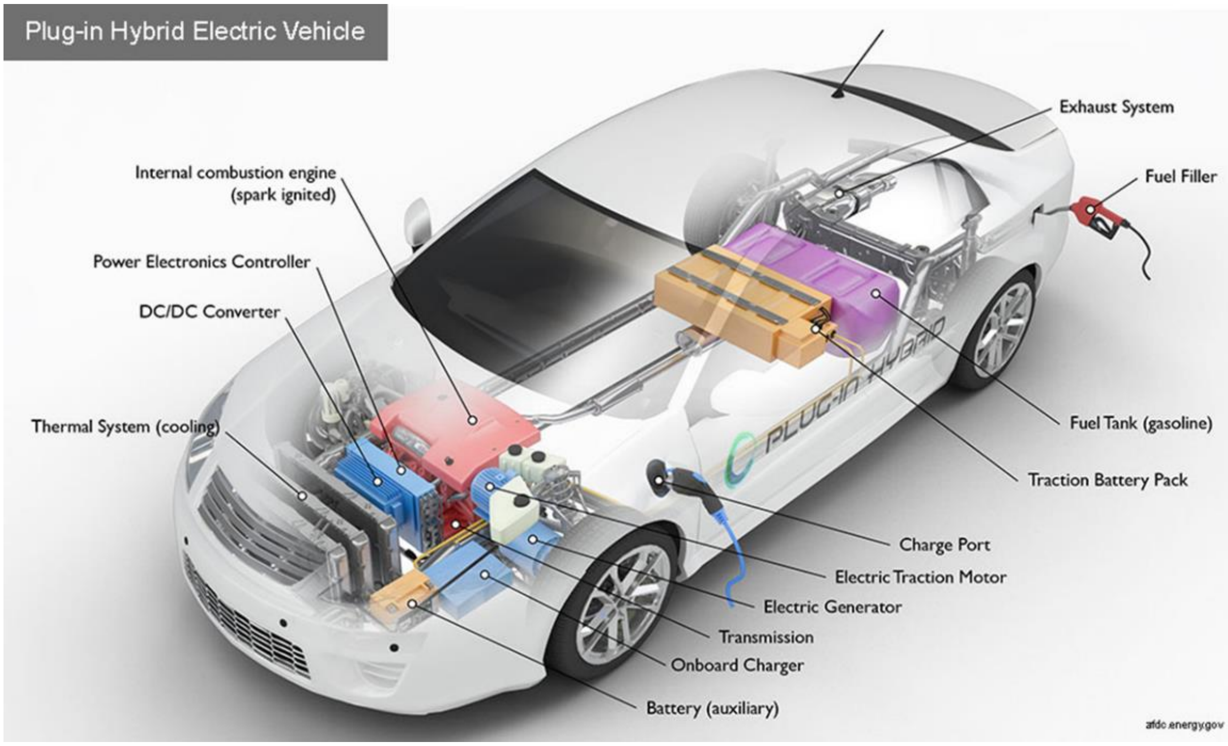


Figure 3.2 Plug-in Hybrid Electric Vehicles (PHEVs) (*53*)

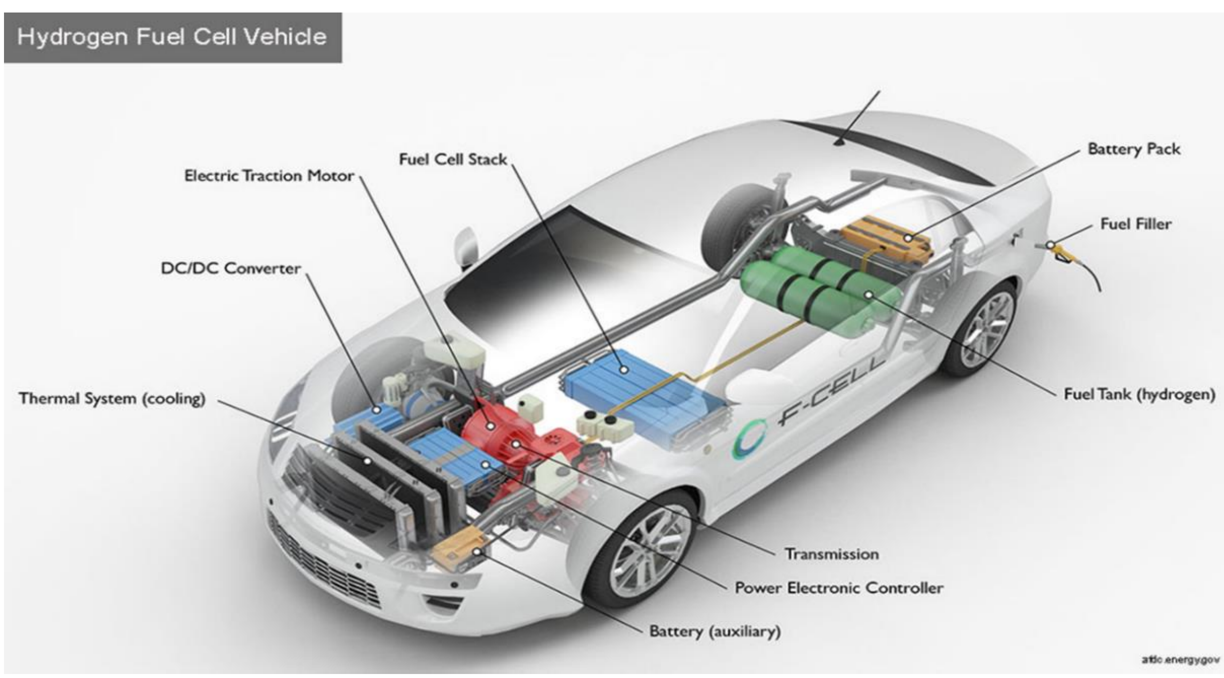


Figure 3.3 Fuel Cell Electric Vehicles (FCEVs) (*54*)

Previous Studies

There have been efforts to explore individual attitudes toward EVs based on surveys. Notably, it was revealed that charger availability in households and awareness of EV technologies had positive impacts on individuals' acceptance of EVs, while electricity price hurt their acceptance of EVs (*55*). In addition, a survey of new-vehicle buyers found that the most frequent concerns about EVs were limited range (mile/battery), charger availability, and high vehicle price (*56*). It also suggested that those who were interested in EVs tended to think that owning EVs would make them look intelligent and responsible for the support of the environment (*56*). Another survey of vehicle consumers revealed that model availability, warranty coverage, and environmental friendliness were the key reasons for choosing EVs, while vehicle price was a critical reason for rejecting EVs (*57*). Further, it was revealed that vehicle consumers' intention to purchase EVs was highly influenced by EV charging time (*58*). On the other hand, it was reported that 19-21% of PHEV and BEV adopters stopped adopting them between 2015 and 2019 mainly due to dissatisfaction with EV charging, preferences for other types of vehicles, and not having level 2 chargers at home (*59*). Recently, there was an attempt to investigate vehicle consumer preferences for vehicle electrification in addition to automation and car-sharing, which identified positive interrelationships among them (*30*).

Although the previous studies have identified some important factors affecting the acceptance or rejection of EVs at an individual level, there is a paucity of studies addressing commercial light-duty fleet owners' preference for EVs. Given that more than 1.4 million vehicles are in use in the commercial sector in the United States as of 2015 (*60*), it would be necessary to investigate their point of view as well as individual drivers' viewpoint regarding vehicle electrification. Another gap in the literature is that few studies have explored the preference for different types of EVs in detail. Although there was a previous attempt to cover the proclivity of the commercial sector to adopt Alternative Fuel Vehicles (AFVs), for instance, it did not classify AFVs into different types (*61*). This study fills these gaps by investigating the commercial light-duty fleet owners' intention to adopt different types of EVs including PHEVs, BEVs, and FCEVs.

METHODOLOGY

Conceptual Framework

As shown in **Figure 3.4**, this study investigates how commercial light-duty fleet owners' intention to adopt EVs can be explained by their company characteristics and specific concerns about EVs. The intention to adopt EVs is divided into the intention to adopt (1) PHEVs, (2) BEVs, and (3) FCEVs. Although the survey data has information on the intention to adopt HEVs, this study does not explore it because the survey data does not have appropriate variables relevant to concerns about HEVs or HEV use. Concerns about EVs consist of specific concerns about PHEVs, BEVs, and FCEVs, while company characteristics include industry types, ownership of different types of EVs, having access to different types of refueling infrastructure, and plans for installing charging infrastructure.

Statistical analysis is performed by estimating rigorous regression models. Specifically, the intention to adopt PHEVs in the future is explained by company characteristics and specific concerns about PHEVs. The intention to adopt BEVs in the future is explained by company characteristics and specific concerns about BEVs. Likewise, the intention to adopt FCEVs in the future is explained by company characteristics and specific concerns about FCEVs.

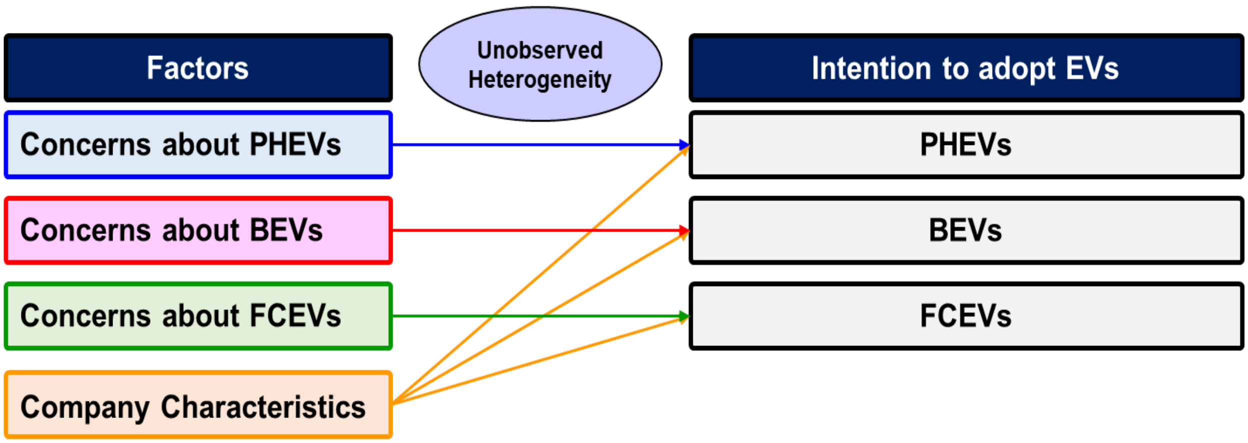


Figure 3.4 Conceptual Framework

Data Source

This study utilizes part of data released by the National Renewable Energy Laboratory, United States Department of Energy(USDOE) which is from the "2019 California Vehicle Survey" conducted by the California Energy Commission (*31*). The survey is mainly a stated preference survey consisting of the survey of residents and commercial light-duty fleet owners in California (*31*). Especially, the commercial survey has interviewed commercial light-duty fleet owners to collect general information about their companies, their concerns about EVs, and their intention to adopt different fuel types for different vehicle classes. It should be noted that "commercial light-duty fleets" in the data refer to those vehicles weighing less than 10,000 pounds including small cars, mid-size cars, full-size cars, Sports Utility Vehicles (SUVs), crossovers, vans, small pickup trucks, and large pickup trucks (*31*). The sample consists of 2,301 companies throughout 20 different types of industry in California based on the 2017 North American Industry Classification System (NAICS) code (*31*). **Table 3.1** shows the survey sample characteristics in terms of industry type and company location. The distribution of location by county is consistent with the distribution of population by county in California (*34*). Meanwhile, 17.8 percent of the sample are classified into the construction industry, 8.8 percent are classified into the professional, scientific, and technical services industry, and 6.6 percent are classified into the healthcare and social assistance industry.

Table 3.2 presents ownership of vehicles by industry in terms fuel types. Overall, a vast majority of commercial light-duty fleet owners rely on gasoline vehicles. In detail, 83.9 percent of commercial light-duty fleet owners have gasoline vehicles. Notably, 90.6 percent and 88.8 percent of the companies in the manufacturing and construction industries have gasoline vehicles, respectively. In addition, 18.6 percent of commercial light-duty fleet owners have diesel vehicles. Specifically, 50.5 percent and 35.0 percent of the companies in the construction agriculture, forestry, fishing, and hunting industry and construction industry have diesel vehicles. On the other hand, EVs are adopted by a minority of commercial light-duty fleet owners. It is revealed that 6.3 percent of commercial light-duty fleet owners have HEVs. Notably, 8.9% of the companies in the wholesale trade industry have HEVs. Besides, 4.7 percent of commercial light-duty fleet owners have PHEVs. Specifically, 11.8 percent of the companies in the healthcare and social assistance industry have PHEVs. In addition, 7.4 percent of commercial light-duty fleet owners have BEVs. Notably, 18.4 percent and 17.8 percent of the companies in the healthcare and social assistance industry and professional, scientific, and technical services industry have BEVs, respectively. Meanwhile, FCEVs are adopted by 0.6 percent of commercial light-duty fleet owners. Specifically, 5.6 percent of the companies in the real estate and rental and leasing industry have FCEVs.

Table 3.3 presents ownership of vehicles by industry in terms of vehicle size. Overall, a majority of commercial light-duty fleet owners have small or large pickup trucks. In detail, small or large pickup trucks are adopted by 53.3 percent of commercial light-duty fleet owners. Specifically, 95.8 percent the companies in the agriculture, forestry, fishing, and hunting industry have small or large pickup trucks. In addition, vans are adopted by 35.7 percent of commercial light-duty fleet owners. Notably, 47.6 percent of the transportation and warehousing industry have vans, respectively. Besides, SUVs or crossovers are adopted by 25.5 percent of commercial light-duty fleet owners. Specifically, 41.4 percent of the companies in the professional, scientific, and technical services industry have SUVs or crossovers. Meanwhile, small, mid-size, and full-size cars are adopted by 27.8 percent of commercial light-duty fleet owners. Notably, 43.1 percent and 42.8 percent of the companies in the professional, scientific, and technical services industry and healthcare and social assistance industry, respectively.

Table 3.1 Survey Sample Characteristics (Commercial Light-Duty Fleet Owners in California)

Sample Characteristics (N=2,301 commercial light-duty fleet owners)	Frequency	%
Industry Type (2017 NAICS Code)		
Construction (23)	409	17.8
Other services (except public administration) (81)	301	13.1
Professional, scientific, and technical services (54)	202	8.8
Retail trade (44)	183	8.0
Manufacturing (31)	181	7.9
Healthcare and social assistance (62)	152	6.6
Wholesale trade (42)	124	5.4
Administrative and support and waste management and remediation services (56)	110	4.8
Agriculture, forestry, fishing, and hunting (11)	95	4.1
Real estate and rental and leasing (53)	90	3.9
Transportation and warehousing (48)	84	3.7
Other	370	16.1
Location by County		
Los Angeles County	640	27.8
Orange County	221	9.6
San Diego County	192	8.3
Alameda County	125	5.4
San Bernardino County	89	3.9
Fresno County	87	3.8
Sacramento County	78	3.4
Riverside County	73	3.2
San Mateo County	65	2.8
Other	731	28.8

Table 3.2 Vehicle Fuel Types by Industry

NAICS Code	Total	Ownership of vehicles by fuel type											
		Gasoline vehicles		Diesel vehicles		HEVs		PHEVs		BEVs		FCEVs	
	Freq.	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
23	409	363	88.8	143	35.0	19	4.6	16	3.9	9	2.2	2	0.5
81	301	268	89.0	37	12.3	21	7.0	5	1.7	12	4.0	2	0.7
54	202	157	77.7	16	7.9	16	7.9	10	5.0	36	17.8	1	0.5
44	183	149	81.4	32	17.5	13	7.1	7	3.8	11	6.0	1	0.5
31	181	164	90.6	24	13.3	9	5.0	7	3.9	9	5.0	1	0.6
62	152	114	75.0	8	5.3	12	7.9	18	11.8	28	18.4	0	0.0
42	124	104	83.9	17	13.7	11	8.9	5	4.0	9	7.3	0	0.0
56	110	95	86.4	30	27.3	5	4.5	5	4.5	3	2.7	0	0.0
11	95	83	87.4	48	50.5	4	4.2	0	0.0	1	1.1	0	0.0
53	90	61	67.8	13	14.4	4	4.4	6	6.7	13	14.4	5	5.6
48	84	70	83.3	25	29.8	5	6.0	6	7.1	3	3.6	0	0.0
Others	370	302	81.6	36	9.7	25	6.8	23	6.2	37	10.0	1	0.3
Total	2,301	1930	83.9	429	18.6	144	6.3	108	4.7	171	7.4	13	0.6

Notes: The NAICS codes can be referred to in **Table 3.1**

Table 3.3 Vehicle Sizes by Industry

NAICS Code	Total	**Ownership of vehicles by size** (less than 10,000 lbs.)							
		Cars (small/mid-size/full-size)		**SUVs or crossovers**		**Vans**		**Trucks** (small/large pickup trucks)	
	Freq.	Freq.	%	Freq.	%	Freq.	%	Freq.	%
23	409	75	18.3	79	19.3	133	32.5	349	85.3
81	301	74	24.6	50	16.6	161	53.5	143	47.5
54	202	87	43.1	83	41.1	43	21.3	60	29.7
44	183	48	26.2	43	23.5	71	38.8	89	48.6
31	181	48	26.5	29	16.0	63	34.8	113	62.4
62	152	65	42.8	54	35.5	61	40.1	28	18.4
42	124	36	29.0	27	21.8	53	42.7	52	41.9
56	110	27	24.5	18	16.4	37	33.6	82	74.5
11	95	15	15.8	27	28.4	6	6.3	91	95.8
53	90	30	33.3	32	35.6	14	15.6	46	51.1
48	84	19	22.6	21	25.0	40	47.6	41	48.8
Others	370	115	31.1	123	33.2	139	37.6	132	35.7
Total	2,301	639	27.8	586	25.5	821	35.7	1226	53.3

Notes: The NAICS codes can be referred to in **Table 3.1**

Analysis Methods

For analysis, this study conducts a descriptive analysis to assess the interest of commercial light-duty fleet owners toward EV adoption and to investigate company characteristics and their concerns about EVs in detail. In addition, for analyzing the relationships between companies' intention to adopt PHEVs, BEVs, or FCEVs and relevant factors, logistic regression models are estimated (*62*). The dependent variables in the models are whether a company considers adopting PHEVs, BEVs, or FCEVs in the future or not. Given that survey data might not capture some influential variables due to a limited number of questions, this study investigates potential unobserved heterogeneity in the impacts of explanatory variables (*63-64*). In order to capture unobserved heterogeneity, this study attempts to estimate random parameters logit models by assuming that the impact of an explanatory variable might vary from company to company (*63-64*).

For the fixed parameters logit models, this study derives the marginal effects of explanatory variables. The marginal effect of an explanatory variable is quantified as the change in the chance that the dependent variable falls into a certain category due to a unit increase in the explanatory variable when the other variables are fixed at their mean values (*65*). Since the explanatory variables in this study have binary outcomes, Yes or No, the mathematical form of marginal effects is written as follows (*66*).

$$\frac{\partial P[Y=i|\boldsymbol{X}]}{\partial X} = \mathrm{P}[Y=i|\boldsymbol{X}, X_k = 1] - \mathrm{P}[Y=i|\boldsymbol{X}, X_k = 0] \quad (1)$$

In equation (1) above, $P[Y = \mathrm{i}]$ is the probability that the dependent variable belongs to a certain category i. Especially for logit models, i can take the value of 0 or 1. While $\boldsymbol{X}$ is a set of explanatory variables, X_k is the kth explanatory variable in a regression model. Accordingly, $X_k = 1$ means that the explanatory variable has the outcome "Yes," while $X_k = 0$ means that it has the outcome "No."

RESULTS

Key Statistics

The key results of the survey are summarized in **Table 3.4** and **Table 3.5**. Most importantly, as shown in **Table 3.4**, 60.9 percent of the companies are willing to adopt either HEVs, PHEVs, BEVs, or FCEVs, while 39.1 percent are not interested in any of them. Specifically, 28.3%, 41.0%, 28.0%, and 7.4% of the companies have the intention to adopt HEVs, PHEVs, BEVs, and FCEVs, respectively, in the future. This reveals that they currently tend to prefer to depend on both batteries and internal combustion engines rather than depending solely on electricity.

As shown in **Table 3.4**, 60.5 percent of the companies are for profit. Concerning industry, 17.8 percent of the companies are categorized as "Construction," while 8.8 percent are categorized as "Professional, scientific, and technical services." Regarding EV ownership, 6.3%, 4.7%, 7.4%, and 0.6% of the companies own HEVs, PHEVs, BEVs, and FCEVs, respectively. When it comes to refueling availability, 6.5 percent of the companies have access to gasoline or diesel refueling facilities. While 3.1 percent of the companies have access to Level 1 (120V) chargers, 6.1 percent have access to Level 2 (240V) chargers and 0.5 percent have access to DC fast chargers. Besides, 0.2 percent of the companies have Hydrogen refueling facilities.

Table 3.5 shows the companies' top concerns about PHEVs, BEVs, and FCEVs in detail.

Table 3.4 Key Statistics: Intention to Adopt EVs and Company Information (N=2,301)

Variable	Frequency	Percentage (%)
Intention to adopt EVs in the future		
Intention to adopt HEVs in the future	652	28.3
Intention to adopt PHEVs in the future	944	41.0
Intention to adopt BEVs in the future	645	28.0
Intention to adopt FCEVs in the future	171	7.4
Intention to adopt HEVs, PHEVs, BEVs, or FCEVs in the future	1,401	60.9
Company Characteristics		
For Profit	1,393	60.5
Industry		
Construction	409	17.8
Wholesale trade	124	5.4
Transportation and warehousing	84	3.7
Healthcare and social assistance	152	6.6
Professional, scientific, and technical services	202	8.8
Other	1,330	57.8
Ownership of EVs		
Ownership of HEVs	144	6.3
Ownership of PHEVs	108	4.7
Ownership of BEVs	171	7.4
Ownership of FCEVs	13	0.6
Ownership of HEVs, PHEVs, BEVs, or FCEVs	387	16.8
Access to gasoline or diesel refueling at or near the company	149	6.5
Access to Level 1(120V) chargers at or near the company	72	3.1
Access to Level 2(240V) chargers at or near the company	140	6.1
Access to DC fast chargers at or near the company	35	1.5
Access to Hydrogen refueling at or near the company	5	0.2
Planning on installing Level 1 chargers in the next 5 years	52	2.3
Planning on installing Level 2 chargers in the next 5 years	148	6.4
Planning on installing DC fast chargers in the next 5 years	43	1.9
Planning on installing Hydrogen refueling capabilities in the next 5 years	7	0.3

Table 3.5 Key Statistics: Top Concerns about EVs (N=2,301)

Variable	Frequency	Percentage (%)
Top Concerns about PHEVs		
Vehicle Price	817	35.5
Limited Number of Seats	192	8.3
Limited Hauling Capacity	869	37.8
Limited Body or Styling of Vehicle	400	17.4
Battery Life Uncertainty	942	40.9
Uncertain Gasoline/Electricity Price	236	10.3
Cost of Installing Charging Infrastructure	831	36.1
Lack of Charging Infrastructure	875	38.0
Charging Time	770	33.5
Uncertain Resale Value	193	8.4
Unreliable Technology	260	11.3
Other	111	4.8
No Concern	139	6.0
No Idea	227	9.9
Top Concerns about BEVs		
Vehicle Price	718	31.2
Limited Range	953	41.4
Limited Number of Seats	158	6.9
Limited Hauling Capacity	736	32.0
Limited Body or Styling of Vehicle	287	12.5
Battery Life Uncertainty	742	32.3
Uncertain Gasoline/Electricity Price	158	6.9
Cost of Installing Charging Infrastructure	600	26.1
Lack of Charging Infrastructure	718	31.2
Charging Time	719	31.3
Uncertain Resale Value	150	6.5
Unreliable Technology	209	9.1
Fear of getting stranded on a job	652	28.3
Other	59	2.6
No Concern	70	3.0
No Idea	281	12.2
Top Concerns about FCEVs		
Vehicle Price	672	29.2
Limited Number of Seats	132	5.7
Limited Hauling Capacity	518	22.5
Limited Body or Styling of Vehicle	279	12.1
Safety of Hydrogen Tank	611	26.6
Uncertain Gasoline/Hydrogen Price	496	21.6
Cost of Installing Fueling Equipment	675	29.3
Lack of Fueling Infrastructure	980	42.6
Uncertain Resale Value	215	9.3
Unreliable Technology	482	21.0
Other	42	1.8
No Concern	76	3.3
No Idea	714	31.0

Regarding PHEVs, 40.9 percent of the companies consider “Battery Life Uncertainty” as one of their top concerns. Moreover, 38.0% and 37.8% of the company have concerns about “Lack of Charging Infrastructure” and “Limited Hauling Capacity,” respectively. In addition, 36.1% of the companies have concerns about the cost of installing charging infrastructure for PHEVs. Meanwhile, 9.9% of the companies have no idea about PHEVs. Concerning BEVs, 41.4 percent of the companies consider “Limited Range” as one of their top concerns. In addition, 32.3% and 32.0% of the companies have concerns about “Battery Life Uncertainty” and “Limited Hauling Capacity,” respectively. Furthermore, 31.3% of the companies have concerns about charging time. Meanwhile, 12.2% of the companies have no idea about BEVs. Regarding FCEVs, 42.6 percent of the companies consider “Lack of Fueling Infrastructure” as one of their top concerns. Besides, 29.3% and 29.2% of the companies have concerns about “Cost of Installing Fueling Equipment” and “Vehicle Price,” respectively. Moreover, 26.6% of the companies have concerns about the safety of Hydrogen tank. Meanwhile, 31.0% of the companies have no idea about FCEVs.

Modeling Results

Intention to Adopt PHEVs in the future

As shown in **Table 3.6**, a fixed-parameter logit model was fitted to understand how explanatory variables affect the probability that a company has intention to adopt PHEVs in the future. No explanatory variables were found to have random parameters. The model was systematically derived by considering the statistical significance and theoretical justification. This study considers the coefficient of an explanatory variable to be meaningful when it is statistically significant at least at the 10% confidence level. All the variables regarding top concerns about PHEVs were included in the model for the sake of completeness. In **Table 3.6**, the coefficients (β's) indicate the relationship between the odds that a company has intention to adopt PHEVs and each explanatory variable. For instance, the coefficient of “Construction” is -0.319, which indicates that the commercial light-duty fleet owners in the construction industry are less likely to be willing to adopt PHEVs in the future. To be specific, if a company belongs to the construction industry, the odds of considering adopting PHEVs in the future decrease by 27.3% (=100-72.7(%)), given that the exponential of the coefficient is 0.727 ($e^{-0.319} = 0.727$). Meanwhile, in **Table 3.6**, the marginal effect (M.E.) of an explanatory variable quantifies the change in the chance that a company is willing to adopt PHEVs in the future due to a unit increase in the variable. For example, the chance of having the intention to adopt PHEVs is reduced by 20.2% when having access to gasoline or diesel refueling available at or near the company.

