MARKET ADOPTION AND IMPACT OF ELECTRIC ROADWAYS ON CRITERIA POLLUTANTS AND GREENHOUSE GAS EMISSIONS

by

Theodora Konstantinou

A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science in Civil Engineering

Lyles School of Civil Engineering

West Lafayette, Indiana

December 2018

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Konstantina Gkritza, Chair

Lyles School of Civil Engineering

Agricultural & Biological Engineering

Dr. Samuel Labi

Lyles School of Civil Engineering

Dr. Hua Cai

Industrial Engineering

Environmental and Ecological Engineering

Approved by:

Dr. Dulcy Abraham

Head of the Graduate Program

To my beloved family

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Konstantina Gkritza for her continuous support, guidance, encouragement and advice during the development of this thesis and my studies in general. I would also like to thank Dr. Samuel Labi and Dr. Hua Cai for serving on my committee and their feedback. Furthermore, I would like to give special thanks to the United States Department of Energy (US DOE) ARPA-E IDEAS program that financially supported my research though the project “Feasibility Analysis of Electric Roadways through Localized Traffic, Cost, Adoption and Environmental Impact Modeling”. Last, but certainly not least, a special thanks goes to my family and friends for their patience, emotional support and positive influence.

Best regards and happy reading,

Theodora Konstantinou
November 2018

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Author: Konstantinou, Theodora. MSCE
Institution: Purdue University
Degree Received: December 2018
Title: Market Adoption and Impacts of Electric Roadways on Criteria Pollutants and Greenhouse Gas Emissions
Major Professor: Dr. Konstantina Gkritza

Traffic is inevitably a major source of air pollution, particularly in urban areas. Efforts are made towards reducing emissions by improving vehicle and fuel technology and promoting alternative, sustainable modes of transportation. Although the emergence of EVs has shown capabilities of decreasing energy use and emissions levels, the EV market is developing slowly mainly due to drivers' range anxiety and charging time. Electric roadways (ERs) have been proposed as a solution to overcome the concerns related to EVs by converting road segments into powered lanes where vehicles can be charged as they move along the roadway. This technology has the potential to increase driving range, decrease battery size and thus, lower the weight and the cost of EVs. In this context, exploring the challenging concept of ERs comes natural.

Since data on the market acceptance and the environmental implications on this technology are limited to non-existent, this thesis has the following objectives: 1) identify the factors that affect the short- and long-term intention to use ERs, 2) estimate the level of adoption of the ER technology and identify characteristics of the market segments and 3) assess the impact of ERs on criteria pollutants and greenhouse gas emissions based on the market adoption results.

To achieve these objectives, a survey of the general population in Los Angeles, California was conducted, gathering 600 responses representative of gender and age in the area. Los Angeles is considered a leader in electro-mobility and thus, a natural choice for the implementation of ERs. The short-or long-term intentions to drive on ERs and purchase an EV knowing about the availability of ERs were found to be correlated and thus, were modeled simultaneously using a bivariate ordered probit model. The compatibility of the ER technology with respondents' lifestyle and needs, respondents' tendency towards using sustainable forms of transportation, respondents' innovativeness and perceived environmental benefits were among the most significant variables found to affect the short-term and long-term intention to use ERs.

The level of adoption of the ER technology and corresponding market segments were identified using a combination of Principal Component Analysis (PCA) and Cluster Analysis. Three clusters emerged from the analysis: early adopters (48.5%), mid-adopters (27.67%) and late adopters (23.83%) that differed in terms of demographics and socioeconomic characteristics, travel and EV charging characteristics and level of awareness.

The adoption levels found were then used to estimate the emissions change due to the implementation of the ERs by 2050. Using the California Air Resources Board's (CARB) 2017 EMissions FACtor model (EMFAC). Two scenarios were examined considering light-duty vehicles (LDVs) in a specific corridor: "with" and "without electrification" scenarios. The results suggested that the ER technology for light-duty vehicles has the potential to provide emission reductions of 4 to 24%. A sensitivity analysis was also conducted to examine the effect of speed on the results.

Turning to the practical implications, this thesis can provide a foundational framework for the evaluation of the ER technology in terms of environmental and economic viability and set the groundwork for future research. Ultimately, the short-term and long-term intention analysis can be used as a draft guide by state and local agencies and inform their strategic short- or long-range plans for mobility. By segmenting potential users, policy makers and transport operators can be informed about the main challenges regarding the promotion of the ER technology to distinct market segments and devise ways to accelerate its adoption. The findings from the impact analysis of ERs on criteria pollutants and greenhouse gases can also inform long-range transportation plans and existing regulations and policies in California and beyond.

1. INTRODUCTION

The chapter provides the theoretical background for this thesis that includes the need for transportation electrification and current barriers to electric vehicle adoption In addition, the research motivation and objectives are discussed, followed by the contributions of the thesis and thesis organization.

1.1 Transportation Electrification

Transportation is recognized as the final frontier for major advancement in energy efficiency. In the United States (US), the transportation sector accounts for 71% of total petroleum consumption and 28% of total greenhouse gas emissions (United States Department of Transportation [USDOT], 2017). Due to the increased travel demand and limited improvements in fuel efficiency, petroleum consumption in the transportation sector has increased by 27% since 1990 (Sieminski, 2017). In particular, over 30% of the US energy use and greenhouse gas emissions and over 50% of air pollution near high-density roadways are attributed to the internal combustion engine (Sieminski, 2017). Road freight transportation is second in the order of energy consumption because it accounts for approximately 20% of all transportation petroleum consumption. As a result, the importance and awareness of the environmental impacts of road transportation is growing rapidly.

Efforts are being made towards reducing emissions and achieving sustainability goals for the transportation sector under the “avoid, shift and improve” strategy (International Energy Agency [IEA], 2017a). “Avoidance” is being achieved by reducing travel distances. For example, the concept of self-contained communities that include mixed types of facilities (residential and business areas at the same location) is a way to decrease the amount of travel. The implementation of integrated urban and transport planning and the optimization of road freight deliveries are another example of this case. “Shift” is being achieved by encouraging the use of sustainable modes of transportation. The increased share of public transport modes in urban passenger transport and the shift from road freight activity to rail and shipping can lead to significant emissions reduction. “Improve” includes all the ways by which vehicle fuel technology can be advanced and the share of these improved vehicles can be accelerated to promote use of low-carbon fuels.

In this context, alternative fuels are part of those policies with the view to achieving the decarbonization of the environment. Alternative fuel vehicles are vehicles that are flexible fuel, or dual-fuel vehicles designed to operate on at least one alternative fuel (Alternative Fuels Data Center, 2017). The Energy Policy Act of 1992 defines an alternative fuel as: biodiesel, natural gas and liquid fuels domestically produced from natural gas, propane (liquefied petroleum gas), electricity, hydrogen, blends of 85% or more of methanol, denatured ethanol, and other alcohols with gasoline or other fuels, methanol, denatured ethanol, and other alcohols, coal-derived, domestically-produced liquid fuels, fuels (other than alcohol) derived from biological materials, P-Series fuels (Alternative Fuels Data Center, 2017).

Among the numerous alternative fuels' solutions, the electrification of transportation has been proven to be a promising way to accomplish the goal of reduced transport carbon footprint. According to the European Commission, "electricity does not only allow delivering energy from renewable sources to the vehicle, but also the possibility to use vehicle batteries connected to the smart grid for temporary storage of energy from fluctuating sources such as solar and wind" (European Commission, 2017). Thus, the emergence of electric vehicles (EVs) is among those technological innovations that can ameliorate fuel efficiency and significantly decrease levels of emissions to a significant extent compared to other initiatives. In contrast to internal combustion engine vehicles, EVs offer high efficiency, high reliability, flexible fuel source, 70% lower operating costs, and zero tailpipe emissions (United States Department of Transportation [USDOT], 2017).

EVs are propelled by the electric energy stored in their batteries and are available in different types that vary in range and capability. More specifically, there are three main categories in which EVs can be classified (Liao et al., 2017; Zero Emission Urban Bus System [ZeEUS], 2016):

- *Hybrid electric vehicles (HEVs)*: these vehicles include both a battery system and a conventional internal combustion engine and can be recharged while braking. These vehicles are able to be based solely on electric energy for a certain distance and when additional range is needed the internal combustion engine is used (Liao et al., 2017).

- *Plug-in electric vehicles:* these are based only on their battery and are plugged into a source of electrical power to be recharged. They can be further classified into plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). The difference between those two subcategories is the fact that PHEVs operate using both their battery and their engine, while battery electric vehicles derive all power from battery packs and have no internal combustion engine, fuel cell or fuel tank (Liao et al., 2017).
- *Fuel cell electric vehicles (FCEVs)*: these vehicles contain a fuel cell system powered by hydrogen that generates electricity to operate the vehicle. Electricity is stored in the battery system of the vehicle. This electricity used to power the vehicle, along with heat and water vapor, are the only byproducts of fuel cells (Zero Emission Urban Bus System [ZeEUS], 2016).

The most widely known mechanism for EV charging is the stationary charging where EVs can be supplied with electric energy only at stationary stations by being plugged into a socket or at stationary facilities by being wirelessly charged. In particular, the main types of EV charging are the following (Alternative Fuels Data Center, 2017):

- AC (alternating current) Level 1 charging station uses a 120-volt current and only requires a power cord that comes with the EV. The charge time is slow at only 3-5 miles per hour of charging (around 8 to 12 hours, depending on the vehicle's battery).
- AC Level 2 charging station uses 240-volt power to enable faster regeneration of an EV's battery system, providing 10-20 miles per hour of charging (around 4 to 6 hours).
- DC (direct current) fast charging station converts high voltage AC power to DC power for direct storage in EV batteries. It uses a 480-volt current and usually provides EVs with 80% charge in 20 to 30 minutes.

Throughout the years, the US government implemented a number of environmental policies and regulations to move from gasoline-fueled to these more efficient vehicles. "Zero-emission vehicle" programs (ZEV) have been established and include key strategies of transport electrification in order to reduce greenhouse gas emissions, air pollution, fossil fuel consumption and energy costs. These programs are implemented by the ZEV states (California, Connecticut, Maryland, Massachusetts, New York, Oregon, Rhode Island and Vermont) which require automakers to follow ZEV mandates, that is to sell a certain number of ZEVs (BEVs, PHEVs and FCEVs) (California Air Resources Board [CARB], 2017b). An agreed collective target of these states is at least 3.3 million ZEVs on the road by 2050, as per the State ZEV Programs Memorandum of Understanding (MOU) (State Zero- Emission Vehicle Programs Memorandum of Understanding, 2013).

There is also an additional factor that can promote embracing these environmentally friendly technologies, namely fuel economy regulations. These regulations incorporate provisions so as to focus more on EVs while assessing corporate averages (International Energy Agency [IEA], 2017b). In this way, Original Equipment Manufacturers (OEMs) are motivated to begin generating EVs, although this minimizes average fuel economy advancement as well as the associated profits provided in the timeframe set by the regulations. Thus, this policy will be one of the primary policies to encourage electro-mobility, provided that it is tightened beyond the efficiency that can be offered from improved ICEs and HEVs (International Energy Agency [IEA], 2017b).

EV financial incentives are another policy geared towards the decarbonization of the environment. These incentives are important for reducing the purchase cost and total cost of ownership associated with EVs (International Energy Agency [IEA], 2017b). Such incentives can take the form of direct rebates, tax breaks or exemptions and are adjusted to account for the vehicles' characteristics in terms of greenhouse gas and pollutant performance and environmental costs. However, according to Hoy and Weken (Hoy & Weken, 2017), financial incentives are most effective when they minimize the EV purchase premium and come with a total cost of ownership advantage compared with conventional internal combustion engine vehicles (ICEV).

Other policies that seek to increase the value proposition of EVs and more specifically, passenger EVs, include waivers on regulations that limit the availability of license plates for ICEVs, exemptions from access restrictions to urban areas, exemptions from usage fees for specific portions of the road network and dedicated parking. Access to publicly-available charging infrastructure, access to bus lanes and high-occupancy vehicle (HOV) lanes, investments in EV infrastructure, tailored EV electricity rates, and outreach to customers by electric utilities and others (International Energy Agency [IEA], 2017b) are also examples of these policies. These targeted policies are best developed at the municipal level and adapted to the local mobility conditions of each urban area.

In conclusion, the electrification of transportation is a concept of much interest due to the increased need to cope with climate and energy goals. This interest can be shown by the fact that the national EV share increased by 29% from 2016 to 2017 with Los Angeles, San Francisco and New York City presenting the highest annual increases (Slowik & Lutsey, 2018). Using different policies and testing various technologies, the electrification of transportation can be advanced “in a manner that benefits all utility customers and users of all forms of transportation, while supporting the evolution of a cleaner grid and stimulating innovation and competition for US companies”, according to the Transportation Electrification Accord (Transportation Electrification Accord, 2018).

1.2 Barriers to EV Adoption

While the emergence of EVs has shown capabilities of decreasing energy use and emissions levels, several reports show that the EV market is developing slowly. More specifically, despite governmental support, the continuous increase in the electric car stock, in EV supply equipment (EVSE) deployment and in electric car sales in the past five years, annual growth rates have been declining (International Energy Agency [IEA], 2017b).