Notably, this model reveals that the commercial light-duty fleet owners’ intention to adopt PHEVs in the future has a positive relationship with the healthcare and social assistance industry, while having a negative relationship with the construction industry. Regarding EV ownership, the intention to adopt PHEVs in the future has a positive relationship with ownership of HEVs and PHEVs, while having a negative relationship with ownership of BEVs. Concerning access to refueling infrastructure, the intention to adopt PHEVs in the future has a negative relationship with having access to gasoline or diesel refueling at or near the company, while having a positive relationship with having plans for installing Level 1 chargers. When it comes to specific concerns about PHEVs, the intention to adopt PHEVs has negative relationships with concerns about limited hauling capacity and unreliable technology of PHEVs. Moreover, the intention to adopt PHEVs in the future has a negative relationship with having no idea about PHEVs.

Table 3.6 Intention to Adopt PHEVs (Fixed-parameter Logit Model)

Variable	$\boldsymbol{\beta}$	**P-value**	**M.E. (%)**
Industry			
*Construction ****	-0.319	0.008	-7.2
*Healthcare and social assistance ***	0.449	0.013	10.1
Ownership of HEVs ***	0.529	0.004	11.9
Ownership of PHEVs ***	0.728	0.004	16.4
Ownership of BEVs ***	-0.783	<0.001	-17.7
Access to gasoline or diesel refueling ***	-0.897	<0.001	-20.2
Planning on installing Level 1 Chargers **	0.677	0.026	15.3
Top Concerns about PHEVs			
Vehicle Price	-0.036	0.719	-0.8
Limited Number of Seats	-0.012	0.938	-0.3
*Limited Hauling Capacity ****	-0.292	0.004	-6.6
Limited Body or Styling of Vehicle	0.132	0.269	3.0
Battery Life Uncertainty	-0.150	0.133	-3.4
Uncertain Gasoline/Electricity Price	0.031	0.829	0.7
Cost of Installing Charging Infrastructure	0.065	0.514	1.5
Lack of Charging Infrastructure	0.001	0.989	0.0
Charging Time	-0.081	0.422	-1.8
Uncertain Resale Value	-0.065	0.684	-1.5
*Unreliable Technology **	-0.238	0.095	-5.4
Other	-0.219	0.302	-4.9
No Concern	-0.087	0.700	-2.0
*No Idea ****	-1.383	<0.001	-31.2
Constant	0.013	0.929	NA
Model Summary	**Value**		
Sample Size (N)	2,301		
McFadden's R^2	0.053		
AIC	2995.09		
BIC	3121.39		

Notes: Significance Level = *** 0.01, ** 0.05, and * 0.1
M.E. indicates the marginal effect of each variable on the chance of having the intention to adopt PHEVs.

Intention to Adopt BEVs in the future

As shown in **Table 3.7**, fixed- and random-parameter logit models were estimated to explain how explanatory variables affect the probability that a company considers adopting BEVs in the future. The fixed-parameter logit model's Akaike Information Criteria (AIC) value is 2,345.65, while the Bayesian Information Criteria (BIC) value is 2,500.66 and McFadden's R squared is 0.161. The random-parameter logit model's AIC value is 2,342.51, the BIC value is 2,503.26, and McFadden's R squared is 0.162. The random-parameter logit model shows a similar performance to that of the fixed-parameter model in terms of goodness of fit, considering the values of McFadden's R^2, AIC, and BIC. Particularly, the random-parameter model shows slight improvements in McFadden's R^2 and the AIC value, but no improvements in the BIC value.

Concerning unobserved heterogeneity, "having access to gasoline or diesel refueling at or near the company" was found to have random parameters in relation to the dependent variable, commercial light-duty fleet owners' intention to adopt BEVs in the future. The mean of its coefficient is estimated to be -2.782 at the 5% level, while the standard deviation is estimated to be 2.954 at the 10% level. This implies that the impact of having access to gasoline or diesel refueling at or near the company on the willingness to adopt BEVs in the future would vary from company to company rather than being fixed. Meanwhile, the negative relationship between the intention to adopt BEVs in the future and having access to gasoline or diesel refueling at or nearby the company indicates that those commercial light-duty fleet owners with access to refueling infrastructure for gasoline or diesel vehicles are likely to have the inertia of relying on internal combustion engine vehicles.

According to the models, notably, commercial light-duty fleet owners' intention to adopt BEVs in the future has positive relationships with the "transportation and warehousing" and "professional, scientific and technical services" industries, while having a negative relationship with the "wholesale trade" industry. In addition, it has a positive relationship with ownership of BEVs. Concerning access to refueling infrastructure, the intention to adopt BEVs in the future has a negative relationship with having access to gasoline or diesel refueling at or near the company, while having a positive relationship with having access to Level 2 chargers. Further, it has a positive relationship with having plans for installing Level 2 chargers and DC fast chargers in the future. Regarding specific concerns about BEVs, the intention to adopt BEVs in the future has a negative relationship with concerns about the limited range of BEVs and the fear of getting stranded on a job. Meanwhile, it has a negative relationship with having no idea about BEVs.

Intention to Adopt FCEVs in the future

As shown in **Table 3.8**, a fixed-parameter logit model was estimated to understand how explanatory variables influence the probability that a company has the intention to adopt FCEVs in the future. The model's AIC value is 1,217.66, the BIC value is 1,315.26, and McFadden's R squared is 0.028. No explanatory variables were found to have random parameters. Notably, this model reveals that commercial light-duty fleet owners' intention to adopt FCEVs in the future has a negative relationship with the construction industry. As expected, the intention to adopt FCEVs in the future has a positive relationship with ownership of FCEVs. Regarding access to refueling infrastructure, the intention to adopt FCEVs in the future has a negative relationship with having access to gasoline or diesel refueling at or near the company. When it comes to specific concerns about FCEVs, the intention to adopt FCEVs in the future has a negative relationship with concerns about the cost of installing fueling equipment for FCEVs. Meanwhile, it has a negative relationship with having no idea about FCEVs.

Table 3.7 Intention to Adopt BEVs (Fixed- and Random-parameter Logit Models)

Variable	Fixed-parameter			Random-parameter	
	β	P-value	M.E.(%)	β	P-value
For Profit	0.372	0.001	6.0	0.377	0.001
Industry					
Construction	-0.264	0.075	-4.3	-0.239	0.112
Wholesale trade	-0.566	0.029	-9.2	-0.569	0.031
Transportation and warehousing	0.549	0.031	8.9	0.544	0.039
Professional, scientific, and technical services	0.299	0.095	4.8	0.302	0.098
Ownership of BEVs	1.698	<0.001	27.5	1.763	<0.001
Access to gasoline or diesel refueling **(Standard Deviation)**	-1.094	<0.001	-17.7	-2.782 (2.954)	0.050 (0.055)
Access to Level 2 chargers	0.695	0.005	11.3	0.765	0.004
Planning on installing Level 2 chargers	1.357	<0.001	22.0	1.477	<0.001
Planning on installing DC fast chargers	0.972	0.014	15.7	1.113	0.011
Top Concerns about BEVs					
Vehicle Price	0.113	0.342	1.8	0.123	0.308
Limited Range	-0.297	0.011	-4.8	-0.305	0.011
Limited Number of Seats	-0.110	0.595	-1.8	-0.060	0.774
Limited Hauling Capacity	-0.211	0.088	-3.4	-0.208	0.100
Limited Body or Styling of Vehicle	0.217	0.162	3.5	0.208	0.192
Battery Life Uncertainty	-0.174	0.150	-2.8	-0.188	0.126
Uncertain Gasoline/Electricity Price	-0.239	0.259	-3.9	-0.258	0.238
Cost of Installing Charging Infrastructure	0.084	0.494	1.4	0.098	0.433
Lack of Charging Infrastructure	-0.179	0.141	-2.9	-0.166	0.182
Charging Time	-0.099	0.411	-1.6	-0.095	0.439
Uncertain Resale Value	0.099	0.621	1.6	0.158	0.444
Unreliable Technology	-0.247	0.181	-4.0	-0.240	0.205
Fear of getting stranded on a job	-0.324	0.009	-5.2	-0.313	0.014
Other	-0.461	0.188	-7.5	-0.444	0.209
No Concern	0.125	0.682	2.0	0.193	0.539
No Idea	-1.350	<0.001	-21.8	-1.349	<0.001
Constant	-0.899	<0.001	NA	-0.942	<0.001
Model Summary	**Value**			**Value**	
Sample Size (N)	2,301			2,301	
McFadden's R^2	0.161			0.162	
AIC	2345.65			2342.51	
BIC	2500.66			2503.26	

Notes:
M.E. indicates the marginal effect of each variable on the chance of having the intention to adopt BEVs.

Table 3.8 Intention to Adopt FCEVs (Fixed-parameter Logit Model)

Variable	$\boldsymbol{\beta}$	**P-value**	**M.E.(%)**
Industry			
Construction *	-0.421	0.078	-2.8
Ownership of FCEVs **	1.501	0.044	10.1
Gasoline or Diesel refueling available **	-1.176	0.025	-8.0
Top Concerns about FCEVs			
Vehicle Price	0.199	0.310	1.3
Limited Number of Seats	0.048	0.888	0.3
Limited Hauling Capacity	-0.233	0.290	-1.6
Limited Body or Styling of Vehicle	0.072	0.777	0.5
Safety of Hydrogen Tank	-0.137	0.504	-0.9
Uncertain Gasoline/Hydrogen Price	-0.223	0.306	-1.5
Cost of Installing Fueling Equipment **	-0.431	0.037	-2.9
Lack of Fueling Infrastructure	0.001	0.996	0.0
Uncertain Resale Value	-0.188	0.520	-1.3
Unreliable Technology	0.002	0.992	0.0
Other	0.713	0.102	4.8
No Concern	0.073	0.871	0.5
No Idea **	-0.597	0.044	-4.0
Constant	-2.090	<0.001	NA
Model Summary	**Value**		
Sample Size (N)	2,301		
McFadden's R^2	0.028		
AIC	1217.66		
BIC	1315.26		

Notes: Significance Level = *** 0.01, ** 0.05, and * 0.1
M.E. indicates the marginal effect of each variable on the chance of having the intention to adopt FCEVs.

Summary of Marginal Effects

According to the modeling results, the marginal effects of explanatory variables on the intention to adopt PHEVs, BEVs, and FCEVs in the future are visualized in **Figures 3.5 to 3.7**. As shown in **Figure 3.5**, the companies in the healthcare and social assistance industry are associated with a higher chance of having the intention to adopt PHEVs in the future by 10.1%. In addition, concerns about the limited hauling capacity are correlated with a lower chance of having the intention to adopt PHEVs in the future by 6.6%. Likewise, ownership of HEVs is associated with a higher chance of having the intention to adopt PHEVs by 11.9%. As shown in **Figure 3.6**, the companies in the transportation warehousing industry and professional, scientific, and technical services industry are correlated with a higher chance of having the intention to adopt BEVs in the future by 8.9% and 4.8%, respectively. Likewise, concerns about the limited range of BEVs are associated with a lower chance of having the intention to adopt BEVs by 4.8%. As shown in **Figure 3.7**, concerns about the cost of installing fueling equipment are correlated with a lower chance of having the intention to adopt FCEVs in the future by 2.9%.

DISCUSSION

Impacts of Industry

Above all, the results reveal that commercial light-duty fleet owners' intention to adopt EVs in the future is fairly influenced by what industry the company belongs to. The findings on industry types might provide insights into the types of industries willing to increase EV adoption in the near future. It will be a key challenge in EV diffusion to find how to make synergetic connections with those industries. Importantly, it is suggested that "healthcare and social assistance," "transportation and warehousing," and "professional, scientific, and technical services" industries tend to be more interested in vehicle electrification. Specifically, the commercial light-duty fleet owners in the "healthcare and social assistance" industry are more inclined to adopt PHEVs in the future, while the companies in the "transportation and warehousing" and "professional, scientific, and technical services" industries are more inclined to adopt BEVs in the future. On the other hand, it is shown that the companies in the "construction" industry are less interested in vehicle electrification in the future. Specifically, construction companies are less inclined to adopt PHEVs, BEVs, or FCEVs.

Impacts of Refueling Capacity

The results show that commercial light-duty fleet owners' intention to adopt EVs is also affected by the refueling facilities they have access. Notably, it is revealed that those companies with gasoline or diesel refueling available tend to be less interested in adopting PHEVs, BEVs, or FCEVs. On the other hand, having access to EV charging stations would increase the intention to adopt EVs in the future. Particularly, when a company has access to Level 2 chargers at or near its location, it is more likely to be willing to adopt BEVs in the future. These results are intuitively reasonable because, with EV chargers nearby, companies can save time and costs for refueling their EVs, including small cars, midsize cars, full-size cars, small pickup trucks, and large pickup trucks in the long run.

Furthermore, having plans for installing refueling capacities also have an impact on the intention to adopt EVs in the future. In detail, having plans for installing Level 1 chargers would strengthen the willingness to adopt PHEVs. Likewise, having plans for installing Level 2 or DC fast chargers would strengthen the willingness to adopt BEVs in the future.

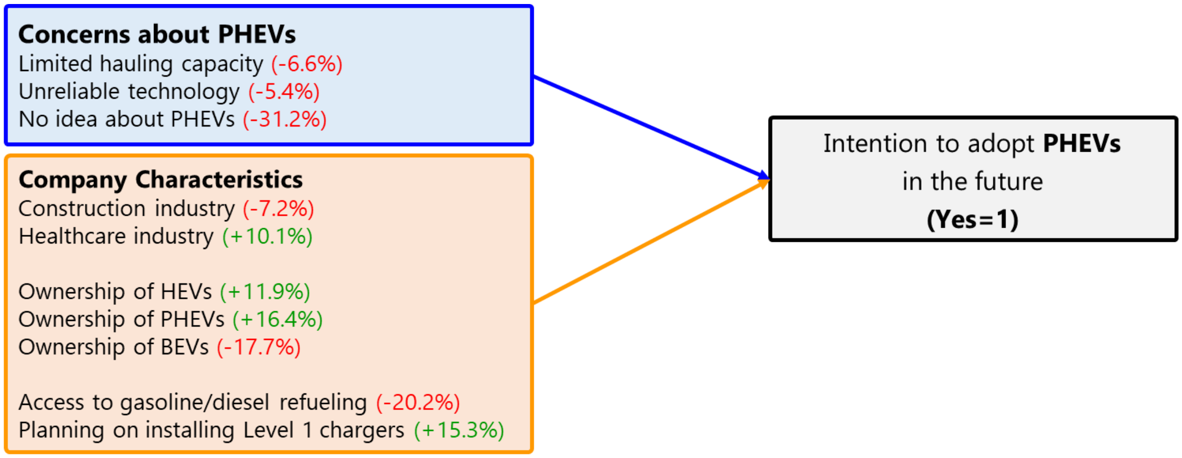


Figure 3.5 Marginal Effects of Explanatory Variables on the Intention to adopt PHEVs

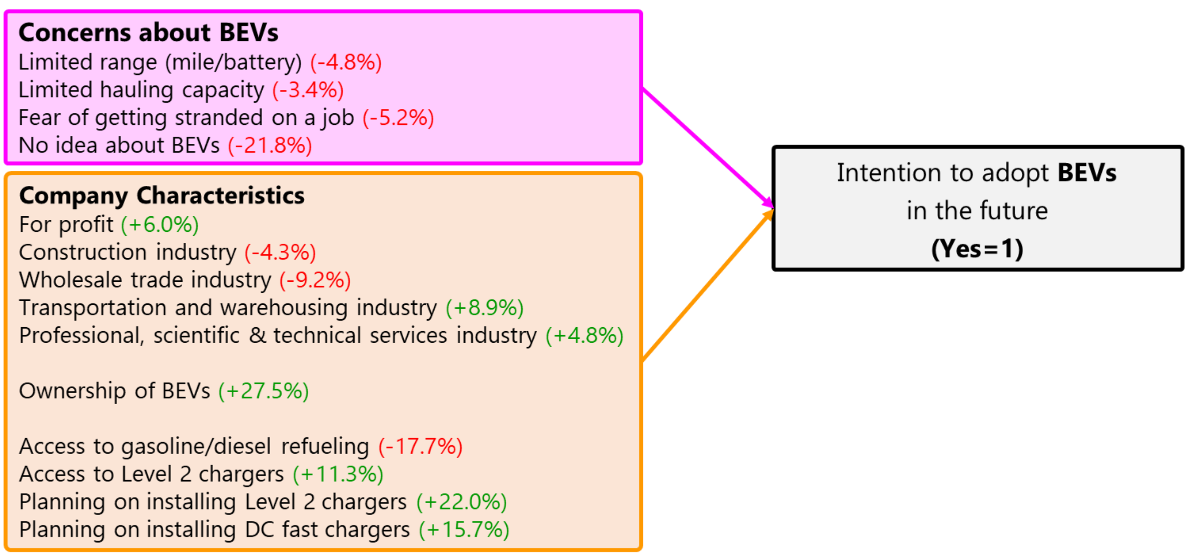


Figure 3.6 Marginal Effects of Explanatory Variables on the Intention to adopt BEVs

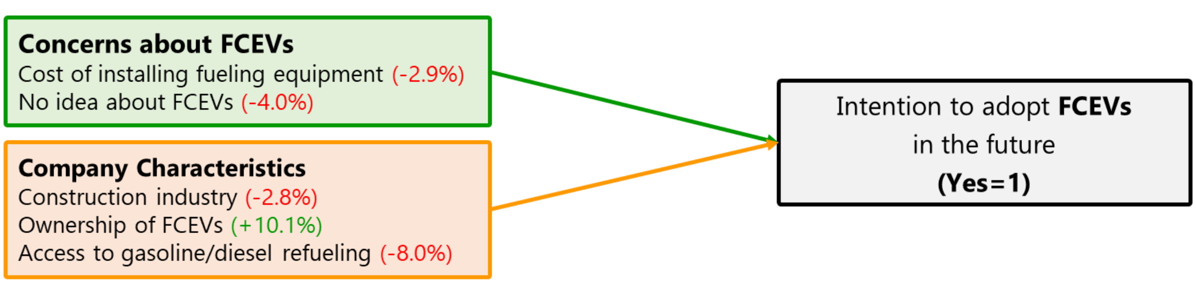


Figure 3.7 Marginal Effects of Explanatory Variables on the Intention to adopt FCEVs

Limitations

As stated earlier, it should be noted that the findings from this study might not be applicable for medium-duty trucks or heavy-duty trucks because the survey accounts for commercial light-duty fleets weighing less than 10,000 pounds, from small cars to large pickup trucks. Future research would need to cover those commercial fleet owners with medium-duty or heavy-duty trucks since they might have unique perceptions of EVs, especially about hauling capacity. In addition, since the survey sample is from a particular region, i.e., California, USA, the results of this study should be interpreted within the context of California. Given that California can be considered one of the leading states in EV adoption with the Clean Vehicle Rebate Program for businesses, part of the survey results could be different if a case study were performed in another region with different contexts (*41*). If a case study were conducted in another state or country with fewer policies to support EV adoptions in the commercial sector, the proportion of the companies that have HEVs, PHEVs, BEVs, and FCEVs would be lower than 6.3%, 4.7%, 7.4%, and 0.6%, respectively. Likewise, the proportion of the companies that have the intention to adopt HEVs, PHEVs, BEVs, and FCEVs in the future would be lower than 28.3%, 41.0%, 28.0%, and 7.4%, respectively. Accordingly, the impact of those variables highly related to the regional contexts would be less generalizable. Even though concerns about vehicle price do not have a significant relationship with the intention to adopt EVs in this study, for instance, the vehicle price-related concerns might have a significantly negative impact on the intention to adopt EVs in other states or countries without a rebate program for businesses. Future research might explore different regions to understand different regional contexts or expand the regional scope to obtain more generalizable insights. Besides, the analysis is solely based on the variables available in the dataset from the survey. For this reason, this study might not have captured some influential factors if the survey had missed any important ones relevant to vehicle electrification.

CONCLUSION

This study investigated commercial light-duty fleet owners' intention to adopt different types of EVs in the future based on data from the 2019 California Vehicle Survey. Descriptive analysis reveals that 60.9 percent of commercial light-duty fleet owners are willing to adopt either HEVs, PHEVs, BEVs, or FCEVs, while 39.1 percent are not interested in any of them. Rigorous statistical analysis identified critical factors influencing commercial light-duty fleet owners' intention to adopt PHEVs, BEVs, and FCEVs, while addressing unobserved heterogeneity. The findings from this study offer practical implications on opportunities and barriers for vehicle electrification from the commercial sector's perspective, which will be a valuable reference for transportation planners, policymakers, and the EV industry, such as vehicle manufacturers.

First, this study provides the EV industry insights into what industries show a high level of interest in vehicle electrification. Given that companies in the "healthcare and social assistance," "transportation and warehousing," and "professional, scientific, and technical services" industries tend to have a higher intention to adopt EVs, the EV industry might have an opportunity to find how to make synergetic connections with those industries. Now that companies that have no idea about EVs are less likely to be willing to adopt EVs, this study also provides the implication that the EV industry would need to make efforts to make the other industries more aware of EV technologies.

In addition, this study provides transportation planners and policymakers with the implication that EV adoption by commercial light-duty fleet owners would be highly dependent on the accessibility of charging infrastructure for PHEVs, BEVs, and FCEVs. This implies that transportation electrification could be considerably delayed solely by a shortage of charging infrastructure. Therefore, it will be critical to endeavor toward sufficient charging infrastructure to deal with different types of light-duty EVs that will be used in a variety of industries.

Furthermore, this study also provides vehicle developers in the EV industry with insights into what aspects of EVs the commercial light-duty fleet owners care about the most. Specifically, the limited hauling capacity of PHEVs, the limited range of BEVs, and the cost of installing fueling equipment for FCEVs would be the most critical barriers to EV adoption by the commercial sector in the future. It is expected that transportation electrification could proceed more successfully if those issues were addressed appropriately.

ACKNOWLEDGMENT

This chapter is based on data released by the National Renewable Energy Laboratory, United States Department of Energy (DOE) from the “2019 California Vehicle Survey” conducted by the California Energy Commission (www.nrel.gov/tsdc). Any opinions, findings, and conclusions, or recommendations in this chapter are those of the authors and do not necessarily reflect the views of those organizations above.

Chapter 4. How Many Battery Electric Vehicle Owners Will Repurchase a Similar Vehicle?

A version of this chapter was originally submitted to and presented at Transportation Research Board 101st Annual Meeting, and was submitted to International Journal of Sustainable Transportation for publication:

Lee, S., Ahmad, N., Son, S., and Khattak, A. (2022) How Many Electric Vehicle Owners Will Repurchase a Similar Vehicle? Transportation Research Board 101st Annual Meeting 2022 (No.22-00240) (*15*).

Lee, S., Ahmad, N., Son, S., and Khattak, A. How Many Electric Vehicle Owners Will Repurchase a Similar Vehicle? Under-review in International Journal of Sustainable Transportation for publication.

ABSTRACT

Vehicle electrification has emerged as a pathway to deal with energy and environmental issues in transportation. As Electric Vehicles (EVs) gain traction with early adopters, there is a need to understand their experiences and their challenges such as range limitations and sparsity of charging infrastructure. Will current Battery Electric Vehicle (BEV) owners repurchase such vehicles in the future? This study sheds light on this question by harnessing data from a carefully designed survey of BEV owners in Jeju, South Korea (N=1,094), implemented in 2018. The survey has valuable information about user perception of BEVs and vehicle features such as range and automation. Among BEV owners, 81.0 percent are found to be willing to (or definitely willing to) repurchase a BEV in the future, while 86.6 percent are found to be satisfied (or very satisfied) with owning a BEV. A rigorous path-analytic framework is developed to quantify the direct and indirect impacts of key factors on willingness to repurchase a BEV in the future while exploring potential unobserved heterogeneity. The results reveal that the often-coupled automation features of BEVs such as collision warning systems were highly associated with greater satisfaction and willingness to repurchase a BEV in the future. Moreover, EV charger availability and policies for helping EV owners in real-time were also found to be influential. This in-depth case study provides meaningful insights into what aspects of vehicle electrification could be improved from the BEV owners' perspective while helping planners, engineers, and policymakers in the transportation field make informed decisions about EV infrastructure.

Keywords: Electric Vehicle, Electric Vehicle Owners, Satisfaction, Repurchase

INTRODUCTION

The surface transportation system has generated environmental issues such as air pollution and greenhouse gas emissions, as well as energy issues through fossil fuels (*67-70*). To address these issues sustainably without imposing restrictions on traffic demand, vehicle electrification has progressed to replace gasoline and diesel with electricity (*19-71*). Once electric vehicles (EVs) successfully penetrate roadways on a significant scale, the transportation system is expected to substantially mitigate these issues depending on what source generates electricity for EVs (*4-5-72*). In practice, EVs are gradually spreading across the world. For instance, the annual sales of plug-in electric vehicles (PEVs) in the United States have gradually increased from 345 units in 2010 to 361,307 units in 2018 (*73*). In South Korea where people can receive a monetary subsidy for EV purchases, the number of registered EVs has increased from 860 units in 2012 to 55,756 units in 2018 (*74-75*). Nonetheless, vehicle electrification still faces many challenges such as technology limitations and infrastructure shortages. Due to those challenges, only a minority of people are currently adopting EVs. For example, the market share of PEVs in the United States was only about 2 percent in 2019 (*73*). In Jeju, South Korea, only 2.8 percent of registered vehicles were EVs in 2018 (*76*). Moreover, California has reported that 19-21% of EV adopters were found to have discontinued adopting EVs between 2015 and 2019 mainly due to charging issues (*16*).

For vehicle electrification to smoothly proceed, it is essential to investigate what EV-related factors encourage (or discourage) vehicle consumers to adopt EVs. Paying attention to Battery Electric Vehicles (BEVs), this study aims to provide vehicle developers with meaningful insights into what aspects of BEVs should be improved from a user perspective, while helping planners, engineers, and policymakers in the transportation field make informed decisions. To accomplish this, it is crucial to explore the viewpoints of two different groups of drivers: BEV owners and non-BEV owners. As early adopters of EV technologies, BEV owners would have quite different viewpoints from those of non-BEV owners due to the gap in BEV use experience. At an early stage of BEV diffusion, the early adopters' decision to (or not to) keep adopting BEVs is highly important. This is because, even if some non-BEV owners start adopting BEVs, diffusion of BEVs will be infeasible in the long run unless BEV owners continue to adopt BEVs in the future. In this regard, this study investigates BEV ownership satisfaction and their willingness to repurchase a BEV in the future. The intellectual merit of this study comes from analyzing these early adopters' perception of BEVs, BEV-related experiences, and vehicle features to figure out what factors regarding BEVs will be important for the progress of vehicle electrification in the future.