As a matter of fact, in 2016, the (global) electric car stock growth was 60%, down from 77% in 2015 and 85% in 2014. The year 2016 was also the first time that year-on-year electric car sales growth had fallen below 50% since 2010. Currently, the global electric car stock is just 0.2% of the total fleet of passenger light-duty vehicles and heavy-duty vehicles, indicating that the scale achieved so far, is still small (International Energy Agency [IEA], 2017b). California is home to almost half of all of the nation’s PEVs; but even in California, only about 5 out of every 1,000 registered vehicles are PEVs.

In general, the extent to which EVs can be adopted and thus, lead to higher air quality depends mainly on their characteristics. According to a wide range of studies, range anxiety, charging time, availability of charging stations and EV purchase cost are essential elements for an EV’s adoption (Boston Consulting Group, 2009; Carley et al., 2013; Hidrue et al., 2011; Philip & Wiederer, 2010; Rezvani et al., 2015; Sierzchula et al. 2014; Virginia Clean Cities, 2010; Wilmink, 2015).

Furthermore, although most EV charging today occurs at home, at work, and at retail and public urban sites, this model only meets the needs of small light duty commuter traffic. If the

EV market share is to grow considerably, research and development will need to focus on progressing in energy storage and in addressing the needs of two different vehicle sectors: longer haul interstate travel and significant energy for larger light duty and heavy-duty vehicles.

In addition, in the case of public charging that offers easy charging access, it is unclear whether public infrastructure can support the EV market. More specifically, Level 2 charging is considered to offer very slow charging to meet consumer demand. On the other hand, Level 3 charging is expensive, requires extensive infrastructure maintenance and lacks US standards set by the Society for Automotive Engineers (SAE) (Chambers, 2011). In addition, charging an EV in DC fast charging stations requires significant on-vehicle battery capacity, which adds substantial vehicle cost and weight to support travel from station to station. It also degrades battery life associated with deep discharge and rapid fast charging cycles (e.g., 80% charge in 30 min). On the other hand, home charging also has its limitations. The two main concerns with home charging are the availability of charging infrastructure for multifamily housing and the permitting and installation process for single family homes (PLANYC, 2010; Dubin et al, 2011).

Due to these concerns, EV adoption is limited, particularly for larger light-duty and heavy-duty vehicles (LDV and HDV), which combined account for over 50% of total US transportation energy use (from all sources, among all transit categories). To illustrate this, PHEVs provide an example of EVs low market adoption. Researchers had predicted that their market penetration would reach 10-15% but it only reached 2.75% in 2015, showing a small increase of only 0.45% between 2007 and 2015 (Balducci, 2008, German, 2015, Ozaki & Sevastyanova, 2011, Greene et al., 2004). The current effort is concentrated to making advancements in battery technology and batteries that would have improved design and charging capabilities (Thackeray et al., 2012, Egbue & Long, 2012). To achieve this, alternative ways of EV charging are being investigated, so as to also reduce the costs associated and the required of effort in terms of battery technology advancement.

An alternative mechanism for EV charging that has been suggested and is being studied is the dynamic charging (or in-motion charging), also referred to as charging-while-driving. Electric roadways (ERs) have been proposed as a solution to overcome the concerns related to EVs by converting road segments into powered lanes (electric roadways). In particular, electric road infrastructure is able to transfer the electrical power to charge EVs efficiently while they move along the roadway through specialized inductive or conductive facilities.

The reason why dynamic charging is increasingly gaining ground is that it can increase driving range, decrease battery size for EVs and use capacitors which would both lower the weight and the cost for the vehicle (Singh, 2016). If the energy for dynamic charging systems is obtained by fossil-free electrical energy sources, then transportation with ERs based on dynamic charging can be carried out nearly free of greenhouse gas-emission (Wang & Mompo, 2014).

1.3 Research Motivation and Objectives

A number of conclusions can be made from the discussion provided in the previous sections. These conclusions, which serve as the motivation of this thesis, are:

- There is an urgent need for decarbonization of the environment.
- The transportation sector contributes to carbonization to a significant degree and thus, awareness with respect to environmental impacts of highway transportation is growing rapidly.
- Among the efforts that are made towards reducing the environmental impacts of highway transportation, the improvement of vehicle fuel technology and efficiency could be one of the most direct ways to improve the situation.
- Among the alternative fuels, electricity is gaining ground, since it allows both delivering energy from renewable sources to the vehicle and using vehicle batteries for temporary storage of energy from fluctuating sources such as solar and wind.
- EV adoption is limited due to certain barriers: range anxiety, charging time, availability of charging stations and EV purchase cost.
- There is a variety of ways to increase the adoption of EVs. Alternative ways of EV charging offer a strong case and can positively affect public’s perception on EVs
- ERs are an innovative way of EV charging that can address most of the limitations associated with EVs.
- There is a need to identify the factors that influence ER demand and estimate ER demand.

Thus, exploring the challenging concept of ERs comes naturally. The goal of this thesis is to assess the market adoption and impact of the technology of ERs on air pollution. In particular, the thesis will proceed with the following primary objectives regarding ERs:

1. Identify the factors that affect technology adoption and more specifically, the short- and long-term intention to use ERs and purchase an EV, knowing about the availability of ERs.
2. Estimate the adoption rates of ERs and conduct market segmentation analysis.
3. Quantify the impact of the ERs on criteria pollutants and greenhouse gas emissions.

To achieve these objectives, a survey of the general population in Los Angeles was conducted. Los Angeles has one of the largest EV market and thus, the area serves as a natural test bed to assess residents' opinion on ERs. The data from the survey is analyzed using econometric models in order to show the factors that affect the short- and long-term intention to use ERs. A cluster analysis is applied to estimate the level of the technology adoption and the characteristics of each cluster-market segment are identified. The adoption rates found are used as inputs in an emissions model to estimate the emissions reduction in the case where the ERs are implemented, assuming different adoption rates and operating speeds. Note that the emissions analysis focuses on estimating tailpipe emissions and thus, infrastructure or vehicle manufacturing emissions are not included.

1.4 Thesis Contribution

This thesis provides a foundational framework for the upcoming technology of ERs and specifically, identifies the important factors that affect the adoption of ERs and associated changes in travel demand and patterns as well as assesses the impact of this technology on criteria pollutant and greenhouse gas emissions. Thus, the outcome of this thesis can inform travel demand models and impact studies, and assist transportation planners, regulators, utilities, and state and local decision-makers.

Moreover, this thesis yields results that can support the evaluation of the technology in terms of environmental and economic viability and set the groundwork for future research, investments or demonstration projects and infrastructure deployment. This thesis provides actionable guidance for accelerating market adoption. The potential adoption of this technology can ultimately lead to significant reductions in energy consumption and greenhouse gas emissions while providing a strong stimulus to the domestic workforce.

1.5 Thesis Organization

This thesis is organized into six chapters:

Chapter 2, *Literature Review*, includes a comprehensive overview of the technology of ERs, previous studies and demonstration projects relating to dynamic charging, the benefits, concerns and other aspects regarding ERs.

Chapter 3, *Research Framework*, *Empirical Setting*, *and Data*, discusses the general methodology that is used to achieve the research goals of this thesis and provide details about the study area selected for the analysis, the tools used (survey design) and data preparation.

Chapter 4, *Market Adoption*, presents the results related to the market adoption of ERs concerning the factors affecting short-term and long-term intention to use ERs and the market segmentation analysis.

Chapter 5, *Impact on Criteria Pollutants and Greenhouse Gas Emissions*, describes the tools used (emissions model chosen) and the results of the environmental impact assessment of ERs.

Chapter 6, *Conclusions*, summarizes the key findings and practical implications, discusses the study limitations, and provides recommendations for future research.

2. LITERATURE REVIEW

This chapter provides a critical synthesis of the literature, regarding different aspects of ERs. The concept of ER technology is defined and the main benefits and concerns related to ERs as well as the optimal locations for implementation and the key stakeholders involved in this technology are discussed. Note that since the electric road industry is relatively new, little research has been conducted in this field so far. Furthermore, the reports that have been published are usually limited to examining only one concept of this technology and examine the potential of this technology on a specific road. The interested reader can refer to Rezvani et al. (2015) for a review of studies on EV adoption. Section 3.3 and the results sections (sections 4.1.3.2 and 4.1.4.2) also mention a few studies related to EV demand and adoption.

2.1 Types of Electric Roadway (ER) Technology

Electric roadway systems can be described as electrified roads that enable dynamic power transfer to the vehicles, as they are operate on the roadway. The electric road recharges the vehicle batteries while in motion and the vehicles receive the power in different ways depending on the technology concept. This method of charging can be referred to as dynamic or in-motion charging (Li & Mi, 2015; Vilathgamuwa & Sampath, 2015) or charging while-driving (Chen et al., 2016).

Electric roads can be accessible to vehicles with electric propulsion as well as conventional fossil fueled vehicles. The electric road system consists of four main subsystems: energy supply, power transfer, the road and the road operation. Starting from the energy supply, ERs should have a continuous energy supply from the national, regional or intermediate electricity grid. The grid is comprised of different voltage levels that depend on what purpose the particular part has in the system and what it is used for. The ERs can be connected to a level that is beyond its own working voltage level (Jelica, 2017).

EVs operating on ERs would be equipped with an energy pick up unit, a small battery and a potentially smaller internal combustion engine (ICE), which allows vehicles to also drive on conventional roads outside the ER network. In addition, more vehicle and infrastructure requirements are needed to be integrated in order to retrofit the EV. Those requirements depend on the type of the technology that is used and are discussed in more detail in the next sections.

ERs are based on two main concepts of dynamic charging, depending on the way the electric power is transferred to EVs. Electrical power can be transmitted by conductive or wireless energy transfer. In particular, with conductive energy transfer, the power transmission is either based on *rails* which are implemented in the road or on *overhead catenary lines* (Moller, 2017). These systems can be achieved by adding new charging infrastructure and new interface components to the EV. The different concepts of energy transfer are described in the following subsections.

2.1.1 Overhead Conductive System

The overhead conductive system consists of overhead contact lines that make power available to vehicles by being connected to the available substations and an active pantograph located on the top of the vehicle. This way, energy is transferred from the overhead lines to the vehicle.

A pantograph is generally composed of a lower arm, an upper arm, a pantograph head, and connections between them (Dahlberg, 2006). The pantograph is on the vehicle and presses against the power line, ensuring a steady connection regardless of the road condition to enable continuous electrical propulsion (Moller, 2017). This system allows for vehicle operation outside the electrical section of the infrastructure consisted of the overhead contact lines. Depending on the operation mode, the pantograph can be raised or lowered automatically or manually while vehicle is moving and thus, enables vehicle flexibility to switch lanes or overtake other vehicles or cross under bridges. This flexibility also applies in the case of vertical movements of the vehicle due to potential height variations or bumps in the road (Jelica, 2017).

This technology is similar to that used for many years for trains and trolley buses. The difference is that in this case, the vehicle is flexible in its movement. Thus, it can be claimed that the overhead conductive system may be a well-tested and proven technology compared to the other dynamic charging systems, the concepts of which had not been directly introduced previously. In general, the overhead line solution has been able to achieve an efficiency of around 80-90% (Siemens, 2012b). The percentage of efficiency depends on various factors such as the material used, the size of the power cables, the speed of the vehicles, etc.

This system can be completely incorporated into existing road infrastructure, without needing significant modifications. The only new additions to the existing system are the overhead wires, the pillars and the pantograph. Safety regulations and standards may apply for these systems so as to prevent from hazards. An example is the regulation, according to which the overhead wires have to be installed in a height of at least 19.685 feet which enables only vehicles with a corresponding size to connect to them (e.g., trucks and buses). Special arrangements may be expected for implementations of the system under bridges and in tunnels which may lead to lower hanging wires (Andersson & Edfeldt, 2013). There is also the argument that overhead lines are perceived as old-fashioned and visually unattractive (Viktoria Swedish ICT, 2014).

2.1.2 Conductive Rail System

In the conductive rail system, the basic principle is a power supply rail that is fully integrated into the road or located on the top of the road. This rail is physically enclosed within the area occupied by the vehicle and is supplied by power boxes that are connected to the electrical grid via transformer substations installed along the roadway at a certain density (Jelica, 2017). The function of the rail is automatic. It is divided into different segments, which are active and powered when a vehicle is detected to drive on each of them.

The vehicle driving on a conductive rail uses a physical pick-up to connect to the electrified rail in the road that is a moveable arm. The mechanical pick-up arm detects the location of the rail in the road and when the vehicle is situated above the rail, it automatically comes in a lowered position so as to come into contact with the conductor. As long as the vehicle is traveling along the rail, the moveable arm is in contact with the road and moves horizontally.

When the vehicle is exiting from the rail track the moveable arm is automatically disconnected and lifted. This provides the vehicle with the ability to be flexible and pass other vehicles while driving. When this disconnection takes place, the vehicle can be operated on battery until it is back again in the vicinity of the track.

In general, the conductive rail approach has a total system efficiency of approximately 82% (Viktoria Swedish ICT, 2014). It is also expected to have a minimal impact on the road in terms of function and maintenance, as rational solutions for installation and maintenance are being developed and tested by different companies around the world that are interested in this concept.

2.1.3 Wireless Charging System

In contrast with the conductive charging systems, wireless charging systems transfer electrical energy wirelessly. Numerous studies have been conducted to investigate this charging system and thus, there is more extensive literature review material to provide.

In-motion wireless power transfer (WPT) is based on the development of both roadway infrastructure and vehicle components (Limb et al., 2016). In this concept, the power transfer happens through charging devices that are implemented into the road and on the vehicle (coils). More specifically, primary WPT pads are embedded underneath the roadway and are connected to the power grid, through cables and power inverters, so as to be supplied with electricity. When the power supply produces an electric current in the primary coils, the coils can produce a time-changing magnetic field (Brecher & Arthur, 2014).

This variable magnetic field can induce an electric current through a secondary coil located on the vehicle that is driving above the electrified segment. The secondary coil or onboard pick-up unit can provide this power to fuel the vehicle's propulsion system and, in this way, run the electric motor/generator to charge the on-board battery (Viktoria Swedish ICT, 2013). Excess power delivered to the vehicle is stored in on-board energy storage systems which include super-capacitors and batteries (Limb et al., 2016).

There are two main approaches to wireless charging: the electromagnetic inductive approach and the magnetic resonant approach. In the inductive charging, the power supplied will be in the form of normal household electricity or alternating magnetic field that is converted to direct current through an in-vehicle rectifier device (Boys & Covic, 2010). The magnetic field generated by the primary coil radiates in all directions and thus, the alternating current (flux) drops rapidly with the distance. As a result, the secondary coil must be located in close proximity with the primary coil to intercept the most flux. This creates a limitation for EVs. In some WPT technologies that use this technology, the top pick up unit is lowered to bring it into the requisite proximity to the bottom coil align precisely to obtain acceptable efficiency. This technology cannot be applied to moving vehicles.

More specifically about the efficiency, the amount of energy that the secondary coil can receive depends on its characteristics, namely the cross section it presents to the magnetic field. More specifically, the optimum amount of energy can be transferred when the secondary coils has identical dimensions with the primary coil and is aligned parallel and with a vertical separation of tens of millimeters (Hassan & Elzawawi, 2015). The separation, alignment and sizes of the respective coils determine the “coupling factor” which has a significant influence on the efficiency of the energy transfer. To illustrate this, perfect coupling, meaning that all the magnetic field generated by the primary coil is captured, has a coupling factor of 1. The key benefit of a closely coupled inductive wireless charging system is its relatively high efficiency. Because of this relatively high efficiency, the transfer of significant power is achieved with speeding up charging cycles.

However, the magnetic field it generates cannot be picked up by another coil (on top of it) unless the two coils are in close proximity. Therefore, in some WPT technologies, the top pick up unit is lowered to bring it into the requisite proximity to the bottom coil align precisely to obtain acceptable efficiency. This technology cannot be applied to moving vehicles.

As an alternative method of wireless charging developed by MIT (Kurs et al., 2007), electric power can be also transferred through magnetic resonance. In this approach, the technique is still “inductive”, since the magnetic field generated by the primary coil induces a current in the secondary coil. However, it is a “non-radiating” wireless charging technique that takes advantage of the stronger coupling that happens between resonant coils, even when they are more separated. In other words, in magnetic resonance wireless charging, electricity can be transferred efficiently without perfect horizontal alignment and thus, without the requirement of closely coupling the coils (Giler, 2009). A further advantage of the technology is its ability to transfer power between a single primary coil and multiple secondary coils. However, this approach exhibits some disadvantages, too. In particular, this system shows relatively low efficiency due to flux leakage, greater circuit complexity and, because of the (typically) high operating frequencies, potential electromagnetic interference (EMI) challenges (Dubal, 2015).

All in all, a tradeoff between efficiency and convenience, such as being able to charge several devices simultaneously, without the need for accurate alignment, should be considered before deciding which approach to use in the design of the ER.

Other alternative ways of wireless charging are being developed as modified or combined versions of the aforementioned two. One representative example is the Shaped Magnetic Field in Resonance (SMFIR), pioneered by OLEV (On-line electric vehicle). According to Suh et al. (2011), this technology is different from the other ones in the following ways: it uses ferrite cores to shape the two-dimensional magnetic field in order to create a “magnetic field path” from the bottom ferrite core to the core attached to a moving vehicle. The high-intensity field is confined in a relatively well-defined space between the ground and the vehicle.

This is equivalent to creating a loop from the poles of the underground ferrite core through the poles of the top ferrite core (an inverse-shaped U) of the pickup unit attached to the vehicle. As the magnetic field oscillates through these ferrite "loops," the energy associated with the magnetic field is picked up using the resonance effect. In order to pick up the magnetic field, the top pick up unit must be in resonance with the field frequency of the lower unit imbedded in the ground, which creates a "continuous loop" of magnetic field (Suh et al., 2011). This is why this technology is called "Shaped Magnetic Field in Resonance" (SMFIR).

It can be easily understood from the above that the coils embedded in the roadway play a major role in the function of the WPT system. The primary coil pads are circular in shape in order to allow the electromagnetic waves to propagate in the most efficient way, minimizing the availability of the waves to be absorbed by the secondary coils (Boys and Covic, 2010). As far as the materials used are concerned, the coils are usually made with Litz wire, so as to prevent the undesirable increases in resistance of the system (Sullivan, 1999) and with aluminum/metal that surrounds the top of the ferrite bars in order to generate the necessary electromagnetic field.

In the wireless charging systems, the levels of efficiency depend on different factors such as the material used, the alignment of the EV with the ER, the alignment of the coils towards each other, the energy source, the traffic conditions and the speed of the vehicle and the distance between the road and the current collector on the vehicle. This distance between the vehicles pick up and the roadway surface, known as air gap, is one of the most critical elements during planning. The relationship between the air gap and the charging efficiency is not linear, but seems to exhibit a polynomial formulation.

In general, misalignments until 100 to 150mm have a relatively marginal impact on the quality of the power transfer but misalignments between 200 and 250mm lead to substantially lower levels of efficiency. Though, the exact degree of efficiency is not straightforward, a transfer of above 150kW per segment may be possible, indicating that heavier vehicles such as trucks with increased demand in electricity can also be powered through this type of technology (Viktoria Swedish ICT, 2013; Singh, 2016).

2.2 Research Studies on Electric Roadway (ER) Technology

There have been different studies on the concept of dynamic charging, in terms of its design and technical analysis, the planning infrastructure, and its economic analysis.

Design and technical analysis

Bolger et al. (1978) studied the design of an electromagnetic coupling mechanism (wireless power transfer), the "Dual Mode Electric Transportation" (DMET), using pure models, circuit analyses and tests of a full-size physical prototype to provide the necessary results on the system characteristics within a network of high speed arterials. This paper includes details on the properties of inductive coupling found such as the design power per passenger cars (20kW), the core material, thickness, the pickup length per passenger car (around 5 feet), the conductor, the magnetic properties, and inductance.

More recently, Shin et al. (2014) presented the design and implementation of a wireless power transfer system for moving EVs. Electrical and practical designs of the inverter, power lines, pickup, rectifier, and regulator as well as an optimized core structure design for a large air gap were described with the view to achieving high output power and power transfer efficiency. More specifically, the results indicated that the implementation of the system needed an amount of power of 100-kW, 80% power transfer efficiency and 10.2 inches of air gap.

Many studies have focused on the problem of the air gap between the pickup unit and the charging infrastructure. These studies have proposed design methods of loosely coupled inductive power transfer systems (Stielau & Covic, 2000; Chen et al., 2010; Wang et al., 2004b; Budhia et al., 2011, Sallan et al., 2009; Imura & Hory, 2011). Research has also been conducted to analyze techniques to improve the efficiency of power transfer, including resonant inverters for wireless power transfer (Abe et al., 1998; Wang et al., 2004a; Meins et al., 2006; Borage et al., 2005; Li and Mi, 2015; Bi et al, 2016; Moller, 2017; Brecher & Arthur, 2014), efficient pickup units (Raabe et al., 2007; Kissin et al., 2011; Elliott et al., 2010), effective pickup tuning methods (James et al., 2005; Zaheer et al., 2010; Covic et al., 2008) and pickup voltage control methods (Wu et al., 2010a).

Stamati & Bauer (2013) investigated design considerations of dynamic charging such as the percentage of road that should be covered, the distribution and the length of the electric segments over the road, the power transfer capability of the system and the total power demand for all the passing-by vehicles using the system. An important finding is that an operating frequency of 100khz in the system would provide high transfer efficiency, given a length of 0.186 miles of the primary coil. In addition, an EV with a battery of typical size (24kWh) could achieve 310.7 miles driving range if the on-road system transfers 25kW, given a 40% coverage of the road.

What is more, there has been an effort for assessing the technical maturity of the electric road systems. Sundelin et al. (2016) evaluated the maturity level of the different ERS technologies using the method associated with Technology Readiness Levels (TRLs) and focuses on the power transfer technology subsystem. Results showed that the maturity of some elements related to the operation of the technology in an open system are not mature enough yet, while the maturity of the technology from a technical perspective is quite high.

Li et al., 2018 evaluated the longitudinal safety of EVs with wireless charging lanes on freeways based on simulations that included deployment of a wireless charging lane and distribution of state of charge (SOC) of EVs. This study showed that the safety of EVs operating in the charging lane is significantly affected by the SOC, with a lower SOC resulting in higher longitudinal crash risks. Another factor was found to be the maximum deceleration before entering the charging lane, being negatively associated with the longitudinal safety of EVs.

Planning infrastructure and optimization

With regard to the planning infrastructure, a number of studies have focused on the implications of dynamic charging to overall transportation network. Sarker et al. (2016) show how to effectively distribute power to the different charging coils along a wireless charging lane in a vehicle-to-infrastructure (V2I) communication system. They proposed a system that generates less communication latency, a balance SOC and less drop in efficiency rates.

Routing algorithms that take dynamic charging into account have also been developed. Li et al. (2016) developed an ant colony optimization based on multi-objective routing algorithm that utilizes communications systems to determine the best route considering the current battery charge.

There have also been recent studies related to the optimal placement of wireless charging lanes. The basic difference in these studies arises in the objective function and/or the type of routes, between the origin and destination that are considered. Recently, Chen et al. (2016) considered the optimal placement of wireless charging lanes when the charging infrastructure is considered to affect the EV driver's route choice. They developed a mathematical model to minimize the total social cost in terms of travel times.

Riemann et al. (2015) analyzed the optimal number and locations of wireless charging facilities for EVs with stochastic user equilibrium model, considering both the facility location and the traffic flow pattern. Their model proved to be effective, since it captured the EV drivers' routing choice behavior towards the EV charging facility availability and congestion effects.

Liu & Song (2017) investigated a deterministic and a robust planning problem of dynamic wireless charging facilities for electric buses. The deterministic model established the bus battery sizes and the allocation of the charging facilities for such system. The robust model showed optimal design that proved strong towards the uncertainty of energy consumption and travel time of buses.

In addition, a project led by Utah State University (Song & Singleton, 2017) produced an optimization framework for the optimal deployment of dynamic charging lanes for plug-in hybrid trucks in an electrified road freight transportation system subject to the budget constraints and equilibrium behavior of drivers. Technology optimization results show that the vehicle characteristics of a WPT EV fleet will consist of 25-mile range EVs with stationary charging at locations stopped greater than one hour and 50 kW charging on high-speed (greater than 30 mph) primary and secondary roadways, representing a total roadway infrastructure cost of $1.45 trillion. When used in conjunction, optimized vehicle and roadway architectures satisfy 97.7% of 24-hour drive cycles, a 22.4% increase from when no in-motion charging is used.

Economic Analysis

As far as the financial aspect of the charging technology is concerned, Ko & Jang (2013) showed that dynamic charging can significantly reduce the high initial cost of EV by allowing the battery size to be downsized. This method could be used to complement other concepts such as battery swapping to reduce driver range anxiety.

A smart charge scheduling model is presented in Li et al. (2015) that maximizes the net profit to each EV participant while simultaneously satisfying energy demands for their trips. Popular BEV models were analyzed and it was shown that they can generate an annual regulation profit of $454, $394 and $318, given average daily driving distances of 20 miles, 40 miles and 60 miles, respectively.

Gill et al.2014 analyzed the costs associated with implementing a dynamic wireless power transfer infrastructure and a business model for the development of a new EV infrastructure. They found that such a system has high costs of construction, maintenance, and operations and that the appropriate business model would be based on a joint company, with public transport agencies like DOT, utility companies and interested private investors as participants collaborating to operate and maintain the system over its life-cycle.

Jeong et al. (2015) conducted economic analysis of dynamically-charged EVs and particularly, the OLEV bus. They quantitatively analyzed the benefits of this system with an economic model of battery size and charging infrastructure allocation, using a mathematical optimization model. They found the thresholds for the battery size reduction and the associated cost savings. He et al. (2013) explored the integrated pricing of electricity in a power network and usage of electric roads. They proposed “first- and second-best pricing” models under different authoritarian regimes that proved to be effective in maximizing the social welfare.