LITERATURE REVIEW

In advance of reviewing previous studies, it is important to clearly define terminologies concerning EVs. In a broad sense, Alternative Fuel Vehicles (AFVs) refer to those vehicles charged with alternative fuels such as electricity and hydrogen (*39-43*). According to the U.S. Department of Energy (DOE), Plug-in Electric Vehicles (PEVs) can be divided into Battery Electric Vehicles (BEVs) powered solely by electricity and Plug-in Hybrid Electric Vehicles (PHEVs) powered by liquid fuels and electricity (*51*). This study provides insights into BEVs as the survey was conducted for BEV owners.

There have been some attempts to conduct surveys to explore the factors affecting EV purchases. It was revealed that consumers' willingness to purchase PEVs would be increased by consumer-related factors such as level of education, possession of conventional hybrid cars, and concerns about the environment (*77*). In addition, consumer-related factors such as age and household income were found to have a positive relationship with ownership of AFVs depending on region (*39-78*). Meanwhile, drivers' EV purchase intentions were found to be affected by vehicle-related factors such as vehicle price and performance as well as policy-related factors such as government subsidies (*79*). Besides, it was found that improvement in charger availability, especially at home, had a great impact on BEV and PHEV sales (*78-80*).

While these studies offer useful insights into EV purchases, there is a gap concerning survey samples. Surveys were often conducted without a clear classification of respondents such as whether they already owned EVs or not. Now that EV owners have more experience with driving an EV than non-EV owners, the viewpoints of EV owners will be quite different from those of non-EV owners. This implies that surveys without consideration of this difference could be at risk of misleading conclusions. In this regard, this study harnesses data from a survey of BEV owners to focus on their point of view.

There have also been attempts to conduct surveys to explore the factors influencing EV ownership satisfaction. Previous studies suggested that EV ownership satisfaction was substantially affected by user experience and charging infrastructure. For example, EV ownership was found to be positively influenced by charger availability in residence but negatively influenced by frequent use of public chargers and charger malfunctions (*81*). Satisfaction with EV charging was also identified to be a key factor having a high impact on the overall satisfaction with owning an EV (*82*). Furthermore, it was revealed that EV ownership satisfaction was dependent on EV range (mile/battery) and understanding of EV policies (*81-82*). Meanwhile, previous studies have also explored EV owners' daily charger use demands. For instance, a survey showed that EV owners preferred to use chargers at home or work when commuting, whereas they preferred to use public charging stations when making a family trip (*83*). Another survey revealed a high demand in Germany for public charging stations, especially with semi-fast chargers (*84*).

Although the aforementioned studies identified influential factors relevant to EV purchase or EV ownership satisfaction, they relied heavily on subjective information (i.e., thoughts or experience) from the respondents. Considering that subjective information may provide limited insights, this study suggests that more objective-level information such as vehicle features needs to be collected. In this regard, this study put significant effort into extracting key information on vehicle features based on a survey of BEV owners. For the sake of appropriateness and fluency, this study systematically categorizes explanatory variables into perceptions of BEVs, vehicle features, and user contexts.

METHODOLOGY

Data Source

This study harnesses data from the "Survey of Battery Electric Vehicle Owners in Jeju" conducted by Jeju Special Self-Governing Province and Jeju Research Institute (JRI) in South Korea. The survey was conducted for EV owners in Jeju, South Korea from December 5th to 14th 2018. By referring to the vehicle registration database in Jeju, surveyors called BEV owners to ask if they could take part in the survey and to arrange the date and time to visit them in person. The respondents answered the questions about their BEV use, stated preferences, and socio-economic information within a carefully designed survey structure (**Figure 4.1**). In in-person interviews, surveyors tried their best to offer careful instructions to respondents in order to avoid potential bias from stated-preference questions. The respondents were asked to provide accurate and honest answers. The survey has a valid sample size of 1,094 respondents. Most importantly, vehicle features were extracted by referring to vehicle models reported by respondents, official websites of automobile companies, and other websites offering a historical database of vehicle models (*85-94*). Given that the survey was conducted in 2018, vehicle features have been estimated with conservative (minimum) values based on vehicle models that were available in the market in 2018 or before. Regarding survey sample characteristics, as summarized in **Table 4.1**, it should be noted that the early adopters of BEVs do not represent the general population of Jeju, South Korea given that their average monthly household income (3.29 thousand USD) is higher than that of the general population (2.33 thousand USD) while they overrepresents middle-aged people and males (*95*). This strengthens the idea that it is reasonable to categorize drivers into early adopters of BEVs and non-BEV owners when exploring their willingness to purchase a BEV. Therefore, the results of this study should be interpreted with a focus on this specific group.

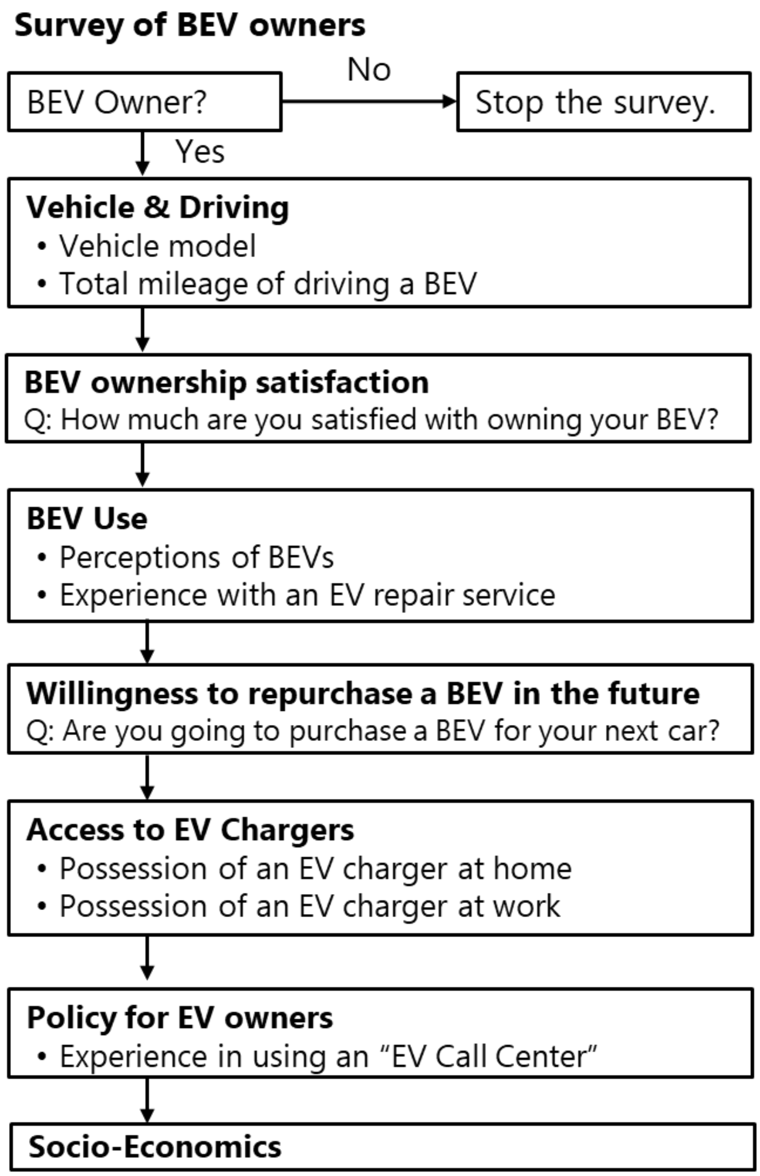


Figure 4.1 Survey Structure

Table 4.1 Survey Sample Characteristics (BEV owners in Jeju, South Korea)

Sample Characteristics (N=1,094 BEV owners)	Survey (2018)	General Population of Jeju (2018)
Average monthly household income		
(KRW in millions)	3.67	2.60
(USD in thousands)	3.29	2.33
Age Group (%)		
20-30	6.1	14.5
30-39	21.7	16.8
40-49	30.8	21.6
50-59	24.2	20.5
60 or more	17.2	26.6
Gender (%)		
Female	33.9	49.5
Male	66.1	50.5

Notes: 1.00 million KRW = 898 USD as of Dec 6, 2018 (*96*)

Conceptual Framework

Based on the theory of post-purchase consumer behavior suggesting that decision to repeat purchases is directly dependent on overall satisfaction, as summarized in **Figure 4.2**, this study attempts to capture the explanatory variables having a direct relationship with willingness to repurchase a BEV as well as the ones having an indirect relationship with it within a path-analytic framework (*97*). The analysis consists of a two-stage ordered logistic regression. In the first stage, "BEV ownership satisfaction" is regressed on explanatory variables that are classified into perceptions of BEVs, vehicle features, and user contexts. Next in the second stage, "Willingness to repurchase a BEV in the future" is regressed on explanatory variables and "BEV ownership satisfaction." In this stage, "BEV ownership satisfaction" connects those explanatory variables from the first stage to the dependent variable, "Willingness to repurchase a BEV in the future."

Modeling Framework

This study applies ordered logistic regression models to explore "BEV ownership satisfaction" and "Willingness to repurchase a BEV in the future" while keeping the ordinal nature of both variables. As summarized in **Table 4.2**, the responses to both variables were collected via a 5-level ordinal scale. The mathematical form is given as (*98-99*):

$$Y^* = \boldsymbol{\beta X} + \varepsilon \tag{1}$$

, where Y^* is the latent variable that is considered exact but unobserved, $\boldsymbol{X}$ is a set of explanatory variables, $\boldsymbol{\beta}$ is a set of coefficients, and ε is the error term. For explore the evidence of unobserved heterogeneity, this study additionally applies the assumption that the impact of an explanatory variable might vary from person to person. In this case, a random-parameter ordered logit model is estimated, where some coefficients can be individual-specific (*98-100*).

The value of the latent variable, Y^*, determines the dependent variable (Y) as follows (*98-100*):

$$\begin{aligned} &\mathrm{Y} = 1 \ \text{ if } \quad Y^* \le \mu_1 \\ &\mathrm{Y} = \mathrm{k} \ \text{ if } \ \mu_{\mathrm{k}-1} < Y^* \le \mu_{\mathrm{k}} \ \text{ when } \ 1 < \mathrm{k} < 5 \\ &\mathrm{Y} = 5 \ \text{ if } \quad \mu_4 < Y^* \end{aligned} \tag{2}$$

, where μ's are thresholds between categories of the dependent variable, Y. In the first model, Y refers to "BEV ownership satisfaction," while it refers to "Willingness to repurchase a BEV in the future" in the second model. The probability that the dependent variable (Y) belongs to a certain level is determined based on the cumulative density function (CDF) of the logistic distribution (*98-100*).

For fixed parameters models, this study derives the marginal effect of each explanatory variable to quantify its exact impacts on the dependent variable. The marginal effect of an explanatory variable refers to the percent change in the chance that the dependent variable belongs to a certain level resulting from a unit increase in the explanatory variable when the other variables are held at their mean values (*65-101-102*). The general form of the marginal effect of a continuous variable is written as (*65-101-102*):

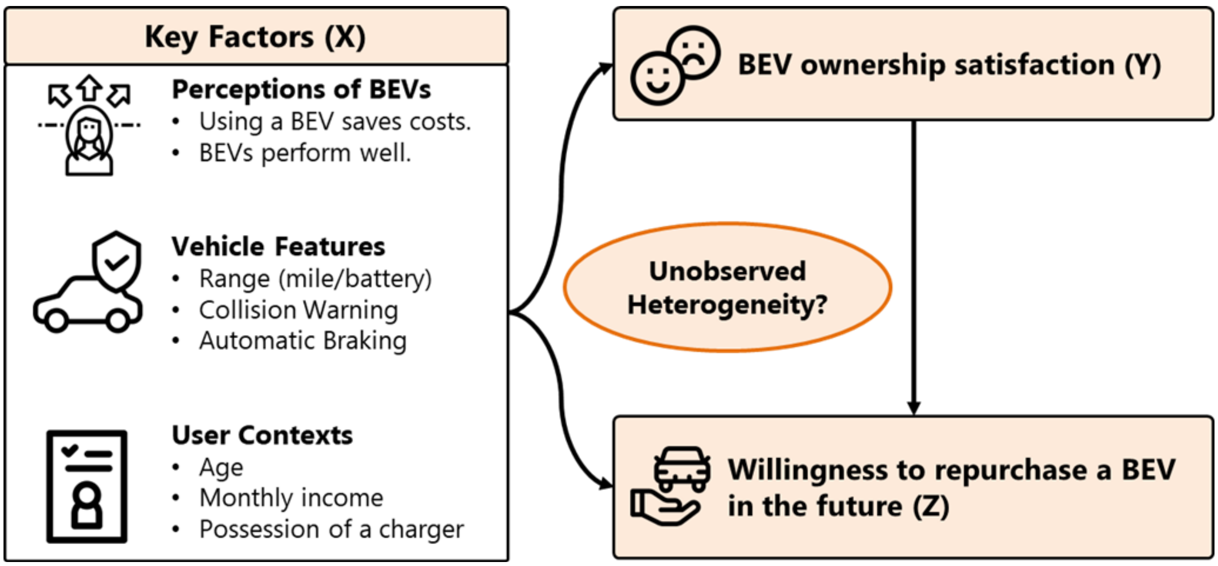


Figure 4.2 Framework of Analysis

$$ME_i(X) = \frac{\partial P[Y=i|X]}{\partial X} = \frac{\partial[F(\mu_i - \beta X) - F(\mu_{i-1} - \beta X)]}{\partial X} = [f(\mu_{i-1} - X\beta) - f(\mu_i - X\beta)]\beta \quad (3)$$

, where $f(z) = dF(z)/dz$ and F denotes the cumulative density function (CDF). Concerning a discrete variable, the form of marginal effects is written as (*65-101-102*):

$$\Delta \mathrm{P}[Y = i|X] = \mathrm{P}[Y = i|X + \Delta X] - \mathrm{P}[Y = i|X] \quad (4)$$

, where ΔX is a discrete unit increase in the explanatory variable X.

RESULTS

Descriptive Statistics

Tables 4.2 and 4.3 show key statistics of important variables from the survey of BEV owners. In the case where a respondent had 2 or more BEVs, answers were provided based on the vehicle he or she had purchased for the first time. Those samples with missing or invalid values were removed so that the statistics have valid and reasonable values. As shown in **Table 4.2**, most importantly, 81.0 percent of the respondents (886/1,094) were willing to (or definitely willing to) repurchase a BEV in the future. On the other hand, 19.0 percent of the respondents (208/1,094) were not willing or not sure whether to purchase a BEV again in the future, which is aligned with the EV discontinuance rate (19-21%) reported by California (*16*). Meanwhile, 88.6 percent of the respondents (947/1,094) were satisfied (or very satisfied) with owning a BEV.

From **Table 4.2**, the relationship between “BEV ownership satisfaction” and “Willingness to repurchase a BEV in the future” is found to have a positive relationship at the 99% confidence level given that a chi-square test of independence provides the Pearson chi-square statistic of 477.63 with 16 degrees of freedom and the p-value lower than 0.001. Notably, 61.6 percent of those who were “very satisfied” with owning a BEV were found to be “definitely willing to repurchase a BEV” in the future. Besides, none of those who were “dissatisfied” with owning a BEV were “definitely willing to repurchase a BEV.” Meanwhile, 1 out of 6 who were “very dissatisfied” with owning an EV was found to be “definitely willing to repurchase a BEV” in the future, which seems to be an exceptional case.

In addition, variables from the survey consist of different perceptions of BEVs and user contexts as shown in **Table 4.3**. Importantly, 28.0 percent of the BEV owners do not think it is easy to charge a BEV, while 41.9 percent do not think it takes a short time to wait to use public chargers. Moreover, it is shown that 75.5 percent of the EV owners have EV chargers at home, while 39.7 percent have access to EV chargers at their workplace. Besides, 70.8 percent of the BEV owners have experience with an EV repair service, while 19.7 percent have experience in using an EV Call Center.

Table 4.4 presents descriptive statistics of vehicle features estimated. Statistics show that the average values of range, number of seats, engine power, and charging time are 143.61 (mile/battery), 4.89, 127.49 hp, and 6.24 hours, respectively. Notably, variables pertinent to automation such as whether a vehicle exhibited features such as a collision warning system or automatic braking system were also extracted. While 32.0 percent of BEVs did not have a collision warning or automatic braking system, 1.0 percent of BEVs had both a collision warning and automatic braking system.

Table 4.2 BEV ownership satisfaction vs. Willingness to repurchase a BEV in the future

BEV ownership satisfaction		**Willingness to repurchase a BEV in the future**					Total
		Not at all	*No*	*Not sure*	*Yes*	*Definitely yes*	
Very dissatisfied	Count	0	0	2	3	1	6
	% within Satisfaction	0.0	0.0	33.3	50.0	16.7	100.0
Dissatisfied	Count	3	8	9	5	0	25
	% within Satisfaction	12.0	32.0	36.0	20.0	0.0	100.0
Neutral or neither	Count	9	16	48	31	12	116
	% within Satisfaction	7.8	13.8	41.4	26.7	10.3	100.0
Satisfied	Count	3	8	74	247	86	418
	% within Satisfaction	0.7	1.9	17.7	59.1	20.3	100.0
Very satisfied	Count	1	2	25	175	326	529
	% within Satisfaction	0.2	0.4	4.7	33.1	61.6	100.0
Total	Count	16	34	158	461	425	1,094
	% within Satisfaction	1.5	3.1	14.4	42.1	38.8	100.0

Table 4.3 Key Statistics of the BEV Owner Survey

Variable	Freq. / Mean	Percent. / S.D.	Min.	Max.
Willingness to repurchase a BEV in the future				
Not at all	16	1.5	0	1
No	34	3.1	0	1
Not sure	158	14.4	0	1
Yes	461	42.1	0	1
Definitely yes	425	38.8	0	1
BEV ownership satisfaction				
Very dissatisfied	6	0.5	0	1
Dissatisfied	25	2.3	0	1
Neutral or neither	116	10.6	0	1
Satisfied	418	38.2	0	1
Very satisfied	529	48.4	0	1
Perception: Using a BEV saves costs. (5-point scale)				
1: Totally disagree	2	0.2	0	1
2: Disagree	5	0.5	0	1
3: Not sure	13	1.2	0	1
4: Agree	191	17.5	0	1
5: Totally agree	883	80.7	0	1
Perception: BEVs perform well. (5-point scale)				
1: Totally disagree	4	0.4	0	1
2: Disagree	22	2.0	0	1
3: Not sure	98	9.0	0	1
4: Agree	357	32.6	0	1
5: Totally agree	613	56.0	0	1
Perception: It is easy to charge a BEV. (5-point scale)				
1: Totally disagree	114	10.4	0	1
2: Disagree	193	17.6	0	1
3: Not sure	353	32.3	0	1
4: Agree	267	24.4	0	1
5: Totally agree	167	15.3	0	1
Perception: It takes a short time to wait for others to use public chargers. (5-point scale)				
1: Totally disagree	150	13.7	0	1
2: Disagree	308	28.2	0	1
3: Not sure	368	33.6	0	1
4: Agree	203	18.6	0	1
5: Totally agree	65	5.9	0	1
Perception: BEVs are safe. (5-point scale)				
1: Totally disagree	26	2.4	0	1
2: Disagree	77	7.0	0	1
3: Not sure	266	24.3	0	1
4: Agree	523	47.8	0	1
5: Totally agree	202	18.5	0	1

Table 4.3 (Continued)

Variable	Freq. / Mean	Percent. / S.D.	Min.	Max.
Age (years) *	47.47	11.54	25	65
Monthly household income (KRW in million) *	3.67	1.99	0.51	9.51
(USD in thousands) *	3.29	1.78	0.45	8.54
Total mileage of driving a BEV (miles in thousands) *	12,253.1	14,976.7	1.2	124,895.6
Possession of an EV charger at home	826	75.5	0	1
Possession of an EV charger at work	434	39.7	0	1
Experience with an "EV repair service"	775	70.8	0	1
Experience in using an "EV Call Center"	215	19.7	0	1

Notes: Variables with * are continuous, which means the first and second columns indicate their mean and standard deviation (S.D.).
1.00 million KRW = 898 USD as of Dec 6, 2018 (*96*)

Table 4.4 Key Statistics of Vehicle Features

Variable	Freq. / Mean	Percent. / S.D.	Min.	Max.
Price (USD) *	32,956	5,423	7,855	42,500
Range (mile/battery) *	143.61	44.90	50.0	238.0
Number of Seats (N) *	4.89	0.56	1	5
Engine Power (hp) *	127.49	36.95	5.0	204.0
Charging time at 240V (hour) *	6.24	2.06	2.5	14.0
Automation Features				
Collision Warning System = No Automatic Braking System = No	350	32.0	0	1
Collision Warning System = Yes Automatic Braking System = No	303	27.7	0	1
Collision Warning System = No Automatic Braking System = Yes	430	39.3	0	1
Collision Warning System = Yes Automatic Braking System = Yes	11	1.0	0	1

Notes: Variables with * are continuous, which means the first and second columns indicate their mean and standard deviation (S.D.).

Modeling Results

Model 1: BEV ownership satisfaction

In the first stage, as summarized in **Table 4.5**, a fixed-parameter ordered logit model of "BEV ownership satisfaction" was estimated with the most important variables based on statistical significance and theoretical justification. This study considers a coefficient meaningful to interpret when its p-value is lower than 0.1. The model has McFadden's R squared of 0.204, which means it fits well with the data. Concerning unobserved heterogeneity, no variables were found to have random parameters in relation to BEV ownership satisfaction. This study did not find evidence of heterogeneity in a sample that comes from a specific region of South Korea, i.e., Jeju Province.

Regarding perceptions of BEVs, as shown in **Table 4.5**, the perception that using a BEV saves costs is found to be the most influential factor to increase BEV ownership satisfaction. Likewise, BEV ownership satisfaction is found to have a positive relationship with perceptions concerning BEV performance, easiness to charge a BEV, waiting time for others to use public chargers, and BEV safety. When it comes to vehicle features, a collision warning system is found to be the most powerful factor to increase BEV ownership satisfaction. In addition, BEV ownership satisfaction has a negative relationship with vehicle price, while having a positive relationship with EV range. Concerning user contexts, BEV ownership satisfaction has a positive relationship with possession of an EV charger at home or work, while having a negative relationship with the experience with an EV repair service. Meanwhile, age is found to have a negative relationship with BEV ownership satisfaction.

Additionally, as shown in **Table 4.6**, this study derived the marginal effect of each explanatory variable to quantify the change in the chance that BEV ownership satisfaction belongs to a certain level due to a unit increase in an explanatory variable when all the other variables are fixed at their mean values. For example, a unit increase in the perception that using a BEV saves costs is correlated with a higher chance of being very satisfied with owning a BEV by 18.04%. Likewise, a collision warning system is associated with a higher chance of being very satisfied by 11.71%.

Model 2: Willingness to repurchase a BEV in the future

In the second stage, a model of "Willingness to repurchase a BEV in the future" was estimated as summarized in **Table 4.7**. A 90% confidence criterion was used to select explanatory variables while "Monthly household income" was included with theoretical justification. The model has a McFadden's R squared value of 0.162. Concerning unobserved heterogeneity, no variables were found to have random parameters in relation to the willingness to repurchase a BEV in the future.

In **Table 4.7**, Model 2 reveals an increase in BEV ownership satisfaction would result in a stronger willingness to repurchase a BEV in the future. By exception, the coefficient of "very dissatisfied" is positive because 4 out of 6 respondents who are "very dissatisfied" are willing to repurchase a BEV in the future. The results also indicate that the willingness to repurchase a BEV has a positive relationship with age and monthly income. Besides, the total mileage of driving a BEV and the experience in using an EV Call Center have a positive relationship with the willingness to repurchase a BEV in the future.

Marginal effects of explanatory variables in Model 2 are summarized in **Table 4.8**. When a BEV owner is very satisfied with owning a BEV, the chance that he or she is definitely willing to repurchase a BEV would be higher by 57.25%, compared to when he or she is neither satisfied nor dissatisfied. Likewise, if a BEV owner has the experience in using an EV Call Center, the chance that he or she is definitely willing to repurchase a BEV in the future increases by 5.25%.