Limb et al. (2017) also conducted an economic viability analysis of in-motion charging applied to the US transportation fleet by comparing the technology to conventional ICE transportation and long-range EV fleet. The results demonstrate that the vehicle equipped with this technology will be an EV with 25 miles of range that would receive 50 kW charging at high-speed (greater than 30 miles per hour. Based on these characteristics, the infrastructure cost concerning the entire EV fleet in the US would be $1.45 trillion. It was also found that the system would have a societal return on investment of 36.7 years, based on $2.5 million per lane-mile annual retrofitting cost and an inventory of 13,788 electrified miles annually.

The study of Fuller (2016) assessed the potential for wireless charging lanes (WCL) to address range and charging issues of EVs via considering travel to regional destinations in California, which indicated that dynamic charging might be a more cost-effective range-extension approach compared to increasing battery capacity. The cost of WCL per lane mile is 4 million dollars (Fuller, 2016), which is approximately 3 times more than that of non-WCL. One method to reduce the cost is to utilize improved charging material with a low price, but this may be impractical in the near future. Another cost reduction measure is to partially deploy WCL on freeways (He et al., 2017).

2.3 Demonstration Projects

This section reviews the studies that have been undertaken and/or are still ongoing so as to examine the ER deployment. These case studies cover both in-motion conductive and inductive charging systems and are analyzed in terms of their goals, achievements, and factors they considered. Table 2.1 summarizes the characteristics and findings of the case studies and research projects in the US and abroad.

2.3.1 Overhead Conductive Systems

In California, US, Siemens and South coast Air Quality Management District (SCAQMD) are currently testing the overhead conductive eHighway system in a one-mile demonstration in the city of Carson, in the proximity of ports of LA and ports of Long Beach (Siemens, 2017a). This project is testing how different plug-in hybrid electric truck configurations interact with the eHighway infrastructure which includes a catenary wire supporting the overhead contact wire, similar to trolley systems or streetcars. Siemens originally presented this innovative "eHighway" concept in 2012. The core element of the system is an intelligent pantograph on the trucks combined with a hybrid drive system. A sensor system enables the pantograph to connect to and disconnect from the overhead line at speeds of up to 90 km per hour. Trucks equipped with the system operate locally emission-free with electricity from the overhead line and automatically switch to a hybrid engine on roads without overhead lines (Siemens, 2012a).

In the specific project, a battery-electric truck, a natural gas-augmented electric truck and a diesel-hybrid truck are driving using this catenary system on the north- and south-bound lanes of South Alameda Street from East Lomita Boulevard to the Dominguez Channel in Carson. The used vehicles are manufactured by Volvo and local truck retrofitters. The demonstration track started the operation within 2017 and thus, the results are not available at the time of writing this thesis. The goal is to set up a zero-emission corridor on Interstate Highway 710 with the view to lowering fossil fuel consumption and CO2 emissions, reducing truck operating costs, and accommodating freight transportation.

The feasibility of integrating overhead contact systems is also being studied throughout Europe. To start with, in Germany, the eHighway technology will be tested on a public highway in Germany. The system is being built as part of the joint project "Electrified, innovative heavy freight transport on autobahns" (ELISA) of Germany's Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB) (Siemens, 2017b). The project is planning to build an overhead contact line for electrified freight transport on a 6.2 mile stretch of a German expressway between the Zeppelinheim/Cargo City Süd interchange at the Frankfurt Airport and the Darmstadt/Weiterstadt interchange (Siemens, 2017b). The line will supply electricity for the electric drive of a hybrid truck. Field trials of the eHighway technology on German highways are planned to begin in 2019.

In Sweden, trials are being conducted as part of the FABRIC project (Feasibility analysis and development of on-road charging solutions for future EVs). The test site in Sweden is using the overhead conductive charging solution on a 1.24 mile stretch of E16 motorway (north of Stockholm) (Siemens, 2015). This demonstration project started in June 2016 and tests two bio-diesel hybrid trucks, manufactured by Scania and adapted, in partnership with Siemens, to operate under the catenary system. The test results will be available within 2019 and are intended to verify the system's suitability for future commercial use with the ultimate goal being to develop a fossil fuel independent transport sector by 2030 (Siemens, 2015).

2.3.2 Conductive Rail Systems

In Sweden, the conductive rail system is being tested through various projects and demonstrations. The techniques that have been developed are based on conductive technology that uses an electric rail installed on roads to power and recharge vehicles during their journey.

The eRoad Arlanda project aimed at building a 1.24-mile demonstration section to apply the conductive rail system for both commercial and passenger vehicles. During 2012-2018 period, a 18-ton battery electric truck carrying freight was being tested in order to determine how well the installation works under normal traffic conditions in various weather conditions (eRoadArlanda, 2017a). An embedded electric rail and a customized energy pick-up integrated into the truck were the two basic systems used for the investigation of electrified shuttle transports along a public road in the vicinity of the Arlanda Airport, Stockholm, Sweden, during 2017-2018 (eRoadArlanda, 2017b). Development and tests were being carried out on a separate enclosed test track. The test track was around 0.22 miles and located on a 6.21-mile section of Road 893 between Arlanda Cargo Terminal and the Rosersberg logistics area. The system has been tested during six winters since 2012 and results showed that it can withstand snow, ice, water, gravel, leaves and other weather effects.

In April 2018, the 1.24-mile section of electric rail has been officially opened, constituting the first public demonstration road of its kind that allowed vehicles to be recharged while driving (eRoadArlanda, 2018). The plan is to expand the system across Sweden. More specifically about the technical details, the eRoadArlanda's technical solution (rail solution from the company Elways) transfers energy from a rail in the road to the vehicle, using a movable arm. The arm detects the location of the rail in the road and as long as the vehicle is above the rail, the contact will be in a lowered position. When overtaking, the contact is automatically raised. The rail, which is connected to the power grid, also functions automatically. It is divided into sections and each individual section is powered only when a vehicle is above it. When a vehicle stops, the current is disconnected. The rail enables the vehicle's batteries to be recharged while powering its passage. The system also calculates the vehicle's energy consumption, which enables electricity costs to be debited per vehicle and user.

The overall goal of the project was to generate knowledge, experience and decision data that could be beneficial to the creation of a platform for the electrification of a larger transport network in Sweden. The investment in the eRoadArlanda project is in line with the Swedish government's target of reducing transportation infrastructure that uses fossil fuels by 70% by 2030 (eRoadArlanda, 2017a). Results from the demonstration project have shown that this system can reduce carbon dioxide emissions up to 90% and at a cost of around $1.93 million per mile, the price of electrification is said to be 50 times cheaper than an urban tram line.

Another Swedish based company, Elonroad, also works on the development of ERs in Lund, southern Sweden together with Lund University. The solution is intended to be used by both moving and stationary electric cars, buses or trucks. Elonroad has constructed a 0.12 miles long test track outside Lund, at LTH, Lund University. The electric road consists of a rail that rises about 2 inches from the surface and has width of around 12 inches, having slantwise sides. A power cable is connected to the power station at the end of the rail. Sliding contacts under the car provides electricity to the onboard charger (Elonroad, 2017). Based on the project's estimations (Elonroad, 2017), the electric road will transfer power up to 240kW with 97% efficiency. In addition, the cost of the system is preliminarily estimated to be $1.4 million per mile.

Since 2012, the French rail transport company Alstom is testing the conductive rail charging system on electric trucks and buses at a facility in Hallered, near Gothenburg, Sweden which is operated by AB Volvo. A 0.29 inches wide track, with a 0.17mile electrified roadway section, is being used for developing the electric road technology (FABRIC, 2017). The system consists of two power lines built into the surface of the road and a current collector on the vehicle that connects to the road. The vehicle integration is being performed as part of the Slide-in research project (Olsson, 2014) and FABRIC Project (FABRIC, 2017). According to the test results, it was found that the system is able to transfer 120 kW of power in total, achieving 93.3% power transfer efficiency.

2.3.3 Wireless Charging Systems

The PATH (Partners for Advance Transit and Highways) program at UC Berkeley, was conducted to build a roadway with EV powered inductively in the end of 1970s (Eghtesadi, 1990). A 60 kW, 35-passenger bus was driven along a 0.13-mile distance road track. Due to limited technology, the operating frequency of Berkeley system was 400 Hz and their efficiency was only 60%. From there, researchers and industry have improved the performance of the dynamic EV charging systems (Vilathgamuwa & Sampath, 2015).

The Sustainable Electrified Transportation Center (SELECT), has been established at Utah State University, US in 2016. This research center initiated the construction of a quarter mile, oval-shaped electrified test track (Electric Vehicle and Roadway (EVR) facility) and has demonstrated that in-motion EVs can be effectively charged using dynamic wireless charging (Morris, 2015; Liu & Song, 2017). The University's campus in Salt Lake City and the Utah Transit Authority have collaborated on demonstrating inductive power transfer for USU's fully electric 20-passenger bus-referred to as the "Aggie Bus".

The "Aggie" bus is the first bus developed and designed by a North American organization that is charged with wireless power transfer technology and is the world's first electric bus with such technology. It can achieve a power level up to 25 kW, greater than 90% efficiency from the power grid to the battery and a maximum misalignment of up to six inches (Utah State University today, 2012). As of 2018, the Aggie buses are in operation through a shuttle service provided to the Utah State University community and are also equipped with an autonomous control kit from Autonomous Solutions Inc. This kit is required to identify inductive power transfer coils embedded in the roadway and to align automatically under various road and weather conditions (Utah House of Representatives, 2017). According to USU, this technology could result in $180 billion in annual cost savings, a 20% reduction in air pollution and a 10% reduction in CO_2 emissions in the United States.

The FABRIC European Project (Feasibility analysis and development of on-road charging solutions for future EVs) is also investigating the feasibility of in-road inductive wireless systems with test sites in France and Italy. The test site in France is supplied with inductive charging system by Qualcomm. The first demonstrations took place at a less than 1-mile (0.062 miles) FABRIC test track at Satory Versailles, recently built by the French research institute VEDECOM. Qualcomm's Halo dynamic EV charging system (DEVC) was integrated into the test track, and the receiving components were installed in two Renault Kangoo EVs. The dynamic charging prototype tested has the capability of charging an EV dynamically at up to 20 kW at highway speeds. Various power levels and scenarios (experiments associated to dynamic inductive charging use on road and periurban highway) are being tested. The expected efficiency of the system is 80%.

In Italy, the existing test track is specifically designed for testing inductive wireless technology under different conditions in urban environment. Two paved lanes are equipped with embedded induction loops able to recharge the EVs while they are driven electric distribution and communication network. The FABRIC test bed is designed and constructed in accordance with safety guidelines and standards to provide at least 0.16 miles of electric car and light-duty vehicle dynamic charging infrastructure. The site is able to support for at least one vehicle and possibly three powered vehicles simultaneously. Two implementations are being investigated. The first implementation is the technology developed by Politecnico di Torino, named POLITO Charge While Driving and the second is the SAET SPA system. The technology is being tested mainly at FIAT vans and is able to achieve power transfer of up to 20kW (POLITO) and 40kW (SAET) at urban speeds. The goal is to achieve wireless power transfer with an efficiency of 70-80%.

So far, preliminary results from the Italian and French test sites showed that the dynamic charged EV represents the most advantageous option in terms of CO_2 emissions, operation costs and total cost of ownership compared with a BEV or a diesel car (FABRIC, 2017).

Bombardier's PRIMOVE e-mobility team has performed a series of tests with a dynamically (inductively) charged hybrid electric truck at a construction site in Mannheim, Germany. The test track used was around 262.5 feet long and consisted of four 65.6 feet long charging segments embedded within the road. These charging segments automatically switch on and off when the vehicle is driving above them supplying it with electrical energy, completely contactless. The truck was found to be able to be inductively supplied with approximately 183 kW, with 89% energy power transfer efficiency (Sundelin, 2016). The test conducted were mainly focusing on increasing safety, stability and accuracy of dynamic, inductive charging and also minimizing the electromagnetic stray field. This was achieved by working with different lengths of the devices embedded into the ground as well as conducting tests to determine the ideal distance between the individual charging segments (Primove, 2016).

Another research project in Lathen, Germany is testing the inductive energy transfer systems for passenger and light commercial vehicles. The company called Integrated Infrastructure Solutions (INTIS) operates its own test center that includes a 0.016-mile-long test track which can be outfitted with inductive coil sections (Integrated Infrastructure Solutions [INTIS], 2016). In particular, three types of vehicles are being tested: an electric sports car, an electric bus and an electric minivan. According to the results from the coil system, the electric sports car can be supplied with up to 30kW, the electric bus with up to 60kW and the electric minivan with up to 30kW. In general, the main road side components for inductive energy transfer systems for stationary or on-the-move applications are all available and can be used for tests up to a transferred power of 200kW at frequencies up to 35 kHz (Integrated Infrastructure Solutions [INTIS], 2016).

In 2016, VICTORIA project (Vehicle Initiative Consortium for Transport Operation and Road Inductive Application) led by Endesa Company, initiated an electric bus route in Malaga, Spain, using inductive power transfer developed by CIRCE. Eight 31.5 inches and 50kW coils will be installed along 0.062 miles (100m) of the route. This prototype was developed for low speeds (6.2 mph). The urban bus from Gulliver is self-guided to assure proper speed or misalignment and is adaptive for conductive and inductive charging (Endesa, 2013). Experimental results in 2017 showed that dynamic charging system's efficiency is 83 % at rated power due to lateral misalignment. It is expected that further testing at different speeds will be carried out within the FABRIC project when the bus becomes available again.

In 2009, the Korea Advanced Institute of Science and Technology (KAIST) started its Online Electric Vehicle (OLEV) project in South Korea. This incorporated a technology called the Shaped Magnetic Field in Resonance (SMFIR) and has been implemented in the shuttle system of the KAIST campus (Suh et al., 2011). KAIST has also deployed trams using this system at the Seoul Grand Park Amusement Park and in 2013 introduced the world's first battery electric bus which travels for a distance of 15 miles between the train station in the city of Gumi and the district of In-dong (Jang et al., 2015).

By then, the initial project had already led to the formation of two spin-off companies, OLEV Korea and OLEV Boston, the latter launched in 2011. Results of the trials so far have shown real-world performance of the OLEV system with 75% to 85% efficiency for charging at 100 kilowatts. The single power electronic has a rate of 20kW and the system has a power rate up to 200kW (20kW/pickup and 5 pickups per bus) (FABRIC, 2014a). The buses can travel at a top speed of around 52.8 miles per hour, but usually travel at approximately 37.3 miles per hour in ordinary service. The advantage to the KAIST/OLEV system is that the rechargeable bus battery is smaller than usual, at only 1/5 the size of a normal electric bus battery. Recharging pads cover only 10–15 percent of the bus route (Suh & Cho, 2017).

Israeli-based start-up ElectRoad also announced successful tests of its dynamic charging system on an 80ft. test track. The company uses conduction coils to power electric cars via magnetic induction and plans to embed them along public transportation routes in Tel Aviv by 2018. Currently, ElectRoad is working on demonstrating the complete system, initially on an electric car and then on a bus platform. The goal is to achieve an efficiency of more than 88% of energy transferred (ElectRoad, 2017).

The Transport Research Laboratory (TRL) in UK has conducted a feasibility study of dynamic inductive power transfer along the network of England's major roads on behalf of Highways England (Transport Research Laboratory, 2015). The project has investigated a number of possible wireless power transfer technologies focusing on those able to function as dynamic wireless power transfer (DWPT) systems for cars, large good vehicles (LGV)/heavy good vehicles (HGV). In total seventeen WPT systems were investigated, eight of which had a dynamic capability. Each system capable of dynamic functionality was evaluated by the project team against a number of metrics covering: power transfer level, operational speed, suitability for different vehicle types and availability for trials (Transport Research Laboratory, 2015). Specifications for the installation of DWPT equipment into vehicles and safety implications were also considered as part of the study. The requirements for EV batteries were found to be dependent on vehicle dynamics, duty cycles and vehicle powertrain technology.

Three types of road construction were considered for DWPT, these being trench-based constructions (where a trench is excavated in the roadway for installation of the DWPT primary coils), full lane reconstruction (where the full depth of bound layers are removed, the primary coils installed and the whole lane resurfaced), and full lane prefabricated construction (where the full depth of bound layers are removed and replaced by pre-fabricated full lane width sections containing the complete in-road system). The system could support both electric and HEVs and would likely impose high peaks and variations in power demand which will be dependent on traffic conditions at the time, based on theoretical results. The system expectations, according to the study, refer to 100-140kW of power transfer and more than 80% overall efficiency. However, this study is a conceptual one, since field trials have not been conducted yet and thus, it is using assumptions and scenarios made by TRL, based on existing ER projects (Transport Research Laboratory, 2015).

Inductive power transfer technology is also being investigated by the University of Auckland in New Zealand (University of Auckland, 2010). The associated research project aims to develop new charging pads that could survive and create new charging materials made of soft composites in a cost-effective manner, without degrading the road performance of the road and ensuring increased service life. This might involve charging coils at intersections, or on slopes to support power transfer for vehicles traveling uphill. This research has been used for limited use on public transportation systems, since it is mainly used to develop fully-functioning inductive power systems for handling materials and factory automation applications. Besides testing the in-motion wireless charging system, the stationary wireless charging is also being explored for PHEVs or BEVs.

Table 2.1: Summary of selected studies on ERs

Reference	Location	Technology			Test track/site	Vehicle Type	Results/Goals
		Overhead Conductive	Conductive rail	Wireless Inductive			
Siemens, 2017a	California, US	X			1-mile test track (demo) in Carson, LA	Battery-electric, natural gas augmented, diesel-hybrid truck	Ongoing Overall goals: zero-emission corridor, reduced truck operating costs
Siemens, 2017b	Germany, EU	X			Demonstration on a 6.2 mile stretch of expressway, Frankfurt	Hybrid electric truck	Field trials start in 2019
Siemens, 2015	Sweden, EU	X			1.24 mile stretch of expressway, north of Stockholm	Bio-diesel hybrid truck	Ongoing Results available within 2019
eRoadArlanda, 2018, 2017	Sweden, EU		X		1.24-mile demonstration, Stockholm Arlanda Airport/0.22-mile test track	Electric truck	Opened in 2018 Tested during six winters since 2012 Measured: 90% reduction in carbon dioxide emissions 50 times cheaper than an urban tram line (at a cost of $1.93 million per mile)

Table 2.1 continued

Elonroad, 2017	Sweden, EU		X		0.12-mile test truck, outside Lund.	Electric vehicles (cars, buses, trucks)	Ongoing Goal: up to 240kW of power transfer with 97% efficiency Preliminary cost estimation: $1.4 million per mile
Olsson, 2014 FABRIC, 2017	Sweden, EU		X		0.17-mile test truck, Hallered, Sweden	Electric trucks and buses	Started from 2012 Measured: 120kW power transfer 93.3% efficiency
Eghtesadi, 1990 Vilathgamuwa and Sampath, 2015	California, US			X	0.13-mile stretch, Berkeley	Battery-electric bus	Measured: Operating frequency of 400 Hz 60% efficiency rate
Utah State University, 2012	Utah, US			X	Shuttle service to Utah State University Community, quarter mile stretch, Logan	20-passenger “Aggie” electric bus	Ongoing Goals: 25 -40kW power transfer 90% efficiency 20% reduction in air pollution 10% reduction in CO_2 emissions $180 billion in annual cost savings

Table 2.1 continued

FABRIC, 2017	France, EU			X	0.062-mile test track, Versailles	Renault Kangoo electric vehicles	Ongoing Goals: 20-40kW at highway speeds, 80% efficiency
FABRIC, 2017	Italy, EU			X	0.16-mile test track, SAET and POLITO solutions, Turin	FIAT electric vans	Ongoing Goals: 20-100kW 70-80% efficiency
Sundelin, 2016 Primove, 2016	Germany, EU			X	262.5-foot test truck, Manheim	Hybrid electric truck	Ongoing Measured: 183kW 89% efficiency
Integrated Infrastructure Solutions [INTIS], 2016	Germany, EU			X	0.016-mile test truck, Lathen	Electric passenger and commercial light vehicles (car, bus, minivan)	Ongoing Measured: 30-70kW power transfer (coil system)
Endesa, 2013	Spain, EU			X	0.062-mile stretch with low speeds (6.2 mph), Malaga	Battery electric bus	Ongoing Goals: 50kW power transfer 83% efficiency
Suh et al., 2011 Jang et al., 2015 Suh & Cho, 2017 FABRIC, 2014a	South Korea, Asia			X	Shuttle system of KAIST campus Trams at Seoul Park Amusement Park, Gumi	Battery electric bus (OLEV buses)	Started from 2009 Already in use Measured: 20-200kW power transfer 75-85% efficiency rate

Table 2.1 continued

ElectRoad, 2017	Israel, Middle East			X	80-foot test track, Tel Aviv	Battery electric car and bus	Ongoing Goals: More than 88% efficiency
Transport Research Laboratory, 2015	United Kingdom, EU			X	Not field trials yet	Electric cars, large good vehicles, heavy good vehicles	Ongoing Not available results-conceptual study Goals: Investigation of different WPT systems, expectations mention up to 100-140kW of power transfer More than 80% efficiency

2.4 Benefits and Concerns about Electric Roadways (ERs)

Electric roads constitute an innovative system that can alter the way EVs can be charged. As with any technology, there are merits and limitations associated with each alternative technique for highway electrification.

2.4.1 Benefits

Electric roads deliver continuous power to vehicles while they are in motion, and thus offer a promising solution to address major barriers to vehicle electrification. In particular, this charging solution offers unlimited range with vehicles that actually cost less to purchase and operate than their internal combustion engine counterparts. This is because reduction in the battery size reduces the vehicle weight. Hence, this advantage will be highly recognized by fleet operators and consumers.

The reduced size of the battery has also important environmental implications, since the emissions embodied in the production of the battery decrease compared to the emissions produced from the battery of a traditional EV. In general, total emissions from light duty vehicles and trucks will be reduced in the long run, as a result of improvements in fuel economy and engine operation (Limb et al., 2017).

In addition, the concept of dynamic charging can increase battery life with reduced discharge cycles and no rapid fast charging, increase productivity by eliminating long charging times, and provide a direct path to higher levels of autonomy (continuous operation, unlimited range, no user interaction required for charging).

Another important implication is that this emerging technology provides a path to creating zero-emission corridors and encouraging electric conversion through infrastructure investment. Thus, local and state agencies that have the goal of reducing carbon traffic emissions can benefit by investing in this promising concept.

For the electrical infrastructure system, the roadway charging solution provides a continuous and relatively predictable load that can be actively controlled. This approach allows actively controlling vehicle charging rates, at the sub-second level, thus managing local grid electrical demand to meet vehicle requirements as long as the total energy is delivered over tens of miles. This represents a paradigm shift away from the fixed location, on-demand, high-peak, fastcharging gas station model currently trending for EV corridors. Fuel savings would be shared between the roadway operator to cover the infrastructure investment and the end user. Another important advantage for broad adoption of in-road charging is providing a single infrastructure solution that is compatible with light to heavy duty vehicles. This eliminates challenges associated with multiple standards for each light duty power level and custom solutions for public transit and freight.

2.4.2 Concerns

On the other hand, the main barriers concerning the electric roads are related to increased complexities on a system level. The conventional transportation system has evolved organically over more than 100 years and constitutes today an open socio-technical system with different standards and regulations and constituted by different, more or less, autonomous and complementary subsystems. These subsystems – the truck, road, and fuel system– are today produced and operated autonomously by different actors, e.g., truck manufacturers, construction companies, road authorities, and oil companies. The electric road technology requires, initially at least, a more closed system-design, where the subsystems are tightly coupled together. The power train of the electric truck needs to be tightly integrated with the power transfer technology, which needs to be integrated with the electric road design, which in its turn needs to be integrated with the regional power grid.

Consequently, there are a number of stakeholders from different industries that are highly interested in the different concepts of electric road technologies, e.g., manufacturers concerning the vehicle and its power-train; railroad manufacturers concerning the power transfer technology and electric roads technology; construction firms concerning the physical infrastructure; and power utilities concerning the electric power supply and operations of the power grid. Moreover, there are several new services required in order to manage ERs, e.g., payment systems, logistics, driver management, electricity metering, and safety. Thus, the complexity of the system may be high. For this reason, software management services may be needed to reduce the complexities of the technological interfaces between the electric road system and its customers.

In addition, one of the main concerns is the cost of the implementation of this infrastructure. The initial cost of this system is rather high. The investment and implementation costs of ERs mainly depend on a wide range of factors (type of technology, road characteristics, existing substations, etc.). Different sources presumed costs of about $2-$4 million per lane-mile (FABRIC, 2014b; Fuller, 2016; Viktoria Swedish ICT, 2013; Moller, 2017). Depending on the business model that will be followed, the implementation and use of dynamic charging systems can incur charges to users that can cover electricity supply costs (FABRIC, 2014b). In the long run, payback periods for the specific technology can decrease, operating costs for the vehicles decrease, and return on investment can be higher. In other words, if the system is implemented at a larger scale, costs can be brought down. Different options of potentially considering tolling systems can lead to a model that can generate revenues for the state, as the technology becomes more and more mature in terms of wider public implementation and acceptance. For this reason, a gradual implementation of ERs from a small system to a large system is recommended.

Turning to the expected maintenance costs, inductive charging systems can be installed under the road without any additional visible infrastructure and without a safety risk and are expected to minimize the need for maintenance. In addition, these systems could potentially be used as heating pavement systems, preventing from frost damages during winter (Moller, 2017). In general, based on rough estimates from case studies, the maintenance costs per year range from 1 to 2% of the total investment costs over the estimated lifespan of the system (Viktoria Swedish ICT, 2013).

The legal aspects and obstacles for ERs have not yet been explicitly defined. Such barriers may include electrical safety laws, environmental laws as well as access to the right-of-way (ICT, 2013). For example, overhead wires have to be installed in a height of at least 19.685 feet which enables only vehicles with a corresponding size to connect to them. Special arrangements may be expected for implementations of the system under bridges and in tunnels which may lead to lower hanging wires (Andersson & Edfeldt, 2013). In general, some of these questions may be easy to solve, but other issues require a real case to be tested and evaluated in the future.