Table 4.5 Model 1: BEV ownership satisfaction

Explanatory Variable	Coefficient	z-stat	P-value
Perception of BEVs (5-point scale)			
Using a BEV saves costs. ***	1.010	7.20	<0.001
BEVs perform well. ***	0.743	7.67	<0.001
It is easy to charge a BEV. ***	0.395	6.42	<0.001
It takes a short time to wait for others to use public chargers. ***	0.264	3.87	<0.001
Perception: BEVs are safe. ***	0.321	4.13	<0.001
Vehicle Feature			
Price (USD in thousand) **	-0.053	-2.09	0.021
Range (mile/battery) **	0.005	2.11	0.018
Automation Features			
Collision Warning = No / Automatic Braking = No	Base	Base	Base
Collision Warning = Yes / Automatic Braking = No ***	0.656	2.60	0.009
Collision Warning = No / Automatic Braking = Yes	0.066	0.42	0.672
Collision Warning = Yes / Automatic Braking = Yes	0.467	0.63	0.526
User Context			
Age ***	-0.018	-3.11	0.002
Possession of an EV Charger at Home ***	0.423	2.83	0.005
Possession of an EV Charger at Work **	0.274	2.07	0.039
Experience with an EV Repair Service ***	-0.546	-3.73	<0.001
Thresholds	**Coefficient**	**z-stat**	**P-value**
μ_1: between Satisfaction Levels 1 and 2	3.371	3.33	0.001
μ_2: between Satisfaction Levels 2 and 3	5.168	5.45	<0.001
μ_3: between Satisfaction Levels 3 and 4	7.266	7.61	<0.001
μ_4: between Satisfaction Levels 4 and 5	10.031	10.16	<0.001
Model Summary	**Value**		
Number of Observations (N)	1,094		
McFadden's R^2	0.204		
AIC	1902.14		
BIC	1992.10		

Notes: Significance Level = *** 0.01, ** 0.05, and * 0.1

Table 4.6 Marginal Effects (Model 1): BEV ownership satisfaction

Explanatory Variable	Marginal Effects (%)				
	Very dissatisfied	Dissatisfied	Neutral or neither	Satisfied	Very satisfied
Perception of EVs (5-point scale)					
Using a BEV saves costs.	-0.54	-1.79	-6.05	-9.66	18.04
BEVs perform well.	-0.40	-1.32	-4.45	-7.10	13.26
It is easy to charge a BEV.	-0.21	-0.70	-2.37	-3.78	7.06
It takes a short time to wait to use public chargers.	-0.14	-0.47	-1.58	-2.53	4.72
BEVs are safe.	-0.17	-0.57	-1.92	-3.07	5.73
Vehicle Feature					
Price (USD in thousands)	0.03	0.09	0.31	0.50	-0.94
Range (mile/battery)	0.00	-0.01	-0.03	-0.05	0.09
Automation Features					
Collision Warning = No Automatic Braking = No	Base	Base	Base	Base	Base
Collision Warning = Yes Automatic Braking = No	-0.32	-1.07	-3.72	-6.59	11.71
Collision Warning = No Automatic Braking = Yes	-0.04	-0.13	-0.42	-0.59	1.18
Collision Warning = Yes Automatic Braking = Yes	-0.25	-0.81	-2.75	-4.57	8.38
User Context					
Age	0.01	0.03	0.11	0.17	-0.32
Possession of an EV Charger at Home	-0.23	-0.75	-2.53	-4.04	7.55
Possession of an EV Charger at Work	-0.15	-0.49	-1.64	-2.62	4.89
Experience with an EV Repair Service	0.29	0.97	3.27	5.22	-9.75

Table 4.7 Model 2: Willingness to repurchase a BEV in the future

Explanatory Variable	**Coefficient**	**z-stat**	**P-value**
BEV ownership satisfaction			
Very dissatisfied *	1.560	1.92	0.055
Dissatisfied ***	-1.162	-2.81	0.005
Neutral or neither	Base	Base	Base
Satisfied ***	1.807	8.43	<0.001
Very satisfied ***	3.597	15.57	<0.001
User Contexts			
Age ***	0.019	3.66	<0.001
Monthly household income (USD in thousands)	0.041	1.17	0.241
Total mileage of driving a BEV (miles in thousand) ***	0.012	2.93	0.003
Experience in using an EV Call Center *	0.287	1.76	0.079
Thresholds	**Coefficient**	**z-stat**	**P-value**
μ_1': between Willingness Levels 1 and 2	-1.575	-3.95	<0.001
μ_2': between Willingness Levels 2 and 3	-0.260	-0.76	0.450
μ_3': between Willingness Levels 3 and 4	1.776	5.20	<0.001
μ_4': between Willingness Levels 4 and 5	4.351	11.89	<0.001
Model Summary	**Value**		
Number of Observations (N)	1,094		
McFadden's R^2	0.162		
AIC	2188.682		
BIC	2248.653		

Notes: Significance Level = *** 0.01, ** 0.05, and * 0.1

Table 4.8 Marginal Effects (Model 2): Willingness to repurchase a BEV in the future

Explanatory Variable	Marginal Effects (%)				
	Not at all	**No**	**Not sure**	**Yes**	**Definitely yes**
EV ownership satisfaction					
Very dissatisfied	-4.57	-9.42	-21.87	22.27	13.59
Dissatisfied	10.59	12.47	-1.76	-18.24	-3.05
Neutral or neither	Base	Base	Base	Base	Base
Satisfied	-4.85	-10.12	-25.38	22.88	17.47
Very satisfied	-5.69	-12.31	-39.99	0.74	57.25
User Contexts					
Age	-0.03	-0.05	-0.15	-0.13	0.35
Monthly Income (USD in thousands)	-0.05	-0.10	-0.31	-0.28	0.74
Total mileage of driving a BEV (miles in thousand)	-0.02	-0.03	-0.09	-0.08	0.22
Experience in using an EV Call Center	-0.39	-0.70	-2.21	-1.97	5.25

Figure 4.3 summarizes the analysis results of this study within the path-analytic framework. For instance, the collision warning system is associated with a higher chance of being very satisfied with owning a BEV by 11.71%, which is indirectly correlated with a higher chance of being definitely willing to repurchase a BEV in the future by 6.70% ($= 11.71\% \times 57.25\%$). Likewise, a unit increase in the BEV range (mile/battery) is associated with a higher chance of being very satisfied with owning a BEV by 0.09%, which is indirectly correlated with a higher chance of being definitely willing to repurchase a BEV in the future by 0.05% ($= 0.09\% \times 57.25\%$). Meanwhile, the experience in using an EV Call Center is directly correlated with a higher chance of being definitely willing to repurchase a BEV in the future by 5.25%. Likewise, a 1000-mile increase in the total mileage of driving a BEV is directly associated with a higher chance of being definitely willing to repurchase a BEV in the future by 0.22%.

DISCUSSION

Importantly, statistics reveal that a vast majority of BEV owners in Jeju, South Korea feel positive about owning a BEV, given that 86.6 percent of the respondents were satisfied (or very satisfied) with owning a BEV, while 81.0 percent were willing to (or definitely willing to) repurchase a BEV in the future. At the same time, the fact that 19.0 percent of the BEV owners were reluctant to repurchase a BEV in the future implies that some of these early adopters might decide to stop purchasing BEVs in the future. The results indicate that BEV ownership satisfaction could drop due to negative perceptions of BEVs, vehicle features, or some user contexts, while willingness to repurchase a BEV in the future could be weakened by a low satisfaction level or some user contexts.

Concerning BEV ownership satisfaction, it is highly influenced by perceptions of BEVs. Particularly, the perception that using a BEV saves costs is the most influential factor to increase satisfaction, which is somewhat consistent with the results from a previous study (*82*). The second most powerful factor is the perception that BEVs perform well, which is also aligned with an existing study (*79*). In addition, BEV ownership satisfaction is positively affected by perceptions that a BEV is easy to charge and that it takes a short time to wait for others to use public chargers. This is fairly in accordance with the previous finding that overall satisfaction hinges upon satisfaction with charging EVs (*82*). Likewise, the perception that BEVs are safe is another influential factor concerning BEV ownership satisfaction.

BEV ownership satisfaction is found to be affected by vehicle features as well. Among vehicle features, notably, a collision warning system is found to be the most powerful factor to increase satisfaction. This implies that BEV owners tend to be more satisfied when they feel safer in their vehicles with automation features. This is one of the key unique findings from this study, which suggests the potential synergy of integrating vehicle electrification with automation. Meanwhile, a BEV owner is likely to be more satisfied when the vehicle has a longer range, which is consistent with an existing study (*81*). It is also revealed that BEV ownership satisfaction has a negative relationship with vehicle price, which is aligned with a previous study (*79*).

Furthermore, BEV ownership satisfaction is also influenced by user contexts. The results indicate that BEV ownership satisfaction is positively related to BEV charger availability at home or work, which is quite consistent with previous studies suggesting the importance of residence charger availability (*80-81*). This seems reasonable because those BEV owners with a charger at home or work might be able to save time and energy to access a charger. It is also shown that the experience with an EV repair service tends to decrease BEV ownership satisfaction. This might be because those BEV owners who had the service are likely to have experienced a critical problem with their vehicles.

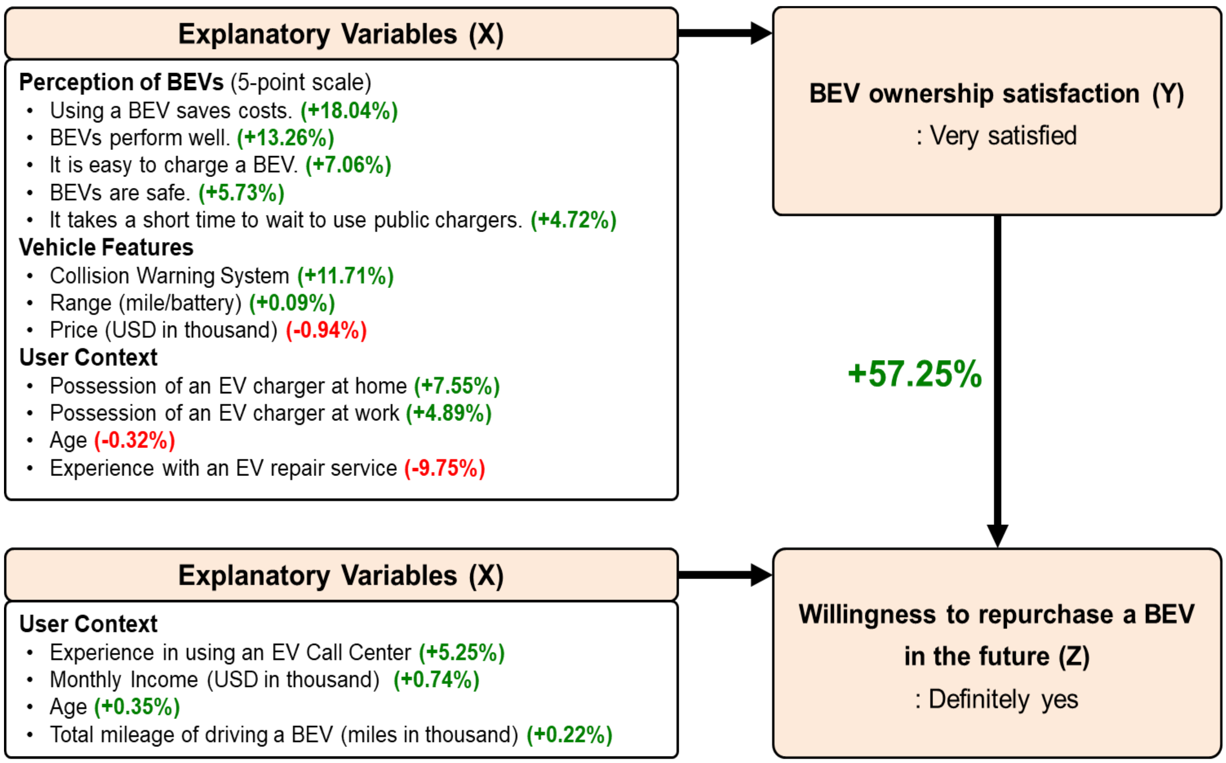


Figure 4.3 Summary of Analysis Results

Regarding willingness to repurchase a BEV in the future, BEV ownership satisfaction is the most influential factor as expected. In addition, the experience in using an EV Call Center is the second most powerful factor. This might be because those who have used EV Call Centers think they will be assisted by an EV Call Center when needed. This is another key unique finding from BEV owners' viewpoint. As a BEV owner drives a BEV more, the owner is more likely to repurchase a BEV in the future, which seems intuitively reasonable. As expected, when it comes to socio-economic aspects, it is revealed that monthly income has a positive relationship with the willingness to repurchase a BEV. Lastly, older BEV owners are more likely to be satisfied with owning a BEV rather than very satisfied, but they are more likely to be definitely willing to repurchase a BEV. This implies that older BEV drivers tend to be less generous with their satisfaction, while at the same time being inclined to keep adopting BEVs.

LIMITATIONS

Considering that the survey results regarding the willingness to repurchase a BEV are highly consistent with the EV discontinuance rate in California reported by UC Davis, the results and findings from this study are considered generalizable to some extent (*16*). Given that Jeju, South Korea, and California are EV-friendly regions with policies to support EV adoptions, the results and findings from this case study can be generalized to those regions with similar contexts in terms of policy (*40-103-104*). However, the average willingness to repurchase a BEV might be lower if a case study were conducted in another region without EV subsidy policies or an EV call center to provide BEV users with real-time information. Accordingly, the statistical relationships quantified in this case study might be weaker if the data captured some unobserved variables related to regional contexts. Future research may attempt to perform additional case studies in other regions or countries to gain evidence for more generalizable findings.

Another limitation of this study is that the data has limited variables about vehicle features, although those variables offer valuable insights regarding BEV re-adoption. Thus, it should be noted that the coefficient of each vehicle-feature variable might have been overestimated. If the data captured more variables on vehicle features, some relationships would be weaker, even if they are statistically significant. Future research may attempt to collect detailed vehicle features directly from a survey.

In addition, although this study attempted to capture as many objective variables as possible, the multiple-choice questions for some subjective issues such as perceptions of BEVs might not have perfectly captured what the respondents thought and how they felt. Meanwhile, since the survey that was conducted by Jeju Special Self-Governing Province and Jeju Research Institute (JRI) in December 2018 collected a large amount of information from a large sample size, it took much time to code the answers to generate, process, clean, and analyze the data. During this time lag, things have somewhat changed in terms of the BEV use especially in Jeju, South Korea, although the findings and implication from this study are considered "still valid" because the changes have not been dramatic so far. The key changes are as follows.

- In Jeju, South Korea, the number of registered BEVs has increased from 15,549 to 25,571 for the period of December 2018 to December 2021 (*75*). Accordingly, its market share has increased from 2.8% to 3.9% during the same period. The BEV diffusion in this region is still at an early stage where the BEV market share is lower than 5% (*75*).
- The subsidy policy for BEV buyers in Jeju, South Korea were in effect in 2018 and are still in effect in 2022 (*103-104*).

- The number of public EV chargers has increased from 2,201 to 4,934 for the period of December 2018 to December 2021. The number, 4,934, in December 2021 is still low compared to the number of BEV owners, 25,571, in Jeju, South Korea (*105*).
- The average range of BEVs estimated by International Energy Agency (IEA) has increased from 186 (mile/battery) to 217 (mile/battery) for the period of 2018 to 2021 (*106*).

CONCLUSION

Based on the results of this study, BEV owners seem fairly satisfied and willing to repurchase a BEV in the future. BEV ownership satisfaction can drop due to negative perceptions of BEVs, vehicle features, or BEV user experience, while willingness to repurchase a BEV in the future can be weakened by a low level of satisfaction. These results lead to practical implications. The findings of this study can provide vehicle developers with insights that BEVs with automation features such as collision warning systems can enhance BEV ownership satisfaction, which would help induce them to keep adopting a BEV. In addition, BEV ownership satisfaction level would drop when BEV owners feel it is difficult to charge a BEV, which might prevent them from repurchasing a BEV in the future. Thus, it will be important to make charging BEVs easier. Besides, BEVs with a longer range (mile/battery) would make BEV owners more satisfied, which would help induce them to continue to adopt BEVs in the future.

For planners, engineers, and policymakers in the transportation field, this study highlights that installation of a sufficient number of public EV charging stations will be necessary to induce BEV owners to repurchase BEVs in the future. This study also implies companies' installation of EV chargers for their employees would help induce BEV owners to continue to adopt a BEV. In light of this, policymakers may need to consider implementing some policies to encourage companies to supply EV chargers for their employees. Furthermore, the results of this study have implications for the EV industry and policymakers—that EV diffusion could be accelerated by providing EV owners with a variety of ways to gain real-time information, such as call centers and smartphone applications. Considering the finding that EV owners' experience in using an EV Call Center directly increases their willingness to repurchase a BEV in the future, BEV owners seem to care about whether they have options to be assisted whenever they need help on the road. When BEV owners have diverse options to obtain helpful information quickly, they will be more willing to repurchase an EV in the future.

ACKNOWLEDGMENT

This chapter is based on the "Survey of Battery Electric Vehicle Owners in Jeju" conducted by Jeju Special Self-Governing Province and Jeju Research Institute (JRI) in South Korea in December 2018. Any opinions, findings, and conclusions, or recommendations in this chapter are those of the authors and do not necessarily reflect the views of those organizations above.

Chapter 5. Advancing Investigation of Automated Vehicle Crashes Using Text Analytics of Narratives and Bayesian Analysis

A version of this chapter has been accepted by Transportation Research Board (TRB) for presentation in TRB 102nd Annual Meeting, and was submitted to Accident Analysis and Prevention for publication:

Lee, S., Arvin, R., and Khattak, A. Advancing Investigation of Automated Vehicle Crashes Using Text Analytics of Narratives and Bayesian Analysis. Transportation Research Board 102nd Annual Meeting 2023 (No.23-00186)

Lee, S., Arvin, R., and Khattak, A. Advancing Investigation of Automated Vehicle Crashes Using Text Analytics of Narratives and Bayesian Analysis. Under-review in Accident Analysis and Prevention for publication.

ABSTRACT

Vehicle automation, manifested in self-driving cars, has the promise to provide safe mobility by reducing human errors. While the testing of automated vehicles (AVs) has improved their roadway performance in recent years, automation technologies are facing challenges such as uncertainty of safety impacts in mixed traffic with human-driven vehicles. This study aims to figure out the gaps in AV safety performance and identify what will be required on a preferential basis for AVs to guarantee an acceptable level of safety performance, especially in mixed traffic, by conducting a thorough analysis of crashes involving levels 2-3 AVs. Based on 148 AV collision reports from California in 2019 and 2020, this study extracts crash-related variables from crash records in a standardized form, crash locations, and, importantly, crash narratives reported by AV manufacturers. Within a path-analytic framework with the frequentist and Bayesian approaches, this study untangles the complex interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes. Results show that 60.1 percent of crashes had a rear-end collision. Particularly, AVs become more vulnerable to rear-end collisions in the automated driving mode than in the conventional mode, given a crash. On the other hand, the automated driving mode would not significantly affect the chance of a sideswipe collision, injury, or AV damage levels. Another interesting finding is that manual disengagement is more likely to happen when an AV interacts with a transit vehicle right before a crash occurs. Moreover, the results suggest that AVs would need more thorough testing to adapt to the critical roadway and infrastructure features such as intersections, ramps, and slip lanes, while roadway infrastructure would require improvements to support transportation automation. The risk factors identified in this study can be considered in AV safety assessment scenarios as well as in future operations of mixed traffic. Further, this study implies that AV crash narratives can be leveraged to improve knowledge of AV safety.

Keywords: Automated Vehicle, Crash, Safety Assessment, Crash Narrative

INTRODUCTION

Transportation automation is widely considered a fundamental solution for the issues of traffic safety, congestion, and mobility. Specifically, crash frequency is expected to be dramatically reduced by removing human errors when the roads have fully automated vehicles (*107*). In addition, traffic flow is expected to become more stable with fully automated vehicles, which would mitigate traffic congestion (*107*). Since fully automated vehicles will be able to move people without requiring them to drive, they are expected to provide those people with physical disabilities and the elderly with additional mobility options (*107*).

Currently, many vehicles are already equipped with advanced driver assistance functions to warn drivers of potential risks on the road so that they can take appropriate and timely actions to avoid a crash (*107*). Moreover, some manufacturers of automated vehicles (AVs) have been testing their vehicles mostly in automation level 2 (Partial Automation) and level 3 (Conditional Automation) on real roads (*108-109*). Since September 2014, for example, the State of California has been allowing AV manufacturers to test their AVs with a driver on the public roads with the requirements that they have to report all the crashes through a standardized form called OL316, all disengagements of AVs experienced, and vehicle miles traveled (VMT) by their AVs (*109*). This policy allows AV manufacturers to deploy their AVs in development on real roads while producing data sources from road tests that can be used for assessing AV safety performance at the society levels (*110*).

One of the critical challenges in transportation automation is that AVs should interact with human-driven vehicles on the road until the market penetration rate of AVs approaches 100 percent. This issue would create uncertainty in traffic safety unless AVs become 100% capable of predicting the movements of human-driven vehicles on the road. For instance, a previous study revealed that low market penetration of AVs with Adaptive Cruise Control (ACC) technologies might slightly compromise traffic stability at intersections (*111*). Likewise, another study showed that the introduction of AVs might slightly increase conflicts at roundabouts (*112*).

By scrutinizing the crash history of AVs tested on the roads, this study aims to assess the current state of AVs in terms of safety and identify what will be required on a preferential basis for AVs to guarantee an acceptable level of safety performance, especially in mixed traffic. Based on the 148 AV collision reports released by the California Department of Motor Vehicles (DMV) in 2019 and 2020, this study structures a comprehensive dataset consisting of key information from crash records, crash locations, and crash narratives reported by AV manufacturers. With the comprehensive dataset, this study explores the relationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes. The findings from this study would provide a thorough understanding of AV-involved crashes while giving AV public agencies and developers helpful feedback on the gaps in automated driving performance. Moreover, the key factors identified in this study can be included in safety assessment scenarios for more efficient and reasonable testing of high-level automation. They can also be considered in developing Vehicle-to-Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication technologies for vehicle connectivity and transportation automation.

LITERATURE REVIEW

As this study covers those crashes involving AVs with partial and conditional automation, this section briefly introduces the automation levels defined by the Society of Automotive Engineers (SAE). As summarized in **Figure 5.1**, the automation levels consist of 6 levels, from Level 0, referring to "No Automation," to Level 5, referring to "Full Automation" (*107-108*). Between the two extremes, there are intermediate levels, including “Driver Assistance (Level 1),” “Partial Automation (Level 2),” “Conditional Automation (Level 3),” and “High Automation (Level 4)” (*107-108*). This study covers crashes involving those AVs in “Partial Automation (Level 2)” and "Conditional Automation (Level 3)," where an AV can perform some driving functions in the automated driving mode, but the driver should be ready to take control of the AV whenever needed (*107-108*).

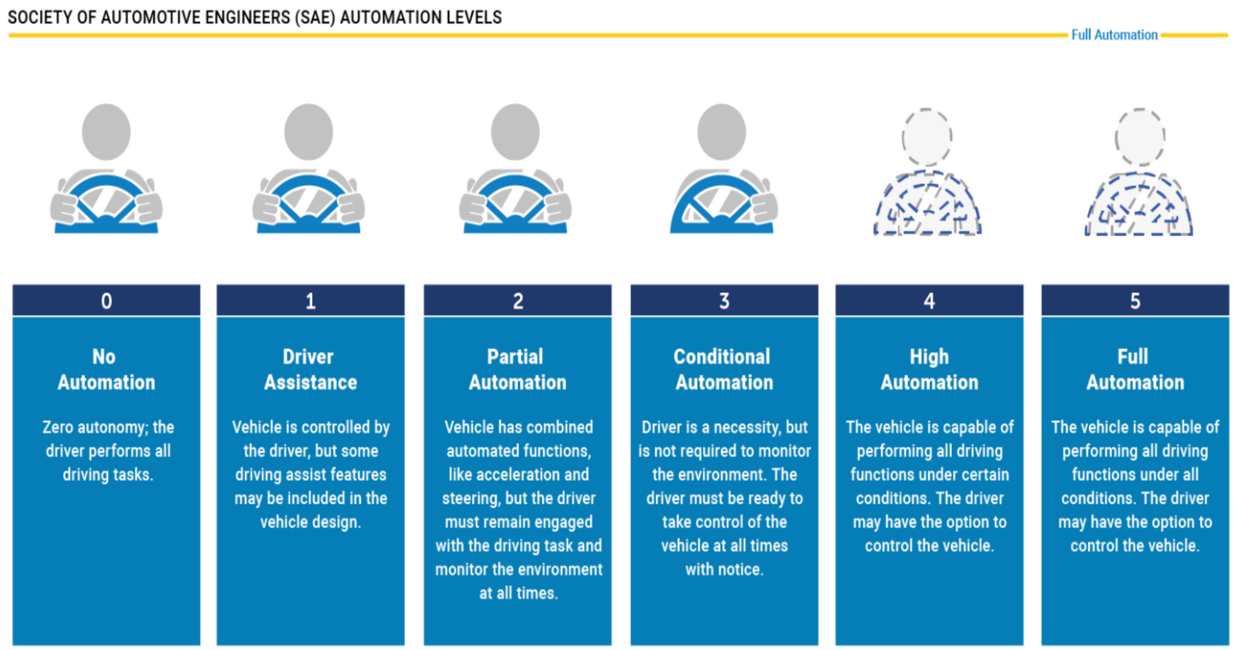


Figure 5.1 SAE Automation Levels summarized by NHTSA (*107*)

There have been efforts to assess AV safety performance, especially referring to AV collision or disengagement reports released by the California DMV, key findings of which are summarized in **Figure 5.2**. Overall, previous studies have attempted to understand basic nature of AV-involved crashes, while inspecting observable facets of them such as crash types and outcomes. Some studies have performed a descriptive analysis of crash records to understand the characteristics of AV-involved crashes (*113-118*). From those studies, rear-end collision was found to be the most frequent type of collision, while AV-involved crashes tend to result in less severe injuries compared to the crashes among human-driven vehicles (*113-114-116-118*). Especially, it was shown that AV-involved crashes had a higher proportion of rear-end collisions than conventional vehicle crashes, while AVs had been struck from behind 4.8 times more frequently than human-driven vehicles (*115-119*).

Besides, some studies have attempted to identify influential factors concerning specific aspects of AV-involved crashes such as crash types, injury, or vehicle damage (*120-122*). It was revealed that rear-end collisions are positively correlated with the automated driving mode, one-way roads, roadways with high traffic volume, intersections, and an AV stopped (*116-117-120-122*). When it comes to injury, those crashes on highways were found to be more likely to result in a higher level of injury severity (*120*). Moreover, injury crashes were found to have a positive relationship with roadside parking, intersections, arterial roads, and rear-end collisions (*122*). Meanwhile, AV damage level was found to have a positive relationship with rear-end collisions, while having negative relationships with the automated driving mode and intersections (*121*). One of the recent studies has investigated AV-involved crashes involving vulnerable road users revealing that those crashes had a positive relationship with crosswalks, intersections, and traffic signals (*123*). Furthermore, there was an effort to cluster the patterns of AV-involved crashes according to crash-related factors such as turning movement, manner of collision, light conditions, and injury severity. (*124*). With AV disengagement reports, a downward trend of disengagement frequency has been captured, while disengagement was found to be a frequent pattern right before an AV-involved crash takes place, having different types of reasons such as a driver's judgment and system failures (*125-127*).

Despite the previous efforts, there are still gaps in understanding AV-involved crashes. First, previous studies tended to provide fragmentary though valuable insights into AV-involved crashes by focusing on a specific crash type or outcome, e.g., rear-end collision and injury (*116-117-120-122-124*). To provide a comprehensive and clear picture of AV-involved crashes, this study attempts to systematically untangle complex interrelationships among a variety of factors related to AV-involved crashes rather than providing fragmentary insights. This includes the development of a path-analytic framework embedded in the safe system approach to account for the elements related to human, vehicles, roadways, and the environment in crash investigation. Second, most studies relied on limited variables, mainly from crash records in a standardized (OL316) form. Although some previous studies performed a text analysis of crash narratives to obtain valuable insights, they did not extract additional variables directly from crash narratives for statistical modeling (*122-123*). Considering that analysis of such narratives can support a better understanding of AV-involved crashes in mixed traffic, this study takes full advantage of multiple data sources to extract as many significant variables as possible. This is done by data linking and analysis of crash narratives to create new variables. Moreover, this study combines the prior knowledge from previous findings and evidence from the sample to generate posterior knowledge, which is done by applying the Bayesian approach. This helps derive more reasonable statistical inferences by reducing potential bias from the sample.