As far as the safety concerns are concerned, concerns related to the electricity of charging zone, damages from tear, wear or rutting during different conditions have been expressed. However, tests are being conducted in the demonstration projects to evaluate several hazard situations before the implementation of the system in real conditions. From these tests, conclusions about the technology implementation will be made and used appropriately. For example, it has been found that for electrical safety reasons, in-road solutions -both inductive and conductive- must consist of short segments 20m (65.6 feet) or even shorter depending on the vehicle length of the shortest vehicles running on the electrified lanes (Viktoria Swedish ICT, 2013). These segments can be activated only when it bears at least one suitable vehicle and thus covering it from any third parties touching it. For all other situations the segment needs to be deactivated.

Since this system is not widely implemented and it is still being tested, it is reasonable that such concerns will be raised. This leads to the conclusion that one of the major weaknesses of this concept is the lack of maturity. The system has not proven itself in a real environment yet and a business model that can support it has not been found. Probably, bus lines and routes (e.g., city to airport connections) will be more appropriate for this technology, since they have steady traffic loads. Besides, as argued in Chen et al. (2016), commercial fleets, such as buses and trucks, are likely to be early adopters of dynamic charging infrastructure due to higher benefits offered to these vehicles.

However, as research progresses and adoption becomes higher, more concrete information from demonstration projects is expected to alter the situation by reaching a higher level of maturity and encourage the investment and use of this system. This is why a study of the market acceptance and the environmental impact of this technology is needed.

2.5 Optimal Locations

The implementation of the ERs can be achieved with two different ways. The first way is the construction of an entirely new road where the ERs technology can be installed. The second is the incorporation of the ERs technology to the existing infrastructure by carrying out some modifications. It is natural to conclude that the first way is more expensive than the second one. However, according to studies, the largest part of the cost comes from the construction and installation work itself, being around a third of the total implementation costs of ERs (Jelica, 2017).

Another aspect related to the implementation of ERs is the identification of their optimal locations in a road network. In order to be effectively implemented, they should be strategically deployed based on important factors that need to be considered. In particular, access to power network constitutes an essential factor, since the goal of implementation is to minimize the energy losses as much as possible (FABRIC, 2014b; Riemann et al., 2015). The distance from substations should also be considered, so as to be less than 0.5 or 1 mile to have a sufficient energy distribution (Siemens, 2017a). Furthermore, proximity to various land uses, such as airports, ports, terminals, courier delivery services, logistic companies and distribution centers also plays a major role in determining the optimal locations for ERs.

In addition, the identification of a suitable location of an ER also depends on the road characteristics and road environment, such as the number of available lanes, length, the physical condition and materials, the geometric design of existing infrastructure etc. (FABRIC, 2014b; Transport Research Laboratory, 2015, Viktroria Swedish ICT, 2013). Another primary factor to be considered is the daily traffic of the road (Stamati & Bauer, 2013). According to Limb et al., (Limb et al, 2017), the deployment of the technology should be based on the largest number of vehicles miles traveled per mile of roadway. Other factors that are expected to affect the decision for the location of ERs are related to the emissions levels of the study area, the temperature and weather conditions and so on (FABRIC, 2017; Viktoria Swedish ICT 2013).

2.6 Stakeholders Involved

In general, the electric road system is a system that needs the consideration of several factors in all the stages of their implementation as well as their operation and maintenance. This is because it is a new technology that is handled in a different manner compared to a conventional road. In the ER concept, the road and the vehicles driving on it interact continuously. Thus, there is an increased need of data collection, so as to monitor the road and its interactions with the vehicles. One important component of the data is the energy consumption of the vehicles that are moving along the ER, since this information can be used by the system operators to establish different business models for the ER (Jelica, 2017). These models need to be flexible, since a large number of stakeholders are involved in this system, such as EV manufacturers, users, regulators (state/national authorities and legislators), state and local agencies, policy-makers and so on. Figure 2.1 below presents the difference between the major stakeholders involved in a typical road system compared to an ER system (Viktoria Swedish ICT, 2013).

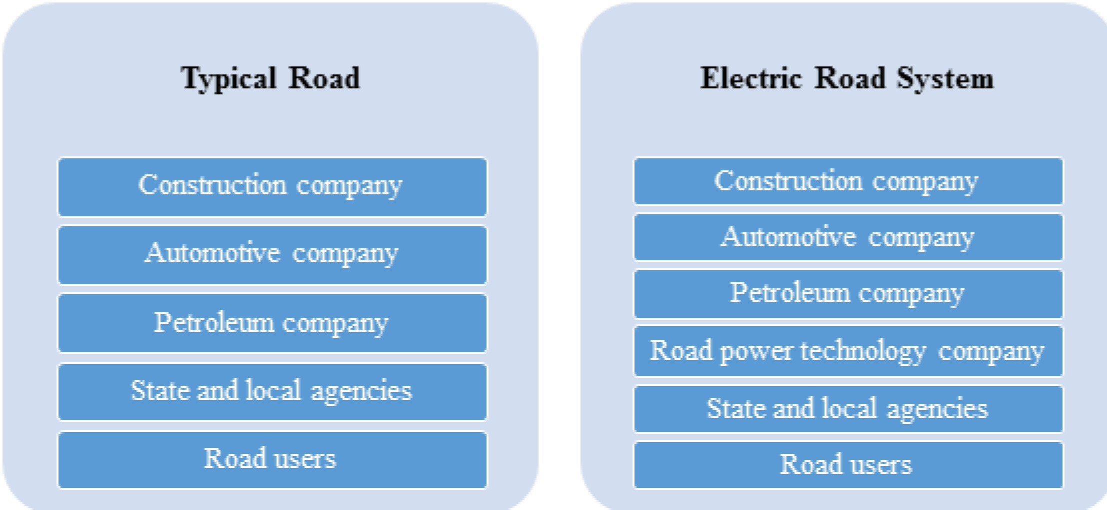

Figure 2.1: Stakeholders of conventional road and ER systems

(Viktoria Swedish ICT, 2013)

2.7 Summary

By closely examining the existing literature regarding ERs, it is possible to gain knowledge on technology details, factors considered in their implementation, expected results from demonstrations and research studies, and lessons learned. However, there is still a long way to go for a full commercial implementation, since this technology requires time to be studied based on the candidate location, be adopted and constructed.

It can also be concluded from the overview of previous studies related to ERs that data on market acceptance on ERs does not currently exist. Existing studies do not provide an understanding of the adoption level of ERs. Localized market data specific to ERs are necessary, as a first step to their implementation. The investigation of first adopters and main concerns related to ERs (technical or non-technical) would provide a roadmap of how this technology should look in the future in order for the stakeholders to select the elements that are necessary and feasible to build and test the system. This way, the users can be satisfied during the system's lifetime and this emerging technology can be properly adjusted to the involved stakeholder's needs.

Similarly, the emissions change based on the implementation of the technology has not been extensively studied on the study area. However, information on the potential of this technology to improve the quality of life may be important.

3. RESEARCH FRAMEWORK, EMPIRICAL SETTING, AND DATA

In this chapter, the research framework to achieve the three objectives of this thesis is discussed. In addition to the general framework, this chapter also presents the empirical setting of the study in order to provide a specific context for the application of the research framework and methodology. Sections 3.3-3.5 offer details about the survey that was designed targeting the general population in the study area. Sampling limitations are also discussed along with the steps that were undertaken in order to overcome any related issues.

3.1 Research Framework

As described in Chapter 1, the general research objectives of this thesis are to evaluate the market adoption and environmental impact of ERs in terms of emissions reduction. The main objectives, together with the specific goals presented, can be achieved by following a proposed research framework. Figure 3.1 presents the basic components within the research framework followed in this study.

As Figure 3.1 shows, the market adoption of ERs is based on the analysis of a) the factors that affect the intention to use the ERs in the short- and long-run so as to indirectly include the time dimension in the analysis and b) the adoption rates and market segments of ERs. For this purpose, a survey of current and potential users of a certain road network is conducted to assess the opinions for this emerging technology and estimate the EV market diffusion, while accounting for human preference heterogeneity, and behavioral and market responses to technological innovations. More specifically, the questionnaire includes questions related to possible factors affecting technology adoption of passenger car drivers that cannot be transferred easily onto the field of commercial-vehicle driving. It reveals respondent’s socioeconomic profile, travel patterns, attitudes towards ERs and other behavioral characteristics that could affect their intention to use the ERs. These characteristics are reflected through stated choice questions that include essential attributes of the technology. More information on the survey design is presented in Section 3.3. This methodology was adopted after reviewing related studies that focused on predicting the market adoption of different technologies (discussed in section 3.3) and served as the basis for the design of the survey questions (e.g., Rogers, 2003; Moons & De Pelsmacker, 2015; Al-Alawi & Bradley, 2013).

Using the data extracted by the survey, appropriate econometric models are estimated to assess market acceptance. The factors that affect short-term and long-term behavioral intention towards ERs are also identified and the market segmentation analysis follows by providing the adoption levels for different market segments. The market segmentation analysis is an important step to understand the target demand and accelerate ER adoption. The findings concerning the adoption rates are then used to evaluate the environmental impact of this technology based on different scenarios that run in the emissions model. The following chapters provide more details of the methodological approach that is used for each objective.

3.2 Empirical Setting

This thesis develops and tests a framework to assess the market acceptance and impact of ERs on criteria pollutants and greenhouse gas emissions. The case study area is the Los Angeles County in California. General EV and travel patterns, environmental issues and basic road network of the study area are presented in Section 3.2.1.

3.2.1 Study Area

The study area selection was based on the examination of EV market share. The implementation of ERs would be more meaningful and effective in an area that is proactive in terms of the large number of registered EVs and the availability of public charging stations and energy networks. Los Angeles is considered a leader in electro-mobility and thus, a natural choice for the implementation of ERs.

3.2.1.1 EV Trends

California plays a substantial role in increasing the EV uptake in the United States due to a combination of policies and promotional activities (e.g., The Zero Emission Vehicle regulation, consumer rebates, access to carpool lanes on congested highways, extensive EV charging infrastructure, progressive electric utility policies, greater model availability and marketing,

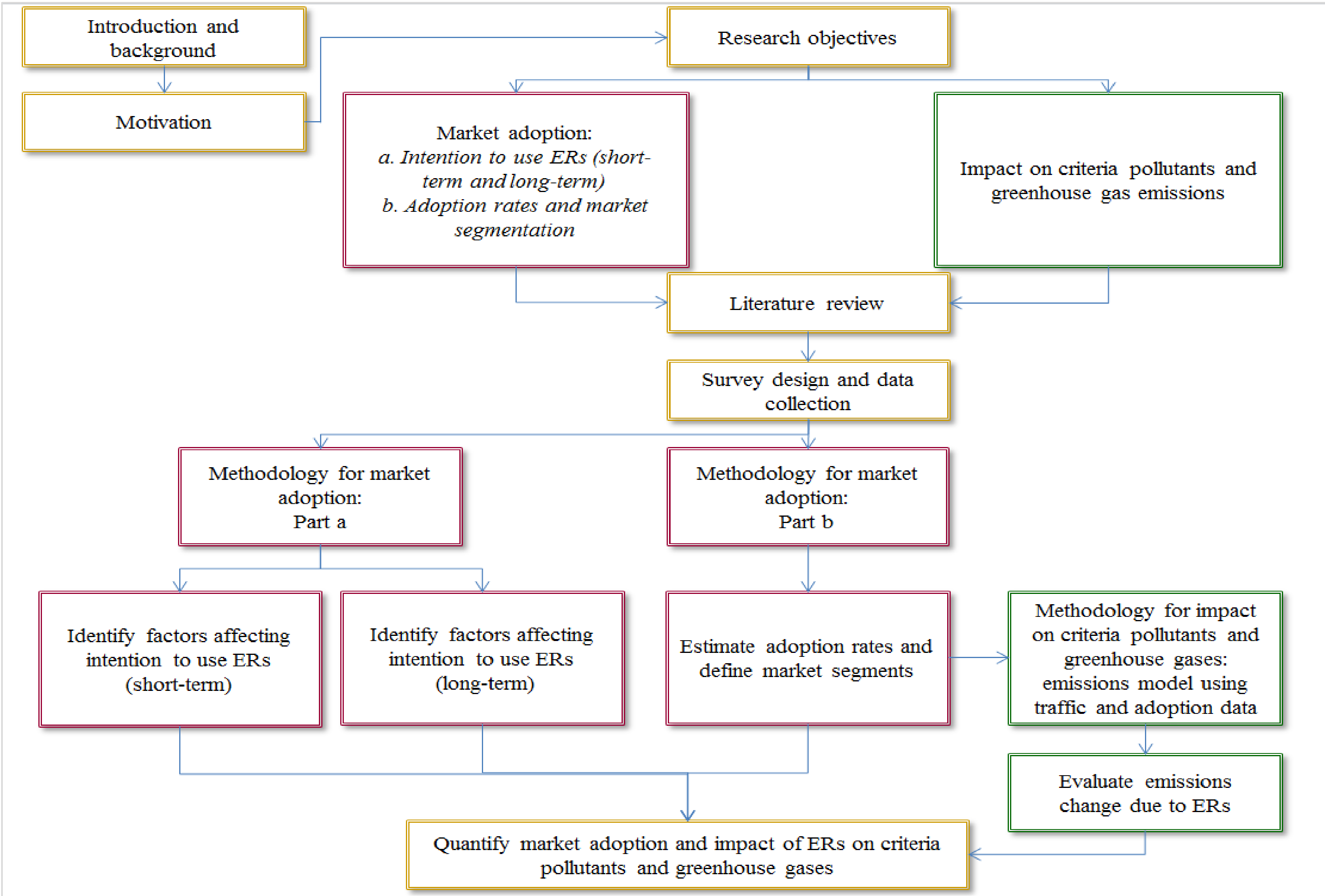

Figure 3.1: Research framework

access to high-occupancy vehicle lanes and continued growth of local EV promotions) (International Council on Clean Transportation [ICCT], 2018).