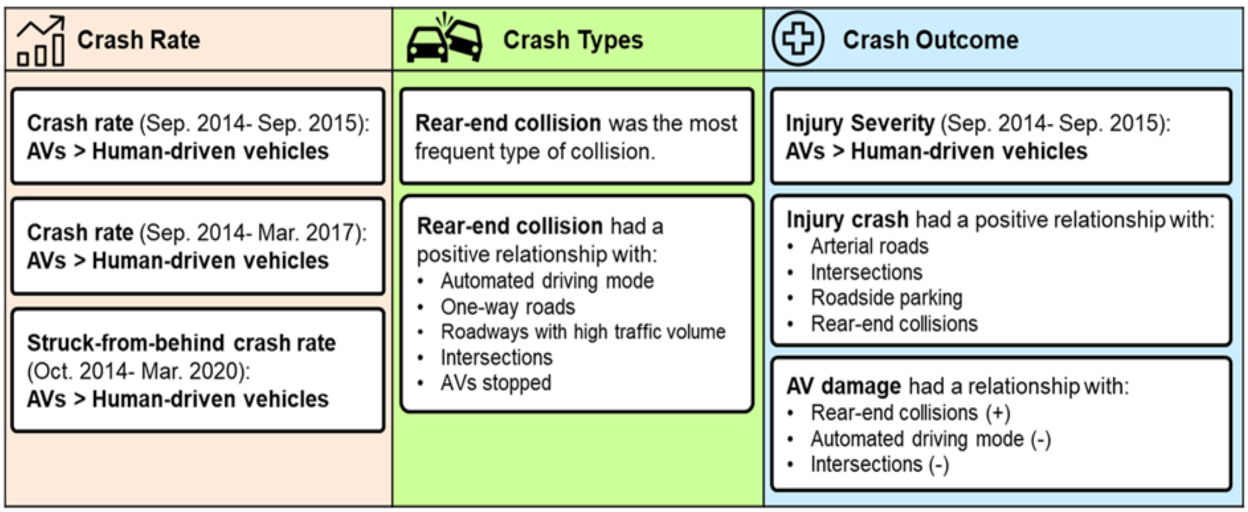


Figure 5.2 Summary of Literature Review

METHODOLOGY

Conceptual Framework

This study consists of two main tasks: (1) Organization of a comprehensive dataset of AV-involved crashes and (2) Statistical analysis with a path analytic framework, as shown in **Figure 5.3**. A comprehensive dataset was organized from crash records, crash locations, and crash narratives in AV collision reports (N=148) released by California DMV in 2019 and 2020. Through this task, this study extracted those crash-related factors that had been confined in crash narratives and crash locations in addition to those factors directly from crash records in a standardized form.

Crash-related variables are categorized into four different layers, i.e., pre-crash conditions, AV driving modes, crash types, and crash outcomes. Importantly, AV driving modes consist of three categories: "Pre-crash Automated → During-crash Automated," "Pre-crash Automated → During-crash Conventional," and "Pre-crash Conventional → During-crash Conventional." In this study, manual disengagement by a driver (Pre-crash Automated → During-crash Conventional) is considered a critical pre-crash behavior that might have an impact on crash types and outcomes based on the literature review (*126*). With the four layers, as visualized in **Figure 5.3**, this study applies a path-analytic framework with statistical modeling to provide a comprehensive and clear picture of AV-involved crashes by systematically connecting the layers within the sequential flow of AV-involved crashes (*128*). In previous crash-related studies, path-analytic frameworks have been found to allow straightforward interpretations with marginal effects as well as exploration of direct and indirect effects (*129-130*). Based on the safe system approach accounting for human, vehicles, roadways, and the environment, the path-analytic framework has been developed in accordance with the insights from the literature review including that (1) crash outcomes can be affected by pre-crash conditions including the roadway and built environment, AV driving modes, and crash types, (2) crash types can be affected by pre-crash conditions and AV driving modes (vehicle and driver factors), and (3) AV driving modes can be affected by pre-crash conditions (*131*). Especially, disengagement by a driver or the automated driving system is a frequent pattern observed right before an AV-involved crash occurs (*125-127*). The framework includes providing refined models on rear-end collision and injury that have been covered by previous studies and providing additional models on AV driving modes, sideswipe collision, and AV damage (*116-117-120-122*).

Data Collection

Source 1. Crash Records in a Standardized Form

From the crash records in OL316 form (**Figure 5.4**), this study extracted variables related to pre-crash conditions, AV driving modes, crash types, and crash outcomes. The variables regarding pre-crash conditions include vehicle manufacturers, such as Cruise LLC and Waymo LLC, vehicle movements, such as the combination of an AV stopped and the second vehicle proceeding straight, the combination of an AV slowing and the second vehicle proceeding straight, the combination of an AV and the second vehicle proceeding straight, the combination of an AV proceeding straight and the second vehicle changing lanes, and the combination of an AV making a left turn and the second vehicle proceeding straight, and AVs' interaction with pedestrians or bicyclists. The variables regarding AV driving modes reported in the form include the automated driving mode and conventional mode. The variables concerning crash types include the manner of collision, such as rear-end collision and sideswipe collision. Crash outcomes include AV damage levels, such as no, minor, moderate, and major damage, and whether a crash injured at least one person.

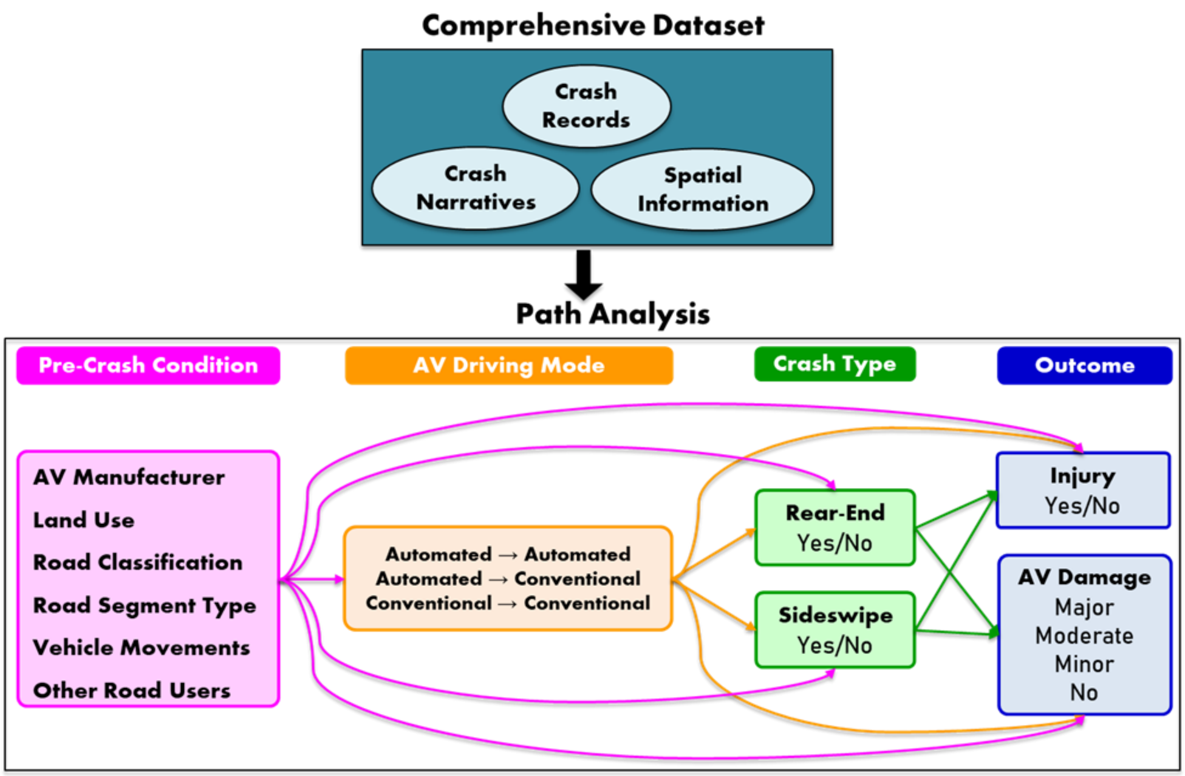
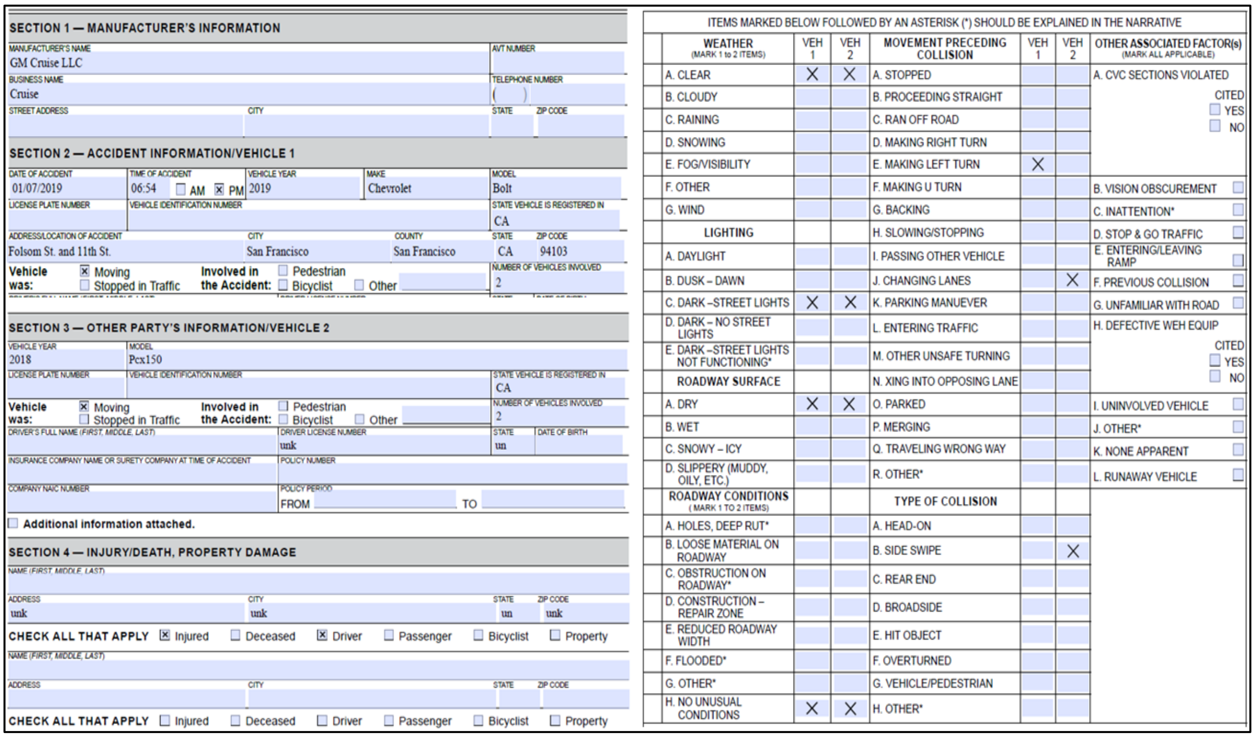


Figure 5.3 Conceptual Framework



SECTION 1 — MANUFACTURER'S INFORMATION

MANUFACTURER'S NAME: GM Cruise LLC
AVT NUMBER:
BUSINESS NAME: Cruise
TELEPHONE NUMBER: ( )
STREET ADDRESS: | CITY: | STATE: | ZIP CODE:

SECTION 2 — ACCIDENT INFORMATION/VEHICLE 1

DATE OF ACCIDENT: 01/07/2019
TIME OF ACCIDENT: 06:54 ☐ AM ☒ PM
VEHICLE YEAR: 2019
MAKE: Chevrolet
MODEL: Bolt
LICENSE PLATE NUMBER:
VEHICLE IDENTIFICATION NUMBER:
STATE VEHICLE IS REGISTERED IN: CA
ADDRESS/LOCATION OF ACCIDENT: Folsom St. and 11th St.
CITY: San Francisco
COUNTY: San Francisco
STATE: CA
ZIP CODE: 94103
Vehicle was: ☒ Moving ☐ Stopped in Traffic
Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other
NUMBER OF VEHICLES INVOLVED: 2

SECTION 3 — OTHER PARTY'S INFORMATION/VEHICLE 2

VEHICLE YEAR: 2018
MODEL: Pcx150
LICENSE PLATE NUMBER:
VEHICLE IDENTIFICATION NUMBER:
STATE VEHICLE IS REGISTERED IN: CA
Vehicle was: ☒ Moving ☐ Stopped in Traffic
Involved in the Accident: ☐ Pedestrian ☐ Bicyclist ☐ Other
NUMBER OF VEHICLES INVOLVED: 2
DRIVER'S FULL NAME (*FIRST, MIDDLE, LAST*):
DRIVER LICENSE NUMBER: unk
STATE: un
DATE OF BIRTH:
INSURANCE COMPANY NAME OR SURETY COMPANY AT TIME OF ACCIDENT:
POLICY NUMBER:
COMPANY NAIC NUMBER:
POLICY PERIOD: FROM TO

☐ Additional information attached.

SECTION 4 — INJURY/DEATH, PROPERTY DAMAGE

NAME (*FIRST, MIDDLE, LAST*):
ADDRESS: unk | CITY: unk | STATE: un | ZIP CODE: unk
CHECK ALL THAT APPLY ☒ Injured ☐ Deceased ☒ Driver ☐ Passenger ☐ Bicyclist ☐ Property
NAME (*FIRST, MIDDLE, LAST*):
ADDRESS: | CITY: | STATE: | ZIP CODE:
CHECK ALL THAT APPLY ☐ Injured ☐ Deceased ☐ Driver ☐ Passenger ☐ Bicyclist ☐ Property

ITEMS MARKED BELOW FOLLOWED BY AN ASTERISK (*) SHOULD BE EXPLAINED IN THE NARRATIVE

WEATHER (MARK 1 to 2 ITEMS)	VEH 1	VEH 2	MOVEMENT PRECEDING COLLISION	VEH 1	VEH 2	OTHER ASSOCIATED FACTOR(s) (MARK ALL APPLICABLE)
A. CLEAR	X	X	A. STOPPED			A. CVC SECTIONS VIOLATED
B. CLOUDY			B. PROCEEDING STRAIGHT			CITED ☐ YES ☐ NO
C. RAINING			C. RAN OFF ROAD			
D. SNOWING			D. MAKING RIGHT TURN			
E. FOG/VISIBILITY			E. MAKING LEFT TURN	X		
F. OTHER			F. MAKING U TURN			B. VISION OBSCUREMENT ☐
G. WIND			G. BACKING			C. INATTENTION* ☐
LIGHTING			H. SLOWING/STOPPING			D. STOP & GO TRAFFIC ☐
A. DAYLIGHT			I. PASSING OTHER VEHICLE			E. ENTERING/LEAVING RAMP ☐
B. DUSK – DAWN			J. CHANGING LANES		X	F. PREVIOUS COLLISION ☐
C. DARK –STREET LIGHTS	X	X	K. PARKING MANUEVER			G. UNFAMILIAR WITH ROAD ☐
D. DARK – NO STREET LIGHTS			L. ENTERING TRAFFIC			H. DEFECTIVE WEH EQUIP
E. DARK –STREET LIGHTS NOT FUNCTIONING*			M. OTHER UNSAFE TURNING			CITED ☐ YES ☐ NO
ROADWAY SURFACE			N. XING INTO OPPOSING LANE			
A. DRY	X	X	O. PARKED			I. UNINVOLVED VEHICLE ☐
B. WET			P. MERGING			J. OTHER* ☐
C. SNOWY – ICY			Q. TRAVELING WRONG WAY			K. NONE APPARENT ☐
D. SLIPPERY (MUDDY, OILY, ETC.)			R. OTHER*			L. RUNAWAY VEHICLE ☐
ROADWAY CONDITIONS (MARK 1 TO 2 ITEMS)			**TYPE OF COLLISION**			
A. HOLES, DEEP RUT*			A. HEAD-ON			
B. LOOSE MATERIAL ON ROADWAY			B. SIDE SWIPE		X	
C. OBSTRUCTION ON ROADWAY*			C. REAR END			
D. CONSTRUCTION – REPAIR ZONE			D. BROADSIDE			
E. REDUCED ROADWAY WIDTH			E. HIT OBJECT			
F. FLOODED*			F. OVERTURNED			
G. OTHER*			G. VEHICLE/PEDESTRIAN			
H. NO UNUSUAL CONDITIONS	X	X	H. OTHER*			

Figure 5.4 Part of AV Collision Report in OL316 Form

Source 2. Crash Narratives

The crash narratives in AV collision reports are provided by AV manufacturers and can help identify the valuable information that the standardized form has failed to capture. This study shows how such data can be leveraged to improve knowledge of AV safety in mixed traffic. Specifically, this study collected additional variables by conducting a text analysis of crash narratives, as shown in **Figure 5.5**. The variable extraction from crash narratives has been performed according to the following procedure.

- Performing a text analysis of all the crash narratives to check word or phrase frequency.
- Comparing the frequently mentioned words or phrases to the items recorded in crash reports.
- Finding out the frequently mentioned words or phrases missing in crash reports.
- Setting a variable corresponding to specific words or phrases.
- Extracting the variable's value for each case by reviewing each crash narrative.
- Including the variable in statistical modeling to check if it has a significant impact.

Text analysis results revealed that the words representing "AVs' yielding or waiting," "AVs' interaction with transit vehicles," and "manual disengagement" were frequently mentioned in crash narratives but not recorded in a standardized form. Accordingly, those variables were extracted from crash narratives to create a comprehensive dataset, as shown in **Figure 5.6**, and they were found to be influential in AV-involved crashes by statistical modeling, which is shown in the section "Results."

Source 3. Spatial Information of Crash Locations

Additionally, this study collected spatial information on crash locations, as shown in **Figure 5.7**, to extract those variables related to the built environment around the places where AV-involved crashes have occurred. By referring to the addresses of accidents and crash narratives available in collision reports, the location of every crash was identified to investigate the characteristics of the place where each AV-involved crash occurred (*132*). As a result, those variables concerning land use, road classification, and road segment types were extracted.

Analysis Methods

As shown in the conceptual framework, the path analysis consists of five regression models, each of which has its response variable respectively: (1) AV driving mode, (2) involving a rear-end collision, (3) involving a sideswipe collision, (4) involving injury to at least one person, and (5) AV damage level. Since "AV driving mode" has three different categories, a multinomial logistic regression is applied. An ordered logistic regression is used for "AV damage level" with ordinal categories. As the remaining response variables have binary outcomes, Yes or No, binary logit models are estimated to figure out their relationships with explanatory variables.

Multinomial Logistic Regression

A multinomial logit model is estimated to describe how pre-crash conditions influence AV driving mode. The mathematical form of multinomial logistic regression is as follows (*35*).

$$\log\left(\frac{\pi_j}{\pi_c}\right) = \alpha + \boldsymbol{\beta X}, j = 1, \dots c, \text{ except for } c. \quad (1)$$

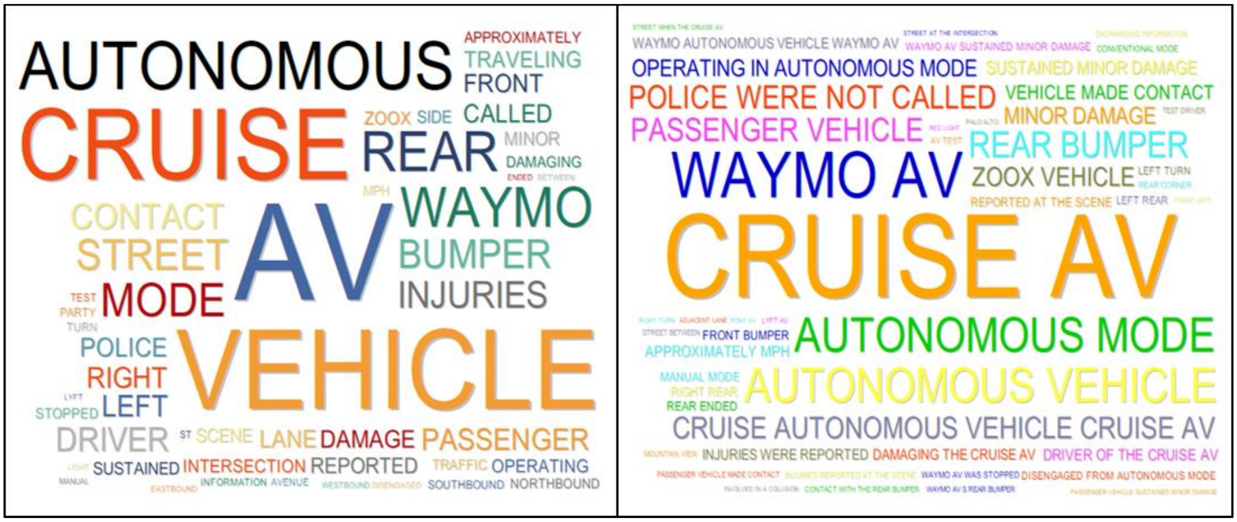


Figure 5.5 Word Cloud (Left) and Phrase Cloud (Right) from Crash Narratives

ID	Narrative	Involving **Yielding or Waiting**	Involving **Transit**	Involving **Manual Disengagement**
100	A Cruise autonomous vehicle ("Cruise AV") operating in autonomous mode, was traveling northbound on Leavenworth Street at the intersection with Post Street when the Cruise AV yielded to a public transit bus changing into the Cruise AV's lane from the right adjacent lane. The driver of the Cruise AV disengaged from autonomous mode and, shortly thereafter, another vehicle made contact with the left rear corner of the Cruise AV, damaging the Cruise AV's left rear fascia and the other vehicle's right front fascia. There were no injuries and police were not called.	1	1	1
101	On December 19, 2019 at approximately 9:44AM, a Zoox vehicle operating in manual mode was struck on the passenger side fender by a bus. The Zoox vehicle was traveling north on Kearny in the right most lane when the bus attempted to lane change in front of the Zoox vehicle, impacting its front passenger side sensors and fender. The bus was traveling less than 2mph when it hit the Zoox vehicle, which was stopped. There were no injuries.	0	1	0
102	A Waymo Autonomous Vehicle ("Waymo AV") was stopped in manual mode in the slip lane from southbound Whisman Station Drive to northbound Central Expressway in Mountain View when it was rear-ended. The Waymo AV test driver was yielding to approaching traffic when a passenger vehicle made contact with the Waymo AV's rear bumper at approximately 2 MPH. The Waymo AV sustained minor damage to its rear bumper, and the passenger vehicle sustained minor damage to its front bumper. No injuries were reported at the scene.	1	0	0

Figure 5.6 Variable Extraction from Crash Narratives

SECTION 2 — ACCIDENT INFORMATION/VEHICLE 1

DATE OF ACCIDENT	TIME OF ACCIDENT	VEHICLE YEAR	MAKE	MODEL
01/07/2019	06:54 ☐ AM ☒ PM	2019	Chevrolet	Bolt
LICENSE PLATE NUMBER	VEHICLE IDENTIFICATION NUMBER			STATE VEHICL
				CA
ADDRESS/LOCATION OF ACCIDENT	CITY	COUNTY		STATE
Folsom St. and 11th St.	San Francisco	San Francisco		CA

A Cruise autonomous vehicle ("Cruise AV"), operating in conventional mode, was making a left turn from northeast bound Folsom Street onto northwest bound 11th Street when a scooterist, attempting to pass the Cruise AV on the left, made contact with the front left side of the Cruise AV, damaging the front left fender, radar, and wheel well of the Cruise AV. The scooterist reported injuries and emergency services and the police arrived at the scene, but the scooterist declined medical treatment. No police report was available at the time of the filing of this report.

Figure 5.7 Spatial Information of Crash Locations

$$\log(\frac{\pi_j}{\pi_c}) = \alpha + \boldsymbol{\beta X}, j = 1, \dots c, \text{ except for } c. \quad (1)$$

In equation (1) above, π_c is the probability that the dependent variable falls into the baseline category (c). Likewise, π_j is the probability that the dependent variable falls into the jth category. In addition, α is the constant, X is a set of explanatory variables, and β is a set of coefficients.

Along with modeling, this study quantifies the marginal effects of explanatory variables. The marginal effect of an explanatory variable is defined as the change in the chance that the dependent variable belongs to a specific category due to a unit increase in the explanatory variable when the other variables are fixed at their mean values (*65*). Because the explanatory variables in this model have binary outcomes, Yes and No, the mathematical form of marginal effect is written as follows (*66*).

$$\frac{\partial P[Y = i|\boldsymbol{X}]}{\partial X} = \mathrm{P}[Y = i|\boldsymbol{X}, X_k = 1] - \mathrm{P}[Y = i|\boldsymbol{X}, X_k = 0] \quad (2)$$

In equation (2) above, $P[Y = \mathrm{i}]$ is the probability that the dependent variable falls into a specific category i. While $\boldsymbol{X}$ is a set of explanatory variables, X_k is the kth explanatory variable in a regression model. Thus, $X_k = 1$ says that the explanatory variable has the outcome "Yes" while $X_k = 0$ says it has the outcome "No."

Binary Logistic Regression

Binary logit models are estimated to explain how pre-crash conditions and AV driving modes affect crash types such as rear-end collision and sideswipe collision. Another binary logit model describes how the odds of injury are affected by pre-crash conditions, AV driving modes, and crash types. The mathematical form of binary logistic regression is as follows (*62*).

$$\log\left[\frac{P(Y=1)}{1-P(Y=1)}\right] = \alpha + \boldsymbol{\beta X} \quad (3)$$

$$P(Y = 1) = \frac{\exp{(\alpha+\boldsymbol{\beta X})}}{1+\exp{(\alpha+\boldsymbol{\beta X})}} = \frac{1}{1+e^{-(\alpha+\boldsymbol{\beta X})}} \quad (4)$$

The equation (4) is derived by re-organizing equation (3), where $P(Y = 1)$ is the probability that the response variable has the outcome "Yes," α is the constant, $\boldsymbol{X}$ is a set of explanatory variables, and $\boldsymbol{\beta}$ is a set of coefficients. Along with binary logit models, the marginal effects of explanatory variables are quantified as in the multinomial logistic regression. The mathematical form of marginal effects in logit models is written as the equation (2) for when $i = 1$ and $i = 0$.