California is the second largest EV market in the world, after China. In particular, the California market-about 96,000 EV sales in 2017 (29% increase since 2016)-accounts for half of the US market and nearly half of cumulative EV sales through 2017 (International Council on Clean Transportation [ICCT], 2018). This compares with California representing about 12% of the US population, 14% of the economy, and 12% of national new light-duty vehicle sales (International Council on Clean Transportation [ICCT], 2018). EV sales in the state since 2011 totaled 269,000, constituting about 48% of US EV purchases (International Council on Clean Transportation [ICCT], 2017). Public vehicle charging infrastructure in California represents 31% of the US infrastructure, and includes a quarter of the public direct-current fast charging (International Council on Clean Transportation [ICCT], 2017).

Among California's cities, Los Angeles stands out in terms of the size of EV market and this is the main reason that it is chosen as the study area of this thesis. Los Angeles had new EV sales of nearly 12,000 during 2017-while the median household income was about $51,000, below the statewide median of $64,000 (International Council on Clean Transportation [ICCT], 2018). More specifically, LA residents purchased more than 38,000 new EVs constituting more than one-fifth of the entire US EV market. In terms of cumulative EV sales, the Los Angeles metropolitan area accounted for more than 143,000 sales from 2010 to 2017 (International Council on Clean Transportation [ICCT], 2018). In 2016, Los Angeles exhibited one the largest annual increases in EV registrations–from about 23,600 to more than 30,000 vehicles-and had 20 to 30 vehicle models available for purchase (International Council on Clean Transportation [ICCT], 2017).

Out of the 344 public charging points in California, as measured at the end of 2017, the EV market share in Los Angeles was 5%, being more than twice the US average. More than 80% of the workplace charging infrastructure is Level 2, and the rest is a mix of Level 1 and direct current (DC) fast charging stations (United States Department of Energy [USDOE], 2016). In particular, based on the ChargeHub charging stations map, in a 9.32-mile radius of Los Angeles, there are 1506 level 2 charging stations (93%) and only 107 level 3 or DC fast charging stations (7%). Thus, level 2 charging stations are more common. The cost of home charging in Los Angeles is around $0.15 per kwh (fuel economy of 2.5 miles per kwh) (Fuller, 2016), while the cost of charging at Level 2 public charging stations is approximately $0.6 per kwh (Southern California Association of Governments [SCAG], 2012). It is important to mention that 54% of the charging stations in LA (1613 in total) are free and are usually Level 1 or Level 2 charging stations.

Different incentives are provided to LA residents in order to increase EV uptake. These incentives include state purchase incentives, city purchase incentives, HOV lane access, parking incentives and "other" incentives, which include exemptions from state and local fees and emissions inspections. The incentives given for the purchase of EVs lower the costs so as to be closer to the cost of traditional vehicles. California's rebates are typically $2,500 for BEVs and $1,500 for PHEVs and the federal rebates are estimated to be $7,500 (International Council on Clean Transportation [ICCT], 2016).

In general, EV adoption in LA can be affected by certain characteristics that exist only in the LA Market. These characteristics are: "(i) high ratio of multifamily housing buildings and renters, (ii) high ratio of new and hybrid cars, and (iii) commuter market with high availability to multiple vehicles per household and limited public transit commuting" (Dubin et al., 2011). Because of these characteristics, the EV market in LA offers great potential. However, public policies and new ideas are needed to encourage investment related to EVs.

Despite the high adoption of EVs in Los Angeles, there is still room for improvement. It is still uncertain whether people will switch to electric mobility, especially for long distance trips. According to a study conducted in 2011 (Dubin et al., 2011), LA residents have concerns about using EVs for long distance trips or about EV charging, indicating that the EV market should be expanded beyond early adopters. The success of the EV market overall will depend on how well the market responds to incentives and whether it can overcome the barriers to adoption through improved technologies.

3.2.1.2 Travel Patterns

The Los Angeles metropolitan area, with nearly two cars per household, has the highest vehicles-per-capita ratio in the world; more than 12 million cars travel on its freeway system every day. According to the 2009 National Household Travel Survey (NHTS) data, 71 % of trips in Los Angeles County are made by a driver alone in a car; 11% carpool; 12% of trips are with public transit, and 6% of trips are made by other modes (walking, biking). According to the 2016

American Community Survey, 69.7% of LA residents commuted by driving alone, 8.7% carpooled, 9.2% used public transportation, and 3.5% walked. Approximately 2.8% commuted by all other means, including taxi, bicycle, and motorcycle (United States Census Bureau, 2016).

The Global Traffic Scorecard (INRIX, 2016) found that Los Angeles residents spent a total of 104 hours driving per person in 2016, resulting in a total cost of $2,408 per driver in 2016. The average commuting trip in Los Angeles is 8.8 miles (Goldstein, 2015b), while the average trip length for all other non-work trip purposes is less than 6 miles (California Department of Transportation, [Caltrans], 2013). In addition, the average amount of time people spend commuting with public transit on a weekday is 81 minutes and the average distance people usually ride in a single trip with public transit is 6.90 miles (Moovit Insights, 2018).

As far as the Goods Movement is concerned, ports of LA and Long Beach play a major role. In particular, based on the EMFAC model 2017 data (California Air Resources Board [CARB], 2017a), in 2017, the annual population of all kinds of trucks was around 2,763,846 trucks in LA. These trucks were making 14,588,307 trips per day in total, which is 10,622,618 vehicle miles traveled per day. The truck traffic constitutes a high proportion of average daily traffic in LA and especially in Lower Los Angeles.

Compared to other US metropolitan areas, Los Angeles has residents that drive more miles per person than would be expected based on the region's overall population density (RAND Corporation, 2008). Hence, the per capita demand for roadways is rather high despite high population density. Therefore, high levels of congestion exist and the most realistic way to reduce it may be to explore ways to manage the demand for driving during the peak hours (RAND Corporation, 2008). It is also important to mention that the statistics presented indicate that drivers make frequent short-distance trips. The short trips, in conjunction with year-round mild climate, provide additional evidence that Los Angeles is an ideal market for EVs.

3.2.1.3 Environmental Issues

It is known that California is one of the most polluted states and has authority under the Clean Air Act since 1967 that allows it to set its own emissions standards, which are tougher than national standards established by the Environmental Protection Agency (EPA). Under the provisions of the Clean Air Act, the California Air Resources Board (CARB) (merger of the Bureau of Air Sanitation and the California Motor Vehicle Pollution Control Board) has adopted, implemented and enforced a wide variety of nation-leading air pollution controls (California Air Resources Board [CARB], 2018).

Different vehicle emissions control strategies have been deployed to deal with the high levels of pollution originating from the traffic of California's States. Among these are (California Air Resources Board [CARB], 2018):

- The first tailpipe emissions standards for hydrocarbons and carbon monoxide (1966), oxides of nitrogen (1971), and particulate matter from diesel-fueled vehicles (1982);
- Catalytic converters, beginning in the 1970s;
- On-board diagnostic, or "check engine" light, systems, beginning with 1988 model-year cars;
- A Zero-Emission Vehicle (ZEV) regulation (1990) that requires manufacturers to produce an increasing number of ZEVs. California's goal is to get 1.5 million zero-emissions vehicles on the state's roads by 2025;
- The nation's first greenhouse gas emissions standards for cars (mandated by the Legislature in 2002 and approved by CARB in 2004); and
- California's Advanced Clean Cars Program (2012), which reduces both conventional "criteria" and greenhouse gas pollutant emissions from automobiles.

Recent strict standards have been established by the state's legislature. A notable example is the California's greenhouse gas reduction program. This program includes specific goals targeting a 40% reduction in greenhouse gas emissions below the 1990 level by 2030 and a 80% reduction below 1990 level by 2050 (United States Environmental Protection Agency, 2018).

Los Angeles is one of the best-known cities that suffer from transportation smog in the 20th century. The millions of vehicles in circulation in conjunction with the additional effects of the Los Angeles/Long Beach port complexes frequently contribute to extremely high levels of air pollution. In particular, the entire area in between Los Angeles Harbor to Riverside has become known as the "Diesel Death Zone" (Discover Magazine, 2013). Especially in the South Coast Air Basin, diesel particulate matter (PM) emitted mostly on freeways and oxides of nitrogen (NO_x) are major non-attainment criteria pollutants and health risk drivers (URS Corporation, 2009).

The report for the mobility plan 2035 for the city of Los Angeles provides information on air pollution (Los Angeles Department of City Planning, 2014). According to the data provided, there were 57 unhealthy air quality days in 2012, when air pollution levels in LA County exceeded federal standards. The annual cost of health impacts from air pollution in the south Coast Air Basin was $22 billion, while more than 2000 premature deaths were recorded per year in greater Los Angeles attributed to air pollution from vehicles. These trends continue until recent years.

According to the study of the American Lung Association, that was conducted during 2014-2016, Los Angeles and especially the Los Angeles/Long Beach area is the area that has the highest level of ozone pollution and is ranked fourth in terms of year-round particle contamination (American Lung Association, 2018). More specifically, it has been found that 18,688,022 people in LA are at risk due to short-term or year-round particle pollution and ozone pollution. The number of Americans exposed to unhealthy levels of air pollution dropped to about 125 million people, down from 166 million in last year's report.

This shows that despite the efforts, air pollution still remains at high levels jeopardizing the quality of life. Since challenges still exist, alternative ways of air pollution mitigation should be investigated, and their environmental impact must be quantified so as to ensure their sustainability. In this context, this study will examine the implementation of the ER technology in a corridor in Los Angeles County, as an alternative way to increase EV adoption and thus, reduce greenhouse gas emissions and other sources of air pollution.

3.2.1.4 Road Network

The City of Los Angeles is served by an extensive network of freeways, streets, and local and regional public transportation systems. Based on the Mobility draft Plan 2035 (Los Angeles Department of City Planning, 2014) that considered 2014 data, in Los Angeles, 86.5 square miles (28% of city's developed road area) are land areas occupied by LA road network. Around 7,500 miles are dedicated to street infrastructure with 60% constituting local streets while 40% are dedicated to arterial and collector streets, while freeways occupy around 181 miles. Out of the 75.2 million miles that are driven on average in the city of Los Angeles on an average day, 53% are on freeways and 47% on "surface" or arterial streets.

The major intercity highway routes are (City of Los Angeles, Department of Transportation, 2012):

-Interstate 5 (north to Sacramento and south to San Diego)

- US Route 101 (north to Santa Barbara)

- Interstate 10: Santa Monica Freeway/San Bernardino Freeway (west to Santa Monica and east to Phoenix, Arizona).

Arterial streets connect freeways with smaller neighborhood streets, and are often used to bypass congested freeway routes and have been labeled as boulevards. Table A.1 in Appendix A summarizes important intracity freeway routes, arterial streets, avenues, bus lines and metro rail lines that constitute the main street grid of the city (Los Angeles County GIS Data Portal, 2010).

3.3 Survey Design

In order to achieve this thesis' objectives, a survey was conducted; the survey instrument is presented in Appendix B1. The questionnaire was based on the supporting literature and educated assumptions and included five main parts:

1) Level of awareness

This section was included since awareness is an internal part of the five-step-making decision process of Diffusion (Rogers, 2003). According to Rogers (2003), the innovation-decision process involves five steps: (1) awareness, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation. Thus, the level of awareness has a potential to affect adoption of innovations and a higher level of awareness can indicate the group of innovators of Rogers' Diffusion of Innovation.

The questions selected were based on the information provided in Section 3.2 and followed an order from general to specific, moving from advances regarding electro mobility to advances related to ERs. They have the goal to assess respondents' level of awareness on topics, such as California's goal concerning zero-emissions vehicles, California's tax rebates for EVs, on-road charging definition and news on ERs (i.e., electrification of a section of I-710).

2) Travel characteristics, EVs, charging habits and ERs

This section contains general information that can influence the level of technology adoption and thus, be used in the analysis. In particular, travel behavior can be a factor of every transportation-related decision and for this reason it was essential to be included in the survey. This part covers topics such as car ownership, fuel type of car owned, miles driven during a year, use of car-sharing services and on demand ride-sharing services, mode choice for different trip purposes, frequency of trips per trip purpose, frequency of travel for short, medium and long distances and factors that affect route choice. The last question asked respondents to indicate the level of importance of factors (the Likert-type scale was used) such as cost, travel time, convenience and comfort, ambience, safety, reliability of travel and familiarity with the route that have been found to affect route choice from supporting literature.