Ordered Logistic Regression

An ordered logit model is applied to describe how AV damage level is influenced by pre-crash conditions, AV driving modes, and crash types. The mathematical form of ordered logistic regression is as follows (*133*). The marginal effects of explanatory variables are derived as in multinomial logistic regression.

$$Y^* = \mathbf{\beta X} + \varepsilon \quad (5)$$

, where Y^* is the latent variable that is exact but unobserved, **X** is a set of explanatory variables, $\boldsymbol{\beta}$ is a set of coefficients, and ε is the error term. The dependent variable is determined by the value of the latent variable, Y^*, as follows (*133*).

$$
\begin{aligned}
&Y = 0 \ \text{(No Damage)} && \text{if } \ Y^* \le \mu_0 \\
&Y = 1 \ \text{(Minor Damage)} && \text{if } \ \mu_0 < Y^* \le \mu_1 \qquad (6) \\
&Y = 2 \ \text{(Moderate or Major Damage)} && \text{if } \ \mu_1 < Y^*
\end{aligned}
$$

, where μ's are the thresholds between the dependent variable categories, Y. The probability that the dependent variable (Y) belongs to a certain level is determined according to the cumulative density function (CDF) of the logistic distribution (*133*).

Bayesian Approach

With the frequentist approach, statistical analysis in this study would have no choice but to rely on the evidence from sample data with 148 crash cases (*134*). This issue might cause biased inferences and interpretations (*134*). To reduce potential bias from the sample, this study applies the Bayesian approach in addition to the frequentist approach. The Bayesian approach helps better understand the underlying relationships between variables by considering both sample data and prior knowledge to derive posterior knowledge (*134*). For Bayesian inference, this study applies informative prior distributions for those variables with appropriate prior knowledge available from literature while applying uninformative prior distributions, including weak normal priors, $\beta_i \sim N(0, 1000)$, and strong normal priors, $\beta_i \sim N(0, 10)$, for those variables without appropriate prior knowledge available (*122*).

RESULTS

Key Statistics

Descriptive statistics of key variables from the comprehensive dataset are summarized in **Table 5.1**. Regarding vehicle manufacturers, 51.4 percent of the crashes involved AVs manufactured by Cruise LLC, while 24.3 percent involved AVs manufactured by Waymo LLC. When it comes to AV driving modes, 94 AVs (63.5%) were operating in the automated driving mode before a crash, 32 of which (21.6%) were manually disengaged by their drivers right before a crash, while 62 AVs (41.9%) remained in the automated driving mode.

Statistics also show spatial information of crash locations. It is revealed that 53.4 percent of the crashes occurred in commercial areas, while 37.8 percent occurred in residential areas. While 79.7 percent of the crashes took place on the street, 6.8 percent occurred on the freeway, expressway, or highway. Besides, 81.8 percent of the crashes occurred at intersections, while 3.4 percent occurred on ramps or slip lanes.

Moreover, statistics offer information on vehicle movements before a crash. It is shown that 22.3 percent of the crashes occurred when an AV was stopped while the second vehicle was proceeding straight. Notably, 28.4% of the crashes took place while an AV was yielding to or waiting for other road users.

Furthermore, statistics provide information on AVs' interaction with other road users before a crash. It is revealed that 4.1 percent of the crashes occurred while an AV was interacting with a transit vehicle. Meanwhile, 7.4 percent of the crashes happened while an AV was interacting with pedestrians or bicyclists.

Finally, statistics show information on crash types and outcomes. It is shown that 60.1 percent of the crashes had a rear-end collision, which is aligned with previous findings that rear-end collision was the most common type of AV-involved crash (*113-114-116-118*). In 95.5 percent of those cases (85 out of 89), AVs were struck by another vehicle. The second most common type of crash was sideswipe collision taking 18.9 percent. In 67.9 percent of those cases (19 out of 28), AVs were struck by another vehicle. Furthermore, it is revealed that 20.9 percent of the crashes resulted in injury to at least one person, while 72.3 percent caused minor damage to AVs.

Analysis Results

AV Driving Mode

Regarding AV driving mode, as summarized in **Table 5.2**, a multinomial logit model (Model 1) was estimated with the explanatory variables related to pre-crash conditions, including AV manufacturers, land use, road classification, roadway segment types, vehicle movements, and other road users. The model's Akaike's Information Criteria (AIC) value is 303.160, while the Bayesian Information Criteria (BIC) value is 399.071. McFadden's R squared is 0.240, which means that the model fits well with the data. This study considers the impact of an explanatory variable meaningful when its estimated coefficient (β) is significant, at least at the 90% confidence level.

Since the category "Pre-crash conventional → During-crash conventional" is the base category of the dependent variable, the coefficients (β's) in **Table 5.2** represent the impacts of explanatory variables on each category compared to the base category, "Pre-crash conventional → During-crash conventional." For example, in Table 2, the coefficient of "Intersection" for the category "Pre-crash automated → During-crash automated" is 2.082. This indicates that "Intersection" is associated with higher odds of "Pre-crash automated → During-crash automated" rather than "Pre-crash conventional → During-crash conventional" by 8.02 times given that $e^{2.082} = 8.02$.

In **Table 5.3**, the marginal effect of an explanatory variable quantifies the change in the chance (%) of each category by a unit increase in each explanatory variable. For instance, the marginal effect of "Freeway/Expressway/Highway" on the category of "Pre-crash automated → During-crash conventional" is 34.5% at the 95% confidence level, which means, given an AV-involved crash, the chance that the AV driver manually switched the mode from the automated driving mode to the conventional mode right before the crash is higher by 34.5% on the freeway, expressway, or highway.

Notably, as shown in **Table 5.2** and **Table 5.3**, the model suggests that manual disengagement right before a crash occurs has a positive relationship with the freeway, expressway, or highway. In addition, manual disengagement is found to have a positive relationship with the interaction between AVs and transit vehicles. Concerning vehicle movements, manual disengagement has a positive relationship with the combination of an AV slowing or stopping and the second vehicle proceeding straight. Likewise, manual disengagement has a positive relationship with the combination of an AV and the second vehicle proceeding straight. Meanwhile, at an intersection, an AV is more likely to operate in the automated driving mode rather than the conventional mode before a crash occurs. Moreover, the AVs manufactured by Cruise LLC or Waymo LLC are less likely to be in the conventional mode before a crash occurs.

Table 5.1 Key Statistics (Sample Size=148)

Variable	Frequency	Percentage (%)
Vehicle manufacturer		
Cruise LLC	76	51.4
Waymo LLC	36	24.3
Other	36	24.3
AV driving mode		
Automated → Automated	62	41.9
Automated → Conventional (Manual Disengagement)	32	21.6
Conventional → Conventional	54	36.5
Land use		
Residential	56	37.8
Commercial	79	53.4
Recreational	9	6.1
Other	4	2.7
Road classification		
Freeway / Expressway / Highway	10	6.8
Street	118	79.7
Other	20	13.5
Road segment type		
Intersection	121	81.8
Ramp / Slip Lane	5	3.4
Other	22	14.8
Vehicle movements (AV, Second Vehicle)		
(Stopped, Straight)	33	22.3
(Slowing/Stopping, Straight)	6	4.1
(Straight, Straight)	18	12.2
(Straight, Changing Lanes)	14	9.5
(Left, Straight)	3	2.0
Other	74	50.0
Involving an AV's yielding or waiting	42	28.4
Other road users		
Involving a transit vehicle	6	4.1
Involving a pedestrian or bicyclist	11	7.4
Crash type		
Rear-End * 85 out of 89 AVs (95.5%) were rear-ended by another vehicle.	89	60.1
Sideswipe * 19 out of 28 AVs (67.9%) were sideswiped by another vehicle.	28	18.9
Other	31	20.9
Involving injury to at least one person	31	20.9
AV damage level		
None	15	10.1
Minor	107	72.3
Moderate	24	16.2
Major	2	1.4

Table 5.2 Model 1 (Multinomial Logit): AV Driving Mode

* Base Category: Pre-crash Conventional → During-crash Conventional

Variable	Pre-crash Automated → During-crash Automated		Pre-crash Automated → During-crash Conventional	
	β	**P-value**	**β**	**P-value**
AV manufacturer				
Cruise LLC	1.793	0.001	3.722	<0.001
Waymo LLC	1.711	0.017	1.632	0.194
Land use				
Residential	-2.206	0.212	-3.953	0.055
Commercial	-2.564	0.151	-4.971	0.019
Recreational	-2.292	0.245	-4.268	0.069
Road classification				
Freeway/Expressway/Highway	0.396	0.717	3.121	0.033
Street	0.415	0.568	.493	0.663
Road segment type				
Intersection	2.082	0.002	2.050	0.021
Vehicle movements: *(AV, 2nd Vehicle)*				
(Stopped, Straight)	0.451	0.423	-.546	0.583
(Slowing/Stopping, Straight)	-0.371	0.804	1.857	0.168
(Straight, Straight)	0.941	0.315	2.247	0.026
(Straight, Changing Lanes)	1.173	0.171	1.353	0.187
Involving an AV's yielding or waiting	0.825	0.151	.682	0.339
Other road users				
Involving a transit vehicle	-0.848	0.546	1.958	0.167
Involving a pedestrian or bicyclist	0.067	0.940	1.152	0.242
Constant	-1.232	0.432	-1.793	0.375
Model Summary	**Value**			
Number of Observations (N)	148			
McFadden's R^2	0.240			
AIC	303.160			
BIC	399.071			

Table 5.3 Marginal Effects in Model 1 (Multinomial Logit)

Variable	**Marginal Effects (%)**		
	Pre-crash Automated → During-crash Automated	**Pre-crash Automated → During-crash Conventional**	**Pre-crash Conventional → During-crash Conventional**
AV manufacturer			
Cruise LLC	7.0	30.9 ***	-37.9 ***
Waymo LLC	21.6	6.4	-28.0 ***
Land use			
Residential	-13.5	-30.5	44.0
Commercial	-12.8	-39.9 **	52.7 **
Recreational	-12.8	-33.6	46.4
Road classification			
Freeway/Expressway/Highway	-16.3	34.5 **	-18.2
Street	4.5	2.7	-7.2
Road segment type			
Intersection	25.8 **	8.5	-34.3 ***
Vehicle movements: *(AV, Second Vehicle)*			
(Stopped, Straight)	13.3	-10.1	-3.2
(Slowing/Stopping, Straight)	-21.8	25.2 **	-3.4
(Straight, Straight)	1.4	19.7 **	-21.2
(Straight, Changing Lanes)	13.0	7.2	-20.2
Involving an AV's yielding or waiting	11.2	1.8	-13.0
Other road users			
Involving a transit vehicle	-32.2	30.1 **	2.0
Involving a pedestrian or bicyclist	-7.6	13.3	-5.8

Notes: Significance Level = *** 0.01, ** 0.05, and * 0.1

Rear-End Collision

Concerning rear-end collision, as shown in **Table 5.4**, binary logit models were estimated with the explanatory variables related to pre-crash conditions and AV driving mode. The frequentist binary logit model (Model 2A) has McFadden's R squared value, 0.371, which means it fits well with the data. For the Bayesian binary logit models, this study applied informative prior distributions, $\beta \sim N(0.75, 0.44)$ and $\beta \sim N(1.96, 0.34)$, for the variables "Intersection" and "Pre-crash automated → During-crash automated," respectively, based on an earlier study (*122*). For the other variables, uninformative prior distributions were applied, including weak normal priors, $\boldsymbol{\beta} \sim N(0, 1000)$, and strong normal priors, $\boldsymbol{\beta} \sim N(0, 10)$. After estimating the Bayesian binary logit models, the model with a lower Deviance Information Criteria (DIC) value was selected (Model 2B).

Estimation results of the frequentist and Bayesian binary logit models are summarized in **Table 5.4**. Regarding the impact of AV driving mode, notably, the frequentist model (Model 2A) estimated the coefficient (β) of "Pre-crash automated → During-crash automated" as 1.524 at the 99% confidence level based solely on the sample, while the Bayesian model (Model 2B) estimated the mean of the coefficient as 1.654 and its 95% credible interval as (0.905, 2.393), as visualized in **Figure 5.8**, by taking both the sample and prior knowledge into account. According to the frequentist model (Model 2A), the marginal effect of this variable is 21.7%, which indicates that the chance of a rear-end collision is higher by 21.7% when an AV is in the automated driving mode compared to when it is in the conventional mode.

According to Models 2A and 2B, most importantly, the chance of a rear-end collision increases when an AV crashes in the automated driving mode compared to when it crashes in the conventional mode. This relationship is aligned with previous findings (*116-121-122*). Another notable observation is that rear-end collisions have a positive relationship with AVs yielding to or waiting for other road users. Besides, rear-end collisions have a negative relationship with an AV's interaction with pedestrians or bicyclists. Regarding vehicle movements, rear-end collisions have a positive relationship with the combination of an AV stopped and the second vehicle proceeding straight, the combination of an AV slowing or stopping and the second vehicle proceeding straight, the combination of an AV and the second vehicle proceeding straight, and the combination of an AV proceeding straight and the second vehicle changing lanes. Meanwhile, intersections are not found to have a significant impact on the chance of a rear-end collision, which is aligned with a previous finding (*122*) and, at the same time, not aligned with other previous findings (*116-120*).

Sideswipe Collision

Regarding sideswipe collision, as shown in **Table 5.5**, binary logit models were estimated with the explanatory variables related to pre-crash conditions and AV driving mode. For the Bayesian binary logit models, this study applied uninformative prior distributions, including weak normal priors, $\boldsymbol{\beta} \sim N(0, 1000)$, and strong normal priors, $\boldsymbol{\beta} \sim N(0, 10)$. After estimating the Bayesian binary logit models, the model with a lower DIC value was selected (Model 3B).

According to Models 3A and 3B, importantly, the chance of a sideswipe collision would not be significantly affected by the AV driving mode, given an AV-involved crash. Meanwhile, Model 3B indicates that the chance of a sideswipe collision is associated with vehicle movements, given an AV-involved crash. Specifically, sideswipe collisions have a negative relationship with the combination of an AV stopped and the second vehicle proceeding straight, as well as the combination of an AV and the second vehicle proceeding straight.

Table 5.4 Models 2A (Frequentist Logit) and 2B (Bayesian Logit): Rear-End Collision

Variable	*Model 2A: Frequentist Logit*			*Model 2B: Bayesian Logit*		
	β	***P-value***	***M.E. (%)***	***Mean(β)***	***95% Credible Interval***	
AV manufacturer						
Cruise LLC	0.741	0.230	10.1	1.055	0.037	2.258
Waymo LLC	0.079	0.928	1.1	0.249	-0.619	1.197
Land use						
Residential	-0.594	0.710	-8.1	-0.981	-1.872	-0.034
Commercial	-0.471	0.767	-6.4	-0.711	-1.758	0.494
Recreational	-0.913	0.620	-12.5	-0.590	-1.598	0.419
Road classification						
Freeway/Expressway/Highway	-1.424	0.326	-19.5	-1.509	-2.991	0.168
Street	-2.283	0.031	-31.2	-2.389	-3.773	-1.056
Road segment type						
Intersection	-0.203	0.770	-2.8	0.074	-0.670	0.803
Vehicle movements: *(AV, Second Vehicle)*						
(Stopped, Straight)	2.417	0.001	33.0	2.351	0.982	3.735
(Slowing/Stopping, Straight)	4.369	0.011	59.7	3.888	1.969	6.215
(Straight, Straight)	2.221	0.007	30.4	1.917	0.573	3.426
(Straight, Changing Lanes)	1.842	0.027	25.2	1.462	0.289	2.737
(Left, Straight)	0.326	0.811	4.5	0.428	-0.964	1.814
Involving an AV's yielding or waiting	1.228	0.045	16.8	1.389	0.473	2.377
Other road users						
Involving a transit vehicle	-0.830	0.461	-11.3	-0.115	-1.532	1.152
Involving a pedestrian or bicyclist	-2.937	0.020	-40.1	-3.172	-4.435	-1.972
AV driving mode *(Base: Pre-crash Conventional → During-crash Conventional)*						
Pre-crash Automated → During-crash Conventional	-0.388	0.590	-5.9	-0.431	-1.587	0.578
Pre-crash Automated → During-crash Automated	1.524	0.009	21.7	1.654	0.905	2.393
Constant	1.145	0.532	NA	1.143	-0.323	2.631
Model Summary						
Number of Observations (N)	148			148		
McFadden's R^2	0.371			NA		
AIC	163.128			NA		
BIC	220.076			NA		
DIC	NA			149.395		

Notes: In Model 2B, an informative prior, $\beta \sim N(0.75, 0.44)$, was applied for "Intersection"; an informative prior, $\boldsymbol{\beta} \sim N(1.96, 0.34)$, was used for "Pre-crash Automated → During-crash Automated"; uninformative priors, $\boldsymbol{\beta} \sim N(0, 10)$, were applied for the other variables.

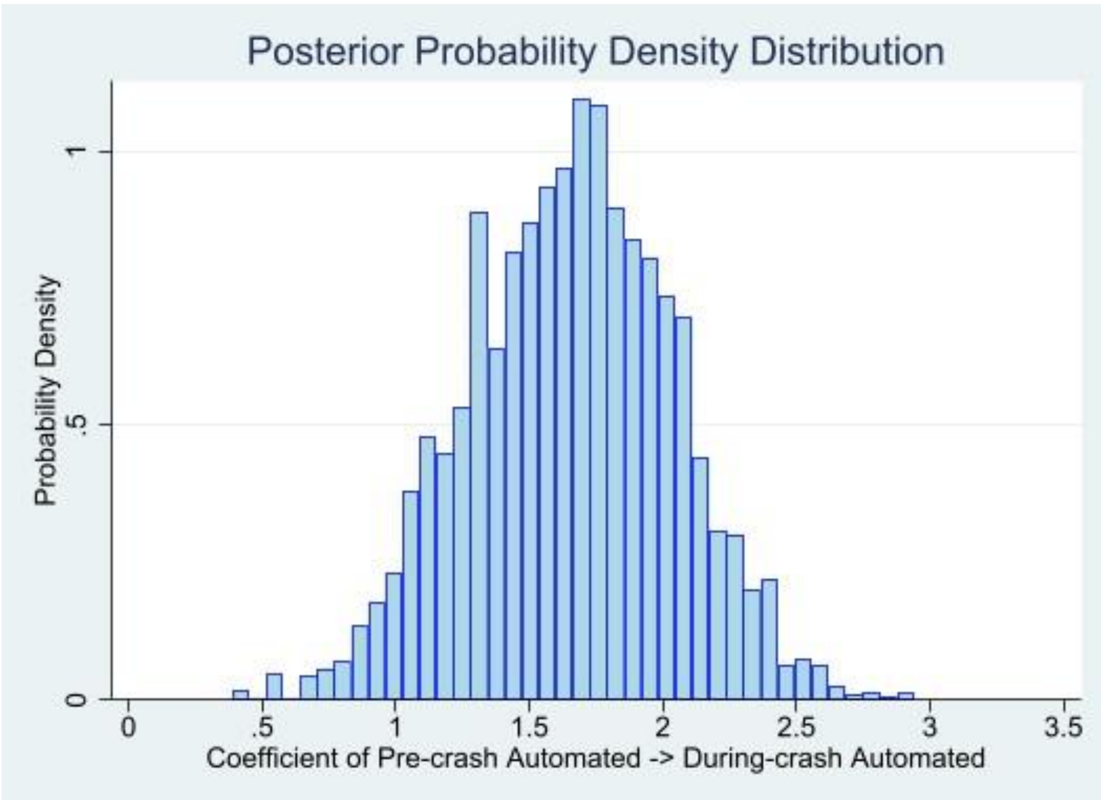


Figure 5.8 Posterior Distribution of Coefficient of "Automated Driving Mode" (Rear-End Collision)

Table 5.5 Models 3A (Frequentist Logit) and 3B (Bayesian Logit): Sideswipe Collision

Variable	*Model 3A: Frequentist Logit*			*Model 3B: Bayesian Logit*		
	β	***P-value***	***M.E. (%)***	***Mean(β)***	***95% Credible Interval***	
AV manufacturer						
Cruise LLC	-0.191	0.752	-2.6	-0.260	-1.066	0.540
Waymo LLC	-0.423	0.638	-5.7	-0.910	-2.109	0.330
Land use						
Commercial	0.592	0.313	8.0	0.617	-0.285	1.486
Recreational	1.306	0.167	17.6	1.008	-0.258	2.276
Road classification						
Street	0.944	0.281	12.7	0.520	-0.290	1.404
Road segment type						
Intersection	-0.141	0.834	-1.9	-0.090	-1.206	1.024
Vehicle movements: *(AV, Second Vehicle)*						
(Stopped, Straight)	-1.282	0.123	-17.2	-1.215	-2.062	-0.356
(Straight, Straight)	-1.366	0.130	-18.4	-1.818	-3.140	-0.465
(Straight, Changing Lanes)	-0.674	0.404	-9.1	-0.742	-2.046	0.505
Involving an AV's yielding or waiting	-0.155	0.802	-2.1	-0.400	-1.488	0.627
Other road users						
Involving a transit vehicle	1.054	0.301	14.2	0.775	-0.237	1.793
Involving a pedestrian or bicyclist	-0.826	0.355	-11.1	-0.913	-2.682	0.581
AV driving mode *(Base: Pre-crash Conventional → During-crash Conventional)*						
Pre-crash Automated → During-crash Conventional	0.346	0.600	5.4	0.272	-0.782	1.325
Pre-crash Automated → During-crash Automated	-0.605	0.308	-7.5	-0.482	-1.245	0.270
Constant	-1.871	0.081	NA	-1.516	-2.580	-0.450
Model Summary						
Number of Observations (N)	148			148		
McFadden's R^2	0.130			NA		
AIC	152.92			NA		
BIC	194.88			NA		
DIC	NA			144.696		
Prior Distributions	NA			N(0, 1000)		

Injury Crash

Concerning injury crashes, as shown in **Table 5.6**, binary logit models were estimated with the explanatory variables related to pre-crash conditions, AV driving mode, and crash types. The frequentist binary logit model (Model 4A) has McFadden's R squared value, 0.376, which means it fits well with the data. For Bayesian binary logit models, this study applied informative prior distributions, $\beta \sim N(2.22, 1.29)$, for the variable "Intersection," based on an earlier study (*122*). For the other variables, uninformative prior distributions were applied, including weak normal priors, $\boldsymbol{\beta} \sim N(0, 1000)$, and strong normal priors, $\boldsymbol{\beta} \sim N(0, 10)$. After estimating the Bayesian binary logit models, the model with a lower DIC value was selected (Model 4B).

Estimation results are summarized in **Table 5.6**. Regarding the impact of "Intersection," the frequentist model (Model 4A) estimated the coefficient (β) as 3.443 at the 90% confidence level based solely on the sample, while the Bayesian model (Model 4B) estimated the mean of the coefficient as 2.256 and its 95% credible interval as (0.835, 3.781), as visualized in **Figure 5.9**, by considering both the sample and prior knowledge. According to the frequentist model (Model 4A), the marginal effect of this variable is 35.4%, which indicates that the chance of injury is higher by 35.4% when an AV-involved crash occurs at an intersection.

According to Model 4A and 4B, importantly, the chance of injury given an AV-involved crash would not be significantly influenced by AV driving mode. As in a previous study, injuries from AV-involved crashes are found to have a positive relationship with intersections (*122*). Additionally, it is revealed that injury crashes have a positive relationship with recreational areas, ramps or slip lanes, and an AV's interaction with pedestrians or bicyclists. When it comes to vehicle movements, injury crashes have a positive relationship with the combination of an AV making a left turn and the second vehicle proceeding straight.

AV Damage Level

Regarding AV damage level, as shown in **Table 5.7** and **Table 5.8**, ordered logit models were estimated with the explanatory variables related to pre-crash conditions, AV driving mode, and crash types. For Bayesian ordered logit models, this study applied uninformative prior distributions, including weak normal priors, $\boldsymbol{\beta} \sim N(0, 1000)$, and strong normal priors, $\boldsymbol{\beta} \sim N(0, 10)$. After estimating the Bayesian ordered logit models, the model with a lower DIC value was selected (Model 5B).

Models 5A and 5B indicate that AV damage level would not be significantly affected by AV driving mode, which conflicts with a previous finding that AV crash severity had a negative relationship with the automated driving mode (*121*). Likewise, AV damage level is not found to have a significant relationship with intersections, which is not in accordance with a previous finding suggesting a negative relationship between them (*121*). These conflicts with previous findings indicate that AV performance might not have improved much over time to better avoid severe damage from a crash at an intersection. While AV damage level is found to have a positive relationship with sideswipe collisions, it is not found to have a significant relationship with rear-end collisions, which conflicts with a previous finding suggesting a positive relationship between AV crash severity and rear-end collisions (*121*). This conflict is probably because AV performance has improved over time to avoid severe damage from a rear-end collision. Furthermore, AV damage level is found to be associated with vehicle movements. Particularly, AV damage level has a positive relationship with the combination of an AV proceeding straight and the second vehicle changing lanes. Likewise, it has a positive relationship with the combination of an AV making a left turn and the second vehicle proceeding straight.

Table 5.6 Models 4A (Frequentist Logit) and4B (Bayesian Logit): Injury Crash

Variable	*Model 4A: Frequentist Logit*			*Model 4B: Bayesian Logit*		
	β	*P-value*	*M.E. (%)*	*Mean(β)*	*95% Credible Interval*	
AV manufacturer						
Cruise LLC	5.062	<0.001	52.0	5.415	3.825	7.323
Waymo LLC	2.019	0.191	20.7	1.907	0.237	3.972
Land use						
Commercial	0.513	0.456	5.3	0.382	-0.457	1.248
Recreational	3.425	0.033	35.2	3.244	1.208	6.007
Road classification						
Street	-1.234	0.173	-12.7	-1.475	-2.756	-0.292
Road segment type						
Intersection	3.443	0.077	35.4	2.256	0.835	3.781
Ramp or Slip Lane	4.980	0.030	51.1	3.560	2.603	4.596
Vehicle movements: *(AV, Second Vehicle)*						
(Stopped, Straight)	1.591	0.055	16.3	1.946	0.438	3.331
(Slowing/Stopping, Straight)	-1.408	0.365	-14.5	-0.707	-2.165	0.663
(Straight, Straight)	1.109	0.148	11.4	1.426	0.147	2.673
(Left, Straight)	4.478	0.039	46.0	4.994	2.549	7.345
Involving an AV's yielding or waiting	0.542	0.410	5.6	0.371	-0.798	1.491
Other road users						
Involving a pedestrian or bicyclist	2.932	0.011	30.1	2.838	1.463	4.215
AV driving mode *(Base: Pre-crash Conventional → During-crash Conventional)*						
Pre-crash Automated → During-crash Conventional	-1.263	0.173	-12.2	-1.037	-2.077	0.327
Pre-crash Automated → During-crash Automated	-0.323	0.660	-3.5	-0.054	-1.190	1.138
Crash type *(Base: Other)*						
Rear-End	0.661	0.471	6.8	0.953	-0.466	2.492
Sideswipe	-0.954	0.408	-9.8	-0.818	-3.295	0.976
Constant	-8.954	0.001	NA	-8.400	-10.825	-6.805
Model Summary						
Number of Observations (N)	148			148		
McFadden's R^2	0.376			NA		
AIC	128.861			NA		
BIC	179.814			NA		
DIC	NA			117.814		

Notes: In Model 4B, an informative prior, $\boldsymbol{\beta} \sim N(2.22, 1.29)$, was applied for "Intersection"; uninformative priors, $\boldsymbol{\beta} \sim N(0, 1000)$, were applied for the other variables.

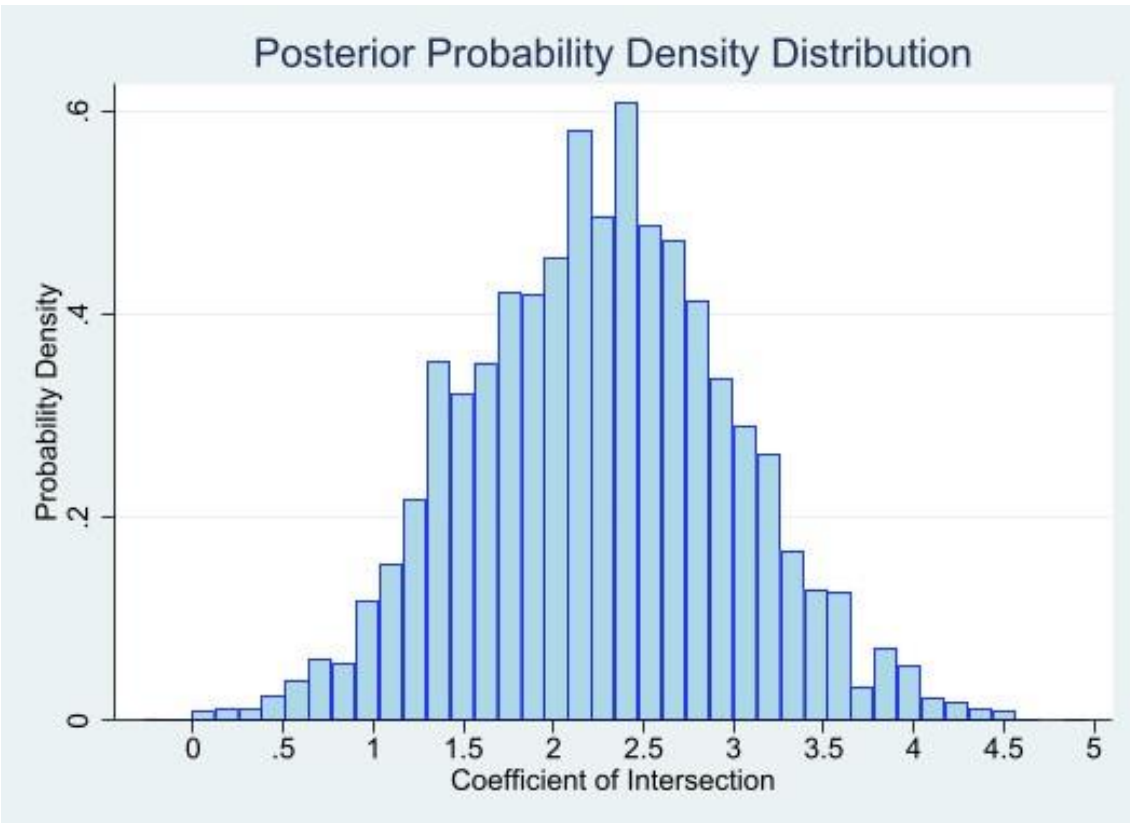


Figure 5.9 Posterior Distribution of Coefficient of "Intersection" (Injury Crash)

Table 5.7 Model 5A (Frequentist Ordered Logit): AV Damage Level

Variable	β	P-value	Marginal Effects (%)		
			None	Minor	Moderate or Major
AV manufacturer					
Cruise LLC	0.111	0.842	-1.0	-0.4	1.4
Waymo LLC	0.246	0.714	-2.1	-0.9	3.1
Land use					
Residential	-0.734	0.538	6.4	2.8	-9.2
Commercial	-1.184	0.319	10.3	4.5	-14.9
Recreational	-1.257	0.377	11.0	4.8	-15.8
Road classification					
Freeway/Expressway/Highway	-0.736	0.395	6.4	2.8	-9.2
Road segment type					
Intersection	0.143	0.810	-1.3	-0.5	1.8
Vehicle movements: *(AV, Second Vehicle)*					
(Stopped, Straight)	0.730	0.205	-6.4	-2.8	9.2
(Slowing/Stopping, Straight)	-0.066	0.952	0.6	0.3	-0.8
(Straight, Straight)	0.387	0.573	-3.4	-1.5	4.9
(Straight, Changing Lanes)	1.163	0.097	-10.2	-4.5	14.6 *
(Left, Straight)	2.660	0.058	-23.2 *	-10.2	33.4 **
Involving an AV's yielding or waiting	0.191	0.701	-1.7	-0.7	2.4
Other road users					
Involving a transit vehicle	0.276	0.782	-2.4	-1.1	3.5
AV driving mode (Base: Pre-crash Conventional → During-crash Conventional)					
Pre-crash Automated → During-crash Conventional	0.489	0.422	-3.3	-4.0	7.3
Pre-crash Automated → During-crash Automated	-0.433	0.391	4.1	1.0	-5.1
Crash type *(Base: Other)*					
Rear-End	0.638	0.269	-5.6	-2.4	8.0
Sideswipe	1.659	0.009	-14.5 **	-6.4	20.9 ***
Threshold parameters					
μ_1	-2.181	0.066	NA	NA	NA
μ_2	2.037	0.087	NA	NA	NA
Model Summary	**Value**				
Number of Observations (N)	148				
McFadden's R^2	0.094				
AIC	243.106				
BIC	297.056				

Notes: Significance Level = *** .01, ** .05, and * .1

Table 5.8. Model 5B (Bayesian Ordered Logit): AV Damage Level

Variable	*Mean(β)*	*95% Credible Interval*	
AV manufacturer			
Cruise LLC	0.019	-0.416	0.494
Waymo LLC	0.255	-0.393	0.923
Land use			
Residential	-0.942	-2.183	0.198
Commercial	-1.169	-2.280	-0.126
Recreational	-1.190	-1.886	-0.483
Road classification			
Freeway/Expressway/Highway	-0.681	-1.921	0.569
Road segment type			
Intersection	-0.067	-0.872	0.750
Vehicle movements: *(AV, Second Vehicle)*			
(Stopped, Straight)	0.503	-0.623	1.471
(Slowing/Stopping, Straight)	-0.119	-1.022	0.693
(Straight, Straight)	0.450	-0.844	1.631
(Straight, Changing Lanes)	1.243	0.262	2.201
(Left, Straight)	2.659	1.639	3.708
Involving an AV's yielding or waiting	0.200	-0.447	0.868
Other road users			
Involving a transit vehicle	0.961	-0.237	2.005
AV driving mode *(Base: Pre-crash Conventional → During-crash Conventional)*			
Pre-crash Automated → During-crash Conventional	0.209	-0.400	0.817
Pre-crash Automated → During-crash Automated	-0.284	-0.845	0.222
Crash type *(Base: Other)*			
Rear-End	0.753	-0.127	1.643
Sideswipe	1.617	0.713	2.479
Threshold parameters			
μ_1	-2.485	-3.669	-1.517
μ_2	1.886	0.820	2.899
Model Summary			
Number of Observations (N)	148		
Prior Distributions	N(0, 1000)		
DIC	228.601		

Key Interrelationships

As shown in **Figure 5.10**, this study generated a summary diagram highlighting the most important interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes. They are summarized according to the marginal effects of explanatory variables in Models 1, 2A, 3A, 4A, and 5A from the frequentist approach. As summarized in **Figure 5.10**, "Intersection" is associated with a higher chance that an AV is in the automated driving mode by 25.8%, given a crash. Simultaneously, the automated driving mode is correlated with a higher chance of a rear-end collision by 21.7%, compared to the conventional mode. Given a crash, consequently, "Intersection" has an indirect impact on the chance of a rear-end collision by 5.6% ($= 25.8\% \times 21.7\%$) while having a direct impact on the chance of injury by 35.4%. Meanwhile, "Involving a transit vehicle" is associated with a higher chance of manual disengagement by 30.1%, given a crash. Ramps or slip lanes are correlated with a higher chance of injury by 35.4%, given a crash. Furthermore, "Sideswipe collision" is associated with a higher chance that an AV has moderate or major damage from a crash by 20.9%.

DISCUSSION

Based on the results above, this study derived practical implications concerning the safety of AVs, which might provide AV developers with helpful feedback on the gaps in automated driving performance. Now that the AV-involved crash cases represent the failures of the automated driving system and the current road infrastructure, the influential factors related to AV-involved crashes identified in this study could be considered in safety assessment scenarios for high-level (Levels 4-5) automation as well as in developing Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) technologies to avoid those failures in the future. Furthermore, they will provide transportation planners and engineers with insights into critical elements to focus on in managing and operating mixed traffic consisting of AVs and human-driven vehicles.

AV Driving Mode

In accordance with a previous study, this study reveals that AVs tend to become more vulnerable to rear-end collisions in the automated driving mode than in the conventional mode (*122*). This implies that automated driving performance might have not yet reached a stable state to avoid rear-end collisions deftly. On the other hand, this study shows that the automated driving mode would not significantly affect the chance of a sideswipe collision or crash outcomes such as injury and vehicle damage. This implies that automated driving performance seems to be no better or worse than human driving regarding sideswipe collisions and crash outcomes.

This study also provides meaningful implications regarding manual disengagement. The fact that a driver manually disengaged the AV right before a crash implies that the AV might have failed to hand over its control to the driver when necessary. Thus, those contributing factors related to manual disengagement could be considered what AVs have difficulty dealing with in their decision to disengage themselves when facing a crash. Specifically, the analysis results imply that AV performance would need improvements to better deal with longitudinal distance from the leading or following vehicle. It is also implied that AV performance would require improvements to better interact with transit vehicles. Moreover, the results offer the insight that drivers tend to be readier to manually disengage their AVs, especially on the freeway, expressway, or highway where speed limits are usually high. Meanwhile, the results imply that drivers prefer to allow their AVs to be in the automated driving mode at an intersection.

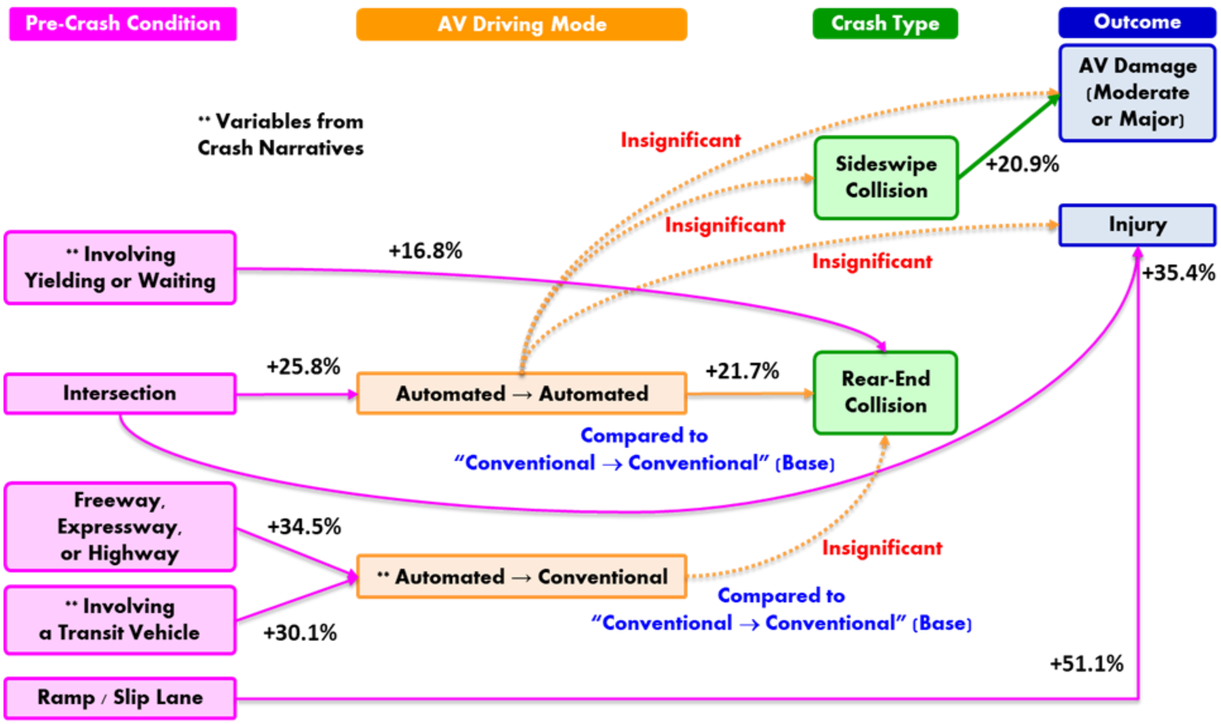


Figure 5.10 Summary of Key Interrelationships

Crash Types

One of the most critical implications regarding crash types is that AV performance would need improvements to better deal with the vehicle following them to avoid a rear-end collision, especially in the automated driving mode. When comparing manual disengagement and the conventional mode, there is no significant difference in the chance of rear-end collision. This implies that an AV will be less likely to have a rear-end collision as it hands over its control to the driver in advance when necessary. When AVs are proceeding straight, they would need to better interact with those vehicles changing lanes around them. Especially when AVs are yielding to or waiting for other road users, they might have difficulty dealing with the vehicle following them.

Crash Outcomes

Based on the results, AVs might have a hard time dealing with a variety of distractions from surroundings in recreational areas. At intersections, AVs usually face different types of elements to care about, such as road signs, traffic signals, and other vehicles coming from different directions. This might take AVs more time to respond to unexpected situations. In this regard, AV performance may need improvements to better deal with many different elements at the same time at an intersection. Meanwhile, injury crashes are more likely to occur on a ramp or slip lane probably because ramps and slip lanes are usually curved, which restricts the sight distance of AVs and allows them a short response time to cope with dangerous situations. This suggests the importance of road infrastructure improvements for transportation automation. Moreover, AV performance would need to better interact with other vehicles, especially when they make a left turn to avoid injury as well as vehicle damage. Furthermore, AV performance may need to be improved to better detect and interact with pedestrians or bicyclists.

Limitations and Future Research

The sample of AV crashes is from a certain region in the United States, i.e., the State of California. This means that the results of this study should be interpreted within the contexts of California rather than being generalized broadly. In addition, since this study only covers AV-involved crashes, the relationships identified in this study are valid only for those cases where AV crashes occurred early in their development. This means that the results might not be valid for those cases where AVs faced a dangerous situation but avoided a crash. Even though this study extracted as much information as possible from multiple data sources, some variables could still be missing beyond the dataset, such as the exact vehicle trajectories and how the vehicle speeds had changed before a crash occurred. Since the sample includes those cases where an AV was struck by another vehicle and those cases where an AV struck another vehicle, future research may attempt to classify AV-involved crashes by whether an AV was striking or being struck to obtain more detailed insights. Given that some relationships identified in this study conflict with previous findings, it will be meaningful to keep track of those relationships with future crash data to figure out how AV performance is being enhanced.

CONCLUSION

Testing of AVs is meant to improve their roadway performance and is providing new empirical evidence about situations requiring safety improvements. To explore their safety performance on roadways, this study has created and structured a unique and comprehensive dataset of 148 AV crashes in California from January 2019 to December 2020. With the safe system path-analytic framework, the frequentist and Bayesian approaches addressing the sequence of events in AV crashes, and extracting valuable information from crash narratives, this study has investigated interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes. Notably, this study provides a deeper understanding of AV crashes by integrating multiple data sources. For instance, the impacts of manual disengagement, AVs' yielding to or waiting for other road users, and AVs' interaction with transit vehicles could not have been identified without extracting additional variables from crash narratives. This new information extracted from crash narratives reported by AV manufacturers helps identify the manual disengagement and AV interactions with public transit vehicles in mixed traffic as the issues that need further investigation. In this regard, this study suggests that AV crash narrative data can be harnessed to improve knowledge of AV safety in mixed traffic.

The study provides several key insights and practical implications as follows. First, AVs, especially in the automated driving mode, would need to better deal with longitudinal distance from the leading or following vehicle on the road. Particularly, the positive relationship between manual disengagement and AVs' interaction with another vehicle proceeding straight implies a potential disparity between the safe distance calculated by the automated driving system and the distance drivers feel safe about. In this regard, it would be desirable to refine the way the automated driving system operates to more naturalistic driving. When AVs yield to other road users, they would need to better detect and warn drivers of the following vehicle approaching from behind to avoid a rear-end collision. Given that AVs may have few options for crash avoidance when they yield to other road users, it may be helpful to explore how equipping human-driven vehicles with (after-market) automation features such as forward collision warning systems to reduce rear-end collisions, which has been suggested by a previous study (*116*). Fundamentally, the connection among vehicles on the roads with V2V communication would be a long-term solution for this issue. To reduce injury crashes, AVs would need more thorough testing to adapt to the critical roadway and infrastructure features such as intersections, ramps, and slip lanes, while roadway infrastructure would require improvements to support transportation automation.

Those risk factors of AV-involved crashes identified in this study can be included in safety assessment scenarios for more efficient and reasonable testing for high-level (Levels 4-5) automation. They can also be considered in developing Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) technologies. Furthermore, the implications derived from this study might give transportation planners and engineers valuable insights into what aspects they may need to take care of in managing and operating mixed traffic with AVs and human-driven vehicles.

ACKNOWLEDGMENT

This chapter is based on "Autonomous Vehicle Collision Reports" released by the California Department of Motor Vehicles in 2019 and 2020. Any opinions, findings, conclusions, or recommendations in this paper are those of the authors and do not necessarily reflect the organization's views above.

Chapter 6. Overall Conclusion

Aiming to provide new knowledge and deep insights regarding the readiness for transportation electrification and automation in terms of safety and future adoption, the dissertation investigated how different types of travelers are going to embrace EV and AV technologies in the future and what specific safety-related challenges the automated driving systems are facing. As a case study of California, **Chapter 2** performed a systematic analysis on how individuals become inclined to use AV-based travel options as well as adopt AFVs including EVs. For this, an "AV inclination index" was developed to quantify individual inclination toward AV-based travel options integrating owning an AV, using AV ride-hailing services, and using SAV ride-hailing services. Importantly, this chapter examined how those people with the experience in owning or leasing an AFV had different inclination toward AV-based travel options from those people without the AFV experience while taking unobserved heterogeneity into account. Considering that the commercial sector has the potential to adopt a considerable amount of EVs in the future, **Chapter 3** explored whether and to what extent commercial light-duty fleet owners would be willing to adopt different types of EVs such as PHEVs, BEVs, and FCEVs. Within a context of California, this chapter identified the critical barriers to EV adoption by commercial light-duty fleet owners and the opportunities for EV diffusion in the commercial sector. Paying attention to early adopters' experiences and perspectives, **Chapter 4** investigated the satisfaction of BEV owners and their willingness to repurchase a BEV in the future. Within a context of Jeju, South Korea, this chapter captured the critical barriers to BEV re-adoption by BEV owners and the opportunities for BEV diffusion. Given that the perceived safety of AVs is one of the key factors associated with individual willingness to use AVs in the future, **Chapter 5** performed an exhaustive analysis on crashes involving Levels 2-3 AVs tested on public roads in California to provide a better understanding of AV safety performance (*10-13*). This chapter showed a big clear picture with key interrelationships among pre-crash conditions, AV driving modes, crash types, and crash outcomes, which provides practical implications for AV safety assessment, roadway infrastructure improvements, and the management and operation of mixed traffic.

As summarized in **Table 6.1**, the dissertation provides the vehicle and transportation industries, engineers, planners, and policymakers with key implications for transportation electrification and automation. The implications have been derived directly based on the findings from each chapter to avoid a logical leap. The key implications are as follows.

- The diffusion of AFVs and AV-based travel options can be disproportionate generating disparities among travelers depending on the level of exposure to shared travel modes in their local area. Especially, the diffusion of AV-based travel options can be disproportionate among travelers depending on whether a person has owned or leased an AFV and whether a person uses shared ride-hailing services. That is, those people with high exposure to shared travel modes or AFVs are more likely to choose AV-based travel options in the future. On the other hand, those people with low exposure to them are less likely to choose AV-based travel options. For a smooth transition to transportation electrification and automation, in this regard, planners and policymakers should be prepared for potential variations in the demand for electrified and/or automated travel modes in the future by taking the aforementioned relationships into account.
- AV-based travel options could attract part of the travel demand of those who are not using carsharing available in the local area, which might impact mode-choice behavior.

- EV adoptions by commercial light-duty fleet owners can be facilitated by lowering the barriers, including the limited hauling capacity of PHEVs, limited range of BEVs, and cost of installing fueling equipment for FCEVs, as well as by collaborating with the "healthcare and social assistance," "transportation and warehousing," and "professional, scientific, and technical services" industries.
- BEV re-adoptions can be supported by low-level vehicle automation, given that having BEVs equipped with automation features such as the collision warning system would support BEV re-adoptions in the future by making current BEV owners more satisfied.
- BEV re-adoptions could be supported by providing real-time information for BEV users.
- The automated driving system requires improvements in dealing with the longitudinal distance from the leading or following vehicle while reducing a potential discrepancy between the safe distance that the automated driving system can deal with and the distance that human drivers feel safe about.
- AVs need more thorough testing to adapt to critical roadway and infrastructure features including intersections, ramps, and slip lanes. At the same time, this issue recommends that engineers, planners, and policymakers be aware that transportation automation can be supported by improving current roadway infrastructure such as intersections, ramps, and slip lanes.
- For more efficient and reasonable testing for high-level (Levels 4-5) automation, safety assessment scenarios can include the risk factors identified in this study such as interaction with transit vehicles, yielding to or waiting for other road users, dealing with longitudinal distance from other vehicles, and operating at intersections, ramps, and slip lanes. These factors can also be considered in managing and operating mixed traffic with AVs and human-driven vehicles as well as in developing Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) technologies.
- AV crash narrative data can be harnessed to improve knowledge of AV safety in mixed traffic.

Since the dissertation is composed of case studies, its results, interpretations, findings, and implications should be understood within the context of the specific region corresponding to each case study. To be specific, each chapter should be understood by the reader within the following contexts.

- **Chapter 2** should be interpreted by the reader within the context of residents aged 18 or more in California. The survey sample is well representative of the general population of California in terms of residency by county and annual household income, although it somewhat under-represents low-income people and over-represents older adults.
- **Chapter 3** should be interpreted within the context of owners of light-duty commercial vehicles weighing less than 10,000 pounds throughout California. The locational distribution of the sample is highly proportional to the population of each county.

Table 6.1 Summary of Implications

<table>
<tr><th rowspan="2">Sector</th><th colspan="2">Key implications</th></tr>
<tr><th>Electrification</th><th>Automation</th></tr>
<tr><td rowspan="5">Vehicle and transportation industries</td><td colspan="2">BEV re-adoptions can be supported by low-level vehicle automation.</td></tr>
<tr><td>An opportunity to have synergetic connections with the “healthcare and social assistance,” “transportation and warehousing,” and “professional, scientific, and technical services” industries</td><td>Safety assessment scenarios for high-level automation can include the risk factors identified in this study (e.g., interaction with transit vehicles, dealing with longitudinal distance from other vehicles, operating at intersections, ramps, and slip lanes).</td></tr>
<tr><td>EV adoptions by commercial light-duty fleet owners can be accelerated by lowering critical barriers (i.e., the limited hauling capacity of PHEVs, limited range of BEVs, and cost of installing fueling equipment for FCEVs).</td><td>A potential disparity between the safe distance of AVs and that of human drivers → AVs need to operate in a more naturalistic way.</td></tr>
<tr><td>BEV re-adoptions can be supported by making it easier to charge BEVs.</td><td>AVs need more thorough testing to adapt to critical roadway and infrastructure features (i.e., intersections, ramps, and slip lanes).</td></tr>
<tr><td>EV diffusion would be highly dependent on the accessibility of charging infrastructure.</td><td>The connection among vehicles on the road would help reduce rear-end crashes.</td></tr>
<tr><td>Engineers</td><td>BEV re-adoptions could be supported by making it easier to charge BEVs.</td><td>Transportation automation can be supported by improving current roadway infrastructure (e.g., intersections, ramps, and slip lanes).</td></tr>
<tr><td rowspan="3">Planners</td><td colspan="2">Part of those people with AFV experience would be more inclined to use AV-based travel options, which might generate variations in the demand for AV-based travel options.
The diffusion of AFVs and AV-based travel options can have disparities among travelers with different levels of exposure to shared travel modes by region.</td></tr>
<tr><td>EV diffusion would be highly dependent on the accessibility of charging infrastructure.</td><td>AV-based travel options would attract part of the travel demand of those who are not using carsharing available, which might impact mode-choice behavior.</td></tr>
<tr><td>BEV re-adoptions could be supported by providing real-time information for BEV users.</td><td>Transportation automation can be supported by improving current roadway infrastructure (e.g., intersections, ramps, and slip lanes).</td></tr>
<tr><td rowspan="3">Policymakers</td><td colspan="2">The diffusion of AFVs and AV-based travel options can have disparities among travelers with different levels of exposure to shared travel modes by region.</td></tr>
<tr><td>BEV re-adoptions could be supported by providing real-time information for BEV users.</td><td>Transportation automation can be supported by improving current roadway infrastructure (e.g., intersections, ramps, and slip lanes).</td></tr>
<tr><td>EV diffusion would be highly dependent on the accessibility of charging infrastructure.</td><td>AV crash narrative data can be harnessed to improve knowledge of AV safety in mixed traffic.</td></tr>
</table>

- **Chapter 4** should be interpreted within the context of BEV owners in Jeju, South Korea. The survey sample does not represent the general population of Jeju, South Korea given that the average monthly household income, the proportion of middle-aged people, and the proportion of males are higher compared to the general population of the region. This demonstrates that BEV owners are a distinctive group of people that deserve an in-depth investigation.
- **Chapter 5** should be interpreted within the context of crashes involving levels 2-3 AVs on the public roads in the state of California.

For future research, more case studies in other regions and countries can be performed with individuals, commercial fleet owners, and AV-involved crashes to obtain evidence and findings that can be generalized to a larger population in the world. In addition, the impacts of key factors on the willingness to embrace EV and AV technologies and AV-involved crashes can be updated by investigating newly generated data in the future. Especially, after levels 4-5 AVs are available and adopted by travelers to a certain degree, it will be valuable to investigate how individuals' proclivity toward or actual use of AV-based travel options affects their EV adoptions. Considering that the dissertation is based on the evidence from the very early stage of transportation electrification and automation, even before high-level AVs are available in the market, future studies might need to be conducted with the evidence from the middle or late stages of transportation electrification and automation in the future to provide insights into how to keep improving the surface transportation system.

REFERENCES

[1] INRIX. *Congestion Costs Each American 97 hours, $1,348 A Year*. https://inrix.com/press-releases/scorecard-2018-us/. Accessed June 23, 2022.

[2] National Highway Traffic Safety Administration (NHTSA). *Fatality Analysis Reporting System (FARS)*. https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars. Accessed June 23, 2022.

[3] United States Department of Energy. *Alternative Fuels Data Center*. https://afdc.energy.gov/data/. Accessed June 21, 2022.

[4] Nichols, B. G., K. M. Kockelman, and M. Reiter. Air quality impacts of electric vehicle adoption in Texas. *Transportation Research Part D: Transport and Environment,* Vol. 34, 2015, pp. 208-218.

[5] United States Department of Energy. *Emissions from Hybrid and Plug-In Electric Vehicles*. https://afdc.energy.gov/vehicles/electric_emissions.html. Accessed November 03, 2021.

[6] National Highway Traffic Safety Administration (NHTSA). *Automated Vehicles for Safety*. https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety. Accessed June 21, 2022.

[7] Mahdinia, I., R. Arvin, A. J. Khattak, and A. Ghiasi. Safety, energy, and emissions impacts of adaptive cruise control and cooperative adaptive cruise control. *Transportation Research Record,* Vol. 2674, No. 6, 2020, pp. 253-267.

[8] California Fuel Cell Partnership. *FCEV Sales, FCEB, & Hydrogen Station Data*. https://cafcp.org/by_the_numbers. Accessed June 21, 2022.

[9] United States Department of Transportation. *Hybrid-Electric, Plug-in Hybrid-Electric and Electric Vehicle Sales*. https://www.bts.gov/content/gasoline-hybrid-and-electric-vehicle-sales. Accessed June 23, 2022.

[10] Nazari, F., M. Noruzoliaee, and A. K. Mohammadian. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C: Emerging Technologies,* Vol. 97, 2018, pp. 456-477.

[11] Howard, D., and D. Dai. Public perceptions of self-driving cars: The case of Berkeley, California.In *Transportation research board 93rd annual meeting, No. 14,* 2014. pp. 1-16.

[12] Barbour, N., N. Menon, Y. Zhang, and F. Mannering. Shared automated vehicles: A statistical analysis of consumer use likelihoods and concerns. *Transport Policy,* Vol. 80, 2019, pp. 86-93.

[13] Jabbari, P., J. Auld, and D. MacKenzie. How do perceptions of safety and car ownership importance affect autonomous vehicle adoption? *Travel behaviour and society,* Vol. 28, 2022, pp. 128-140.

[14] Lee, S., N. Ahmad, and A. Khattak. Adoption of Electric Vehicles: Is the Commercial Transportation Sector Interested? Presented at Transportation Research Board 101st Annual Meeting, Washington, D.C., 2022.

[15] Lee, S., N. Ahmad, S. Son, and A. Khattak. How Many Electric Vehicle Owners Will Repurchase a Similar Vehicle? Presented at Transportation Research Board 101st Annual Meeting, Washington, D.C., 2022.

[16] Hardman, S., and G. Tal. Discontinuance Among California's Electric Vehicle Buyers: Why are Some Consumers Abandoning Electric Vehicles?In, University of California, Berkeley. Institute of Transportation Studies, 2021.

[17] Society of Automotive Engineers (SAE) International. *SAE Levels of Driving Automation*. https://www.sae.org/blog/sae-j3016-update. Accessed June 23, 2022.

[18] Hackbarth, A., and R. Madlener. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment,* Vol. 25, 2013, pp. 5-17.
[19] Liu, J., A. Khattak, and X. Wang. The role of alternative fuel vehicles: Using behavioral and sensor data to model hierarchies in travel. *Transportation Research Part C: Emerging Technologies,* Vol. 55, 2015, pp. 379-392.
[20] Jansson, J., T. Pettersson, A. Mannberg, R. Brännlund, and U. Lindgren. Adoption of alternative fuel vehicles: Influence from neighbors, family and coworkers. *Transportation Research Part D: Transport and Environment,* Vol. 54, 2017, pp. 61-73.
[21] Li, X., C. Liu, and J. Jia. Ownership and usage analysis of alternative fuel vehicles in the United States with the 2017 national household travel survey data. *Sustainability*, Vol. 11, No. 8, 2019, p. 2262.
[22] Petschnig, M., S. Heidenreich, and P. Spieth. Innovative alternatives take action–Investigating determinants of alternative fuel vehicle adoption. *Transportation Research Part A: Policy and Practice,* Vol. 61, 2014, pp. 68-83.
[23] Bansal, P., and K. M. Kockelman. Forecasting Americans’ long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, Vol. 95, 2017, pp. 49-63.
[24] Sharma, I., and S. Mishra. Modeling consumers' likelihood to adopt autonomous vehicles based on their peer network. *Transportation Research Part D: Transport and Environment*, Vol. 87, 2020, p. 102509.
[25] Shabanpour, R., N. Golshani, A. Shamshiripour, and A. K. Mohammadian. Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. *Transportation Research Part C: Emerging Technologies*, Vol. 93, 2018, pp. 463-478.
[26] Menon, N., Y. Zhang, A. Rawoof Pinjari, and F. Mannering. A statistical analysis of consumer perceptions towards automated vehicles and their intended adoption. *Transportation planning and technology*, Vol. 43, No. 3, 2020, pp. 253-278.
[27] Asgari, H., and X. Jin. Incorporating attitudinal factors to examine adoption of and willingness to pay for autonomous vehicles. *Transportation Research Record,* Vol. 2673, No. 8, 2019, pp. 418-429.
[28] Sener, I. N., J. Zmud, and T. Williams. Measures of baseline intent to use automated vehicles: A case study of Texas cities. *Transportation research part F: traffic psychology and behaviour,* Vol. 62, 2019, pp. 66-77.
[29] Irannezhad, E., and R. Mahadevan. Examining factors influencing the adoption of solo, pooling and autonomous ride-hailing services in Australia. *Transportation Research Part C: Emerging Technologies*, Vol. 136, 2022, p. 103524.
[30] Khattak, A., N. Ahmad, and B. Wali. Consumer Preferences for Automation, Electrification, and Carsharing.In *Transportation Research Board 99th Annual Meeting, Washington DC*, 2020.
[31] National Renewable Energy Laboratory. *Transportation Secure Data Center*. www.nrel.gov/tsdc. Accessed May 5, 2021.
[32] United States Census Bureau. *American Community Survey: Income in 2019 (California)*. https://data.census.gov/cedsci/table?g=0400000US06&tid=ACSST1Y2019.S1901. Accessed September 12, 2022.
[33] ---. *American Community Survey: Demographic and Housing Estimates in 2019 (California)*.

https://data.census.gov/cedsci/table?g=0400000US06&tid=ACSDP1Y2019.DP05. Accessed September 12, 2022.
[34] ---. *County Population Totals: 2010-2019 (California)*. https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html. Accessed September 12, 2022.
[35] Agresti, A. *An introduction to categorical data analysis*. John Wiley & Sons, 2018.
[36] Tay, R. A random parameters probit model of urban and rural intersection crashes. *Accident Analysis & Prevention*, Vol. 84, 2015, pp. 38-40.
[37] Milton, J. C., V. N. Shankar, and F. L. Mannering. Highway accident severities and the mixed logit model: an exploratory empirical analysis. *Accident Analysis & Prevention*, Vol. 40, No. 1, 2008, pp. 260-266.
[38] McLachlan, G. J., and D. Peel. *Finite mixture models*. John Wiley & Sons, 2004.
[39] Liu, J., A. J. Khattak, X. Li, and X. Fu. A spatial analysis of the ownership of alternative fuel and hybrid vehicles. *Transportation Research Part D: Transport and Environment*, Vol. 77, 2019, pp. 106-119.
[40] California Air Resources Board. *Clean Vehicle Rebate Program (CVRP)*. https://ww2.arb.ca.gov/sites/default/files/movingca/cvrp.html. Accessed October 25, 2022.
[41] ---. *Clean Vehicle Rebate Program (CVRP) for Businesses*. https://ww2.arb.ca.gov/sites/default/files/movingca/cvrp_business.html. Accessed October 25, 2022.
[42] Blink Mobility. *BlueLA*. https://blinkmobility.com/. Accessed October 25, 2022.
[43] Liu, J., X. Wang, and A. Khattak. Customizing driving cycles to support vehicle purchase and use decisions: Fuel economy estimation for alternative fuel vehicle users. *Transportation Research Part C: Emerging Technologies*, Vol. 67, 2016, pp. 280-298.
[44] United States Department of Energy. *Where the Energy Goes: Electric Cars*. https://www.fueleconomy.gov/feg/atv-ev.shtml. Accessed November 3, 2021.
[45] Gao, Z., Z. Lin, and O. Franzese. Energy consumption and cost savings of truck electrification for heavy-duty vehicle applications. *Transportation Research Record*, Vol. 2628, No. 1, 2017, pp. 99-109.
[46] INSIDE EVs. *U.S. Plug-In Electric Car Sales Charted: 2019*. https://insideevs.com/news/393629/us-plugin-sales-charted-2019/. Accessed July 5, 2021.
[47] Braz da Silva, M., and F. Moura. Electric vehicle diffusion in the Portuguese automobile market. *International Journal of Sustainable Transportation*, Vol. 10, No. 2, 2016, pp. 49-64.
[48] The International Organization of Motor Vehicle Manufacturers. *Motorization Rate 2015 – Worldwide*. https://www.oica.net/category/vehicles-in-use/. Accessed July 5, 2021.
[49] Harrington, W., and A. Krupnick. Improving fuel economy in heavy-duty vehicles. *Resources for the Future DP*, 2012, pp. 12-02.
[50] Graham, L. A., G. Rideout, D. Rosenblatt, and J. Hendren. Greenhouse gas emissions from heavy-duty vehicles. *Atmospheric Environment*, Vol. 42, No. 19, 2008, pp. 4665-4681.
[51] United States Department of Energy. *Electric Vehicles*. https://afdc.energy.gov/vehicles/electric.html. Accessed May 10, 2022.
[52] ---. *Fuel Cell Electric Vehicles*. https://afdc.energy.gov/vehicles/fuel_cell.html. Accessed May 5, 2021.
[53] ---. *How Do Plug-In Hybrid Electric Cars Work?* https://afdc.energy.gov/vehicles/how-do-plug-in-hybrid-electric-cars-work. Accessed May 10, 2022.

[54] ---. *How Do Fuel Cell Electric Vehicles Work Using Hydrogen?* https://afdc.energy.gov/vehicles/how-do-fuel-cell-electric-cars-work. Accessed May 10, 2022.
[55] Baptista, P., C. Rolim, and C. Silva. Plug-in vehicle acceptance and probable utilization behaviour. *Journal of Transportation Technologies,* Vol. 2, No. 01, 2012, p. 67.
[56] Axsen, J., and K. S. Kurani. Hybrid, plug-in hybrid, or electric—What do car buyers want? *Energy Policy,* Vol. 61, 2013, pp. 532-543.
[57] Jabbari, P., W. Chernicoff, and D. MacKenzie. Analysis of electric vehicle purchaser satisfaction and rejection reasons. *Transportation Research Record,* Vol. 2628, No. 1, 2017, pp. 110-119.
[58] Junquera, B., B. Moreno, and R. Álvarez. Analyzing consumer attitudes towards electric vehicle purchasing intentions in Spain: Technological limitations and vehicle confidence. *Technological Forecasting and Social Change,* Vol. 109, 2016, pp. 6-14.
[59] Hardman, S., and G. Tal. Discontinuance among California's electric vehicle buyers: Why are some adopters abandoning electric vehicles? , 2020.
[60] Statistica. *Number of commercial vehicles in use in the U.S. from 2005 to 2015*. https://www.statista.com/statistics/274375/commercial-vehicles-in-use-in-the-us/. Accessed May 5, 2021.
[61] Ahmad, N., B. Wali, and A. Khattak. The Proclivity of Commercial Transportation Sector to Adopt Alternative Fuel Vehicles in the Future: Application of Machine Learning Methods. Presented at The 99th Annual Meeting of the Transportation Research Board, Washington D.C. , 2020.
[62] Kleinbaum, D. G., K. Dietz, M. Gail, M. Klein, and M. Klein. *Logistic regression*. Springer, 2002.
[63] Truong, L. T., H. T. Nguyen, and R. Tay. A random parameter logistic model of fatigue-related motorcycle crash involvement in Hanoi, Vietnam. *Accident Analysis & Prevention,* Vol. 144, 2020, p. 105627.
[64] Mannering, F. L., V. Shankar, and C. R. Bhat. Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic methods in accident research,* Vol. 11, 2016, pp. 1-16.
[65] Norton, E. C., B. E. Dowd, and M. L. Maciejewski. Marginal effects—quantifying the effect of changes in risk factors in logistic regression models. *Jama,* Vol. 321, No. 13, 2019, pp. 1304-1305.
[66] Long, J. S., and J. Freese. *Regression models for categorical dependent variables using Stata*. Stata press, 2006.
[67] Zhang, K., and S. Batterman. Air pollution and health risks due to vehicle traffic. *Science of the total Environment,* Vol. 450, 2013, pp. 307-316.
[68] Finkelstein, M. M., M. Jerrett, and M. R. Sears. Traffic air pollution and mortality rate advancement periods. *american Journal of epidemiology,* Vol. 160, No. 2, 2004, pp. 173-177.
[69] Uherek, E., T. Halenka, J. Borken-Kleefeld, Y. Balkanski, T. Berntsen, C. Borrego, M. Gauss, P. Hoor, K. Juda-Rezler, and J. Lelieveld. Transport impacts on atmosphere and climate: Land transport. *Atmospheric Environment,* Vol. 44, No. 37, 2010, pp. 4772-4816.
[70] Eberle, U., and R. Von Helmolt. Sustainable transportation based on electric vehicle concepts: a brief overview. *Energy & Environmental Science,* Vol. 3, No. 6, 2010, pp. 689-699.

[71] Nykvist, B., F. Sprei, and M. Nilsson. Assessing the progress toward lower priced long range battery electric vehicles. *Energy Policy,* Vol. 124, 2019, pp. 144-155.
[72] Ferrero, E., S. Alessandrini, and A. Balanzino. Impact of the electric vehicles on the air pollution from a highway. *Applied energy,* Vol. 169, 2016, pp. 450-459.
[73] INSIDE EVs. *U.S. Plug-In Electric Car Sales Charted: 2019*. https://insideevs.com/news/393629/us-plugin-sales-charted-2019/. Accessed April 08, 2021.
[74] BusinessKorea. *Electric Vehicle Prices to be Halved by 2025*. http://www.businesskorea.co.kr/news/articleView.html?idxno=60769. Accessed July 21, 2021.
[75] Ministry of Land Infrastructure and Transport (MOLIT) of Republic of Korea. *MOLIT Statistics System*. http://stat.molit.go.kr/portal/cate/engStatListPopup.do. Accessed April 08, 2021.
[76] Jeju Special Self-Governing Province. https://www.jeju.go.kr/open/stats.htm. Accessed April 08, 2021.
[77] Carley, S., R. M. Krause, B. W. Lane, and J. D. Graham. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. *Transportation Research Part D: Transport and Environment,* Vol. 18, 2013, pp. 39-45.
[78] Federal Highway Administration (FHWA). *National Household Travel Survey (NHTS)*. https://nhts.ornl.gov/downloads. Accessed April 08, 2021.
[79] Lin, B., and W. Wu. Why people want to buy electric vehicle: An empirical study in first-tier cities of China. *Energy Policy,* Vol. 112, 2018, pp. 233-241.
[80] Lin, Z., and D. L. Greene. Promoting the market for plug-in hybrid and battery electric vehicles: role of recharge availability. *Transportation Research Record,* Vol. 2252, No. 1, 2011, pp. 49-56.
[81] Son, S., and S. Lee. Analyzing Satisfaction of Battery Electric Vehicle Users and Factors Associating with the Satisfaction: A Case Study of Jeju. 2019.
[82] Kwon, Y., S. Son, and K. Jang. User satisfaction with battery electric vehicles in South Korea. *Transportation Research Part D: Transport and Environment,* Vol. 82, 2020, p. 102306.
[83] Jabeen, F., D. Olaru, B. Smith, T. Braunl, and S. Speidel. Electric vehicle battery charging behaviour: findings from a driver survey.In *Proceedings of the Australasian Transport Research Forum*, 2013.
[84] Anderson, J. E., M. Lehne, and M. Hardinghaus. What electric vehicle users want: Real-world preferences for public charging infrastructure. *International Journal of Sustainable Transportation,* Vol. 12, No. 5, 2018, pp. 341-352.
[85] KIA Motors. https://www.kia.com/kr/e-brochure.html. Accessed April 03, 2020.
[86] General Motors. https://www.gm.com/. Accessed April 03, 2020.
[87] Renault Samsung Motors. https://www.renaultsamsungm.com/. Accessed April 03, 2020.
[88] NISSAN. https://www.nissanusa.com/vehicles/new.html. Accessed April 03, 2020.
[89] Bayerische Motoren Werke AG. https://www.bmw.com/en/index.html. Accessed April 03, 2020.
[90] Hyundai Motors. https://www.hyundai.com/kr/en/main. Accessed April 03, 2020.
[91] Semisysco Smart EV. http://smart-ev.co.kr/. Accessed April 03, 2020.
[92] Mercedes-Benz. https://www.mercedes-benz.com/en/#. Accessed April 03, 2020.
[93] Automobile Catalog. https://www.automobile-catalog.com. Accessed April 03, 2020.

[94] WattEV2Buy. https://wattev2buy.com/. Accessed April 03, 2020.
[95] Statistics Korea. https://kostat.go.kr/portal/eng/index.action. Accessed September 27, 2022.
[96] International Monetary Fund (IMF). *Exchange Rate Archives by Month*. https://www.imf.org/external/np/fin/data/param_rms_mth.aspx. Accessed July 15, 2021.
[97] Mothersbaugh, D. L., and D. I. Hawkins. *Consumer Behavior: Building Marketing Strategy*. McGraw-Hill Education New York, NY, USA, 2015.
[98] Wang, X., and K. M. Kockelman. Use of heteroscedastic ordered logit model to study severity of occupant injury: distinguishing effects of vehicle weight and type. *Transportation Research Record,* Vol. 1908, No. 1, 2005, pp. 195-204.
[99] Baetschmann, G., K. E. Staub, and R. Winkelmann. Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society. Series A (Statistics in Society),* 2015, pp. 685-703.
[100] Hedeker, D., and R. D. Gibbons. MIXOR: a computer program for mixed-effects ordinal regression analysis. *Computer methods and programs in biomedicine*, Vol. 49, No. 2, 1996, pp. 157-176.
[101] Greene, W. Marginal effects in the censored regression model. *Economics Letters,* Vol. 64, No. 1, 1999, pp. 43-49.
[102] Boes, S., and R. Winkelmann. Ordered response models. *Allgemeines Statistisches Archiv,* Vol. 90, No. 1, 2006, pp. 167-181.
[103] Ministry of Environment Republic of Korea. https://me.go.kr/. Accessed September 30, 2022.
[104] ---. *EV Archive*. https://www.ev.or.kr/. Accessed September 30, 2022.
[105] Jeju Research Institute. *Jeju EV Report*. https://www.jri.re.kr/contents/index.php?mid=0413. Accessed September 30, 2022.
[106] International Energy Agency. Global EV Outlook 2022.In, 2022.
[107] National Highway Traffic Safety Administration (NHTSA). *Automated Vehicles for Safety*. https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety. Accessed April 8, 2021.
[108] Society of Automotive Engineers (SAE). *Levels of Driving Automation*. https://www.sae.org/news/2019/01/sae-updates-j3016-automated-driving-graphic. Accessed April 8, 2021.
[109] California Department of Motor Vehicles. *Autonomous Vehicle Tester Program*. https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/testing-autonomous-vehicles-with-a-driver/. Accessed April 8, 2021.
[110] Sohrabi, S., A. Khodadadi, S. M. Mousavi, B. Dadashova, and D. Lord. Quantifying the automated vehicle safety performance: A scoping review of the literature, evaluation of methods, and directions for future research. *Accident Analysis & Prevention,* Vol. 152, 2021, p. 106003.
[111] Arvin, R., A. J. Khattak, M. Kamrani, and J. Rio-Torres. Safety evaluation of connected and automated vehicles in mixed traffic with conventional vehicles at intersections. *Journal of Intelligent Transportation Systems,* Vol. 25, No. 2, 2020, pp. 170-187.
[112] Deluka Tibljaš, A., T. Giuffrè, S. Surdonja, and S. Trubia. Introduction of Autonomous Vehicles: Roundabouts design and safety performance evaluation. *Sustainability,* Vol. 10, No. 4, 2018, p. 1060.
[113] Schoettle, B., and M. Sivak. A preliminary analysis of real-world crashes involving self-driving vehicles. *University of Michigan Transportation Research Institute*, 2015.

[114] Favarò, F. M., N. Nader, S. O. Eurich, M. Tripp, and N. Varadaraju. Examining accident reports involving autonomous vehicles in California. *PLoS One,* Vol. 12, No. 9, 2017, p. e0184952.
[115] Petrović, Đ., R. Mijailović, and D. Pešić. Traffic accidents with autonomous vehicles: type of collisions, manoeuvres and errors of conventional vehicles' drivers. *Transportation research procedia,* Vol. 45, 2020, pp. 161-168.
[116] Ashraf, M. T., K. Dey, S. Mishra, and M. T. Rahman. Extracting rules from autonomous-vehicle-involved crashes by applying decision tree and association rule methods. *Transportation Research Record,* Vol. 2675, No. 11, 2021, pp. 522-533.
[117] Kutela, B., R. E. Avelar, and P. Bansal. Modeling automated vehicle crashes with a focus on vehicle at-fault, collision type, and injury outcome. *Journal of transportation engineering, Part A: Systems,* Vol. 148, No. 6, 2022, pp. e04022024-e04022024.
[118] McCarthy, R. L. Autonomous Vehicle Accident Data Analysis: California OL 316 Reports: 2015–2020. *ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg,* Vol. 8, No. 3, 2022.
[119] Goodall, N. J. Comparison of automated vehicle struck-from-behind crash rates with national rates using naturalistic data. *Accident Analysis & Prevention,* Vol. 154, 2021, p. 106056.
[120] Wang, S., and Z. Li. Exploring the mechanism of crashes with automated vehicles using statistical modeling approaches. *PLoS One,* Vol. 14, No. 3, 2019, p. e0214550.
[121] Xu, C., Z. Ding, C. Wang, and Z. Li. Statistical analysis of the patterns and characteristics of connected and autonomous vehicle involved crashes. *Journal of safety research,* Vol. 71, 2019, pp. 41-47.
[122] Boggs, A. M., B. Wali, and A. J. Khattak. Exploratory analysis of automated vehicle crashes in California: A text analytics & hierarchical Bayesian heterogeneity-based approach. *Accident Analysis & Prevention,* Vol. 135, 2020, p. 105354.
[123] Kutela, B., S. Das, and B. Dadashova. Mining patterns of autonomous vehicle crashes involving vulnerable road users to understand the associated factors. *Accident Analysis & Prevention,* Vol. 165, 2022, p. 106473.
[124] Das, S., A. Dutta, and I. Tsapakis. Automated vehicle collisions in California: Applying Bayesian latent class model. *IATSS Research,* Vol. 44, No. 4, 2020, pp. 300-308.
[125] Guo, X., and Y. Zhang. Maturity in Automated Driving on Public Roads: A Review of the Six-Year Autonomous Vehicle Tester Program. *Transportation Research Record,* 2022, p. 03611981221092720.
[126] Song, Y., M. V. Chitturi, and D. A. Noyce. Automated vehicle crash sequences: Patterns and potential uses in safety testing. *Accident Analysis & Prevention,* Vol. 153, 2021, p. 106017.
[127] Boggs, A. M., R. Arvin, and A. J. Khattak. Exploring the who, what, when, where, and why of automated vehicle disengagements. *Accident Analysis & Prevention,* Vol. 136, 2020, p. 105406.
[128] Lleras, C. Path analysis. *Encyclopedia of social measurement,* Vol. 3, No. 1, 2005, pp. 25-30.
[129] Liu, J., and A. J. Khattak. Gate-violation behavior at highway-rail grade crossings and the consequences: using geo-spatial modeling integrated with path analysis. *Accident Analysis & Prevention,* Vol. 109, 2017, pp. 99-112.

[130] Ahmad, N., B. Wali, A. J. Khattak, and E. Dumbaugh. Built environment, driving errors and violations, and crashes in naturalistic driving environment. *Accident Analysis & Prevention*, Vol. 157, 2021, p. 106158.
[131] United States Department of Transportation. *What is a Safe System Approach?* https://www.transportation.gov/NRSS/SafeSystem#:~:text=It%20is%20a%20holistic%20and,in%20place%20to%20protect%20everyone. Accessed September 27, 2022.
[132] Google. *Google Maps*. https://www.google.com/maps. Accessed April 15, 2021.
[133] Baetschmann, G., K. E. Staub, and R. Winkelmann. Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, Vol. 178, No. 3, 2015, pp. 685-703.
[134] Wagenmakers, E.-J., M. Lee, T. Lodewyckx, and G. J. Iverson. Bayesian versus frequentist inference.In *Bayesian evaluation of informative hypotheses*, Springer, 2008. pp. 181-207.

VITA

Mr. Steve Lee was born in Columbus, Ohio, and grew up in Seoul and other cities in South Korea. Steve is a citizen of both the United States and South Korea. He started his undergraduate study in Civil and Environmental Engineering (CEE) at Seoul National University (SNU) in 2008 and earned his B.S. degree in 2012. He continued to major in CEE concentrating on transportation engineering at SNU and earned his M.S. degree in 2014. During Sep. 2014 - Mar. 2017, he worked as a researcher at Korea Institute of Civil Engineering and Building Technology (KICT) participating in research projects on traffic operation and management. In 2019, he came back to the United States to start a Ph.D. course at the University of Tennessee, Knoxville. His research focus has been on the readiness for transportation electrification and automation in terms of safety and future adoption. Throughout his career so far, he has worked and performed research primarily on traffic operation, traffic management, transportation electrification, and transportation automation.