In an effort to capture the travel habits of LA residents specifically, the section of travel characteristics also included questions on the frequency of travel on indicative highway and transit corridors (e.g., I-710, I-210, Vermont Avenue and Metro Orange Line). However, additional corridors were added, since there was an interest to investigate whether alternative routes are more frequently used by LA residents and thus, can also be considered as candidate corridors for electrification, as opposed to the proposed ones. There were two different questions for highway corridors (i.e., freeways and arterial streets) and transit corridors (i.e., BRT lines) in order to avoid any confusion of respondents. At this point, it is acknowledged that the corridors provided constitute a small sample of the road network and that data on current use of these corridors already exist. The ultimate goal though is to correlate this information with people's responses to other questions.

The second part of this section is dedicated to EVs and contains questions related to EV use, EV charging habits, state of battery charge and importance of factors affecting EV purchase. The inclusion of these factors were based on an extensive literature review on EV studies, part of which has been presented in Section 1.2 when the main EV barriers were discussed (Boston Consulting Group, 2009; Beresteanu and Li, 2011; Burgess et al., 2013; Carley et al., 2013; Diamond, 2009; Gallagher & Muehlegger, 2011; Hidrue et al., 2011; Philip & Wiederer, 2010; Rezvani et al., 2015; Sierzchula et al. 2014; Tran et al., 2013; Virginia Clean Cities, 2010; Wilmink, 2015).

The third part of the section included general questions on ERs, as a first step to understand respondents' perception on them. The goal of this section was to investigate what respondents think about the potential of on-road charging considering access restrictions for electric charging and the potential of on-road charging in future years and for different trip purposes. There were also questions aiming to capture thresholds that will motivate the purchase of an EV and use of the technology for different trip purposes/ trip lengths, to capture how much more respondents are willing to pay for using the technology compared to alternative ways of charging and how likely they are to take the public transit to their destination, knowing that electric buses operate on electric lanes. The questions included in this subsection were based on the literature provided for the concept of ERs, considering user needs and technology potential.

3) General thoughts and opinions on ERs

This section is crucial for the analysis of the market adoption. It includes questions that constitute components of the behavioral intention to use ERs or questions that reflect the potential benefits and concerns of ERs that were presented in the literature review (Section 2.4). Additional questions examined the public's interest in purchasing EVs based on the availability of electric roadway infrastructure, public's intention to drive on ERs and the intention to switch from personal vehicles in favor of traveling by electric buses (operating on ERs). In particular, three components based on the Diffusion of Innovation (relative advantage/disadvantage, compatibility and complexity) are included, subjective and personal moral norms, two components that may affect the perceived behavioral control (habits, self-efficacy, safety), and the component of environmental concerns and sustainability to capture potential habitual factors and preferences that are not based on rational decisions.

More specifically, the majority of the questions attempted to capture the following components of existing theories or case studies are presented in Table 3.1 on the next page.

It is important to mention that the questions of this section were formed in a way so as to have a hypothetic approach and to help respondents answer in a meaningful way, even though they are not familiar with or have little exposure to the concept. The section has also questions that may seem redundant, but this is how hypotheses can be tested based on the well-established theories from social sciences and psychology that were previously presented. A 5-point Likert-type scale was used for the structure of these questions based on the theoretical model, ranging from 1 as strongly disagree to 5 as strongly agree.

4) Willingness-to-pay scenarios

The purpose of this section is to capture people's willingness-to-pay for using ERs for their daily commute regarding different lane configurations (routes) for the implementation of the technology in Los Angeles. In particular, two cases are considered: commute by taking a freeway and commute by taking an arterial road. "Cheap talks" and text are provided to account for any hypothetical bias. The thought-process of developing this section is the following: the state of mind of the user when responding is that he/she is driving an EV and he/she needs to charge it.

The options are to charge it as the EV moves along on ERs or continue driving on the non-electric (conventional) lane(s) and take a detour to charge it in the stationary charging stations.

These options assume that if the driver has sufficient state of charge (SOC) and does not need to stop to charge the vehicle, he/she will likely not use the electrified lane.

The lane configurations provided in the willingness-to-pay scenarios are as follows:

a) All lanes are non-electric (conventional): typical lanes where on-road-charging is not available with a mix of traffic (light-duty vehicles, trucks); in this case, people will need to stop to charge your EV.

b) On-road charging is available on one lane; the other lanes are conventional; a mix of traffic (light-duty vehicles conventional and electric, trucks) can drive on the electrified lane (electrified lane with mixed traffic).

c) On-road charging is available on one lane; the other lanes are conventional; only EVs can drive on the electrified lane (electrified lane exclusive for EVs).

Different hypothetical scenarios are constructed consisting of the aforementioned alternative options and two attributes, in order to examine the respondents' route decision. The attributes considered are the user cost for each alternative route to reach the final destination (including charging cost) and the total trip time from the origin to the final destination, including any activities during the trip (e.g., stop for charging the EV). These attributes have been used in other choice experiments for different technology options or not (Hoen & Koetse, 2014; Shin et al., 2015). The appropriate number of the hypothetical scenarios will be based on the fractional factorial design to achieve orthogonality and not having confounded main effects. The number of scenarios found is eight scenarios in each case (freeway and arterial road). In Appendix B2, the fractional factorial design table is provided (Table B2.1). The assumptions made and the values of the parameters used in the scenarios, including the parameters used in the script and the parameters used as attributes-factors (cost and travel time) are based on the literature review and are presented thoroughly in Appendix B2 (Table B2.2). Note that the willingness-to-pay analysis was beyond of the scope of this thesis, and as such, the willingness-to-pay estimates are not included herein.

Table 3.1: Components included in Section 3 of the survey

Section	Component	General description	Literature
General thoughts and behaviors	Innovativeness	5 adopter categories (innovators; early adopters; early majority; late majority; laggards)	Rogers, 2003
	Environmental concerns	Reflects on habitual factors related to environment	Bamberg & Möser, 2007, Thøgersen & Olander, 2006, Roy et al., 2005, Bamberg, 2003
	Sustainability	Reflects the preference for sustainable modes of transport	Moons & De Pelsmacker, 2015
	Habits	Habits towards use of cars	Moons & De Pelsmacker, 2015 Aarts et al., 1997b Klöckner & Matthies, 2004 Gärling et al., 1997 Norman & Smith, 1995
Opinions on ERs	Relative advantage	Whether an individual believes that the new idea is better/worse than the one is replaced	Rogers, 2003 Moons & De Pelsmacker, 2015
	Complexity	How easily the new idea will be used	Rogers, 2003 Moons & De Pelsmacker, 2015
	Compatibility	Whether the new idea is compatible towards individual's values and needs	Rogers, 2003

Table 3.1 continued

	Attitudes towards use	Reflects people's opinion about driving on electric roadways	Rogers, 2003 Ajzen, 1991 Moons & De Pelsmacker, 2015 Payre et al., 2014 Petschnig et al., 2014, Jansson, 2011
	Subjective norms	Reflects external social pressures	Ajzen, 1991
	Personal moral norms	Implies that an individual considers himself/herself responsible for adopting a behavior morally	Ajzen, 1991, Fagnant & Kockelman, 2015, Petschnig et al., 2014, Heath & Gifford, 2002,
	Self-efficacy	Whether people consider themselves capable to do the specific task.	Moons & De Pelsmacker, 2015 Ajzen, 1991
	Perceived behavioral control	How an individual perceives the intention to drive on electric roadways	Ajzen, 1991 Fagnant & Kockelman, 2015 Nysveen et al., 2005
	Emotions	Emotions towards a complex innovative and eco-friendly product may be a key determinant towards the intention to drive on electric roadways	Moons & De Pelsmacker, 2015 Perlusz, 2015 Bagozzi et al., 1999 Han et al., 2017
	Safety	Captures safety concerns while driving on electric roadways Ease to use of electric roadways, shared use of electric roadways or separate.	Andersson & Edfeldt, 2013 Viktoria Swedish ICT, 2013

<u>5) Sociodemographic questions</u>

Lastly, typical sociodemographic questions were added in the final questionnaire in order to relate the respondents' characteristics of the previous sections to a specific sociodemographic profile. Particularly, questions were added about the gender, age group, employment situation, annual household income, highest level of education, race, ethnicity, people living in a household, children living in a household, holders or driver's license and brief crash history. These questions may evaluates whether variations in the behavior towards electro-mobility and ERs is associated with differences in socioeconomic and demographic groups.

The development of the questionnaire was a collaborative and iterative process. The general basic guidelines were followed in order to write questions that will elicit accurate answers to the research questions and will encourage respondents to respond the questions in an easy way. After the questionnaire was drafted and reviewed, it was pretested so as to make final changes before sending the survey. Pretesting a survey is an essential step in the questionnaire design process to evaluate how people respond to the overall questionnaire and specific questions. That said, a small sample was used to pretest it and provided comments and feedback regarding the formulation and the interpretation of the questions.

Since the goal was to keep the questionnaire as clear and simple as possible (based on Lohr, 2009), closed questions directly associated with the topics of interest were preferred. The number and choice of response options offered as well as the order of questions and answer categories can influence how people respond to closed-ended questions. Thus, more general questions were introduced first and more specific questions about EVs and ERs were presented after to avoid contrast effects. The majority of answers included categories so as to help the respondent remember the responses that might otherwise be forgotten and feel less tired or pressured throughout the survey.

Ordinal response categories of some questions were presented sequentially and this way, respondents could easily place their responses along the continuum. As far as the question wording is concerned, simple and concrete language was used and words that may be viewed as biased were avoided. Definitions were provided in every question that included specific terms related to ERs and double negatives or unfamiliar abbreviations or jargon that can result in respondent confusion were avoided. The demographic questions were written according to the Census Bureau which has conducted a great deal of experimental research to determine effects of alternate wordings and orderings of these questions. The answer categories of those questions were also adjusted so as to reflect the socioeconomic conditions of the study area.

It is important to mention that all the documents associated with the survey were reviewed and the final questionnaire was submitted for approval under the Institutional Review Board with Protocol # 1711019932.

The survey designed belongs to the category of stated preference surveys. Stated preference surveys are widely applied in the areas of marketing and demand modeling and are efficient for exploring hypothetical choice situations and innovative applications with which consumers are not familiar with and thus, there are not revealed preference data on which to rely (Fujii & Gärling, 2003). Stated preference surveys have the advantage of flexibility, meaning that they can be used to construct realistic scenarios for most new policies (Fujii & Gärling, 2003; Whitehead et al., 2008). Hence, they are the most important source of data for modeling and representing people's opinions when faced with new technologies, particularly if the technology examined is very different from existing alternatives, such as the technology of ERs.

However, one limitation of the stated preference survey is its hypothetical nature (Whitehead et al., 2008). Respondents are exposed to some unfamiliar situations in which they had to provide their opinion about topics for which they have no knowledge, experience or awareness. Thus, there is uncertainty about the validity of the responses. Respondents may have given truthful answers that are limited by the level of their exposure to the concept (Whitehead et al., 2008). On the other hand, respondents may have given trivial answers due to the hypothetical nature of the questions included in the survey.

This limitation was addressed by appropriate data preparation and then data analysis. In particular, prior to analysis and modeling, data screening was performed in order to identify cases of over-coverage (where people not in the target population are not screened out of the sample), missing values, passive or unengaged responses, and outliers (Section 3.5). These cases can cause behavior-intention inconsistencies and thus, were carefully removed from the sample, always ensuring that there is enough number of responses. Proper modeling can also overcome this limitation. The data was further analyzed by using suitable econometric and other methodologies in order to achieve the thesis objectives.

3.4 Sampling

Sampling (i.e., selecting a sub-set of a whole population) is often done for reasons of cost and practicality. In any case, it is important that the sampled population and the target population should be similar to one another. In an ideal scenario, the target population is identical with the population sample, a situation which is the main requirement of a good sample. In most surveys, however, a good and representative sample with external validity is the goal in order to achieve known precision and accuracy characteristics in the population.

The target population of this thesis' questionnaire was people who are LA residents and over 18 years with the objective to collect a representative sample of Los Angeles. The questionnaire was distributed online in Purdue Qualtrics through LightspeedGMI which has a panel that resides in LA area. The data collection period was from May 11th 2018 to June 3rd 2018.

The determination of the minimum sample size (adequacy analysis) is an essential step of the analysis, since it is needed to ensure a certain precision or degree of confidence in the estimated value of population parameter, given the standard deviation. The parameters that affect the sample size are the margin of error, the confidence level and the population of Los Angeles. In particular, the margin of error (MoE) (or "precision") is the positive or negative deviation of the estimated parameters from its true value. The confidence level or interval associated with the estimate of a population parameter is a measure of the precision of that estimate and thus, the confidence of the sample. The following equation gives the relationship between the minimum sample size needed (n) and the aforementioned parameters:

$$n = \left(\frac{z_{\alpha/2} * \sigma}{MoE}\right)^2 \qquad \text{Equation 3.1}$$

where $z_{\alpha/2}$ is the Z-value corresponding to an area of α/2 to the left of the curve of the standard normal distribution, MoE is the margin of error and σ is the standard deviation. Since the standard deviation is unknown, a value of 0.5 is used as a conservative assumption. Usually a confidence level of 95% is utilized, corresponding to a z-value of 1.96. Assuming a MoE of 4%, the minimum sample size (n) is equal to 600 completed responses.

Although the goal was to follow the method of random sampling, the survey was distributed on-line and thus, a simple random sample identical to the target population could not be achieved. This case of selection bias (under-coverage) may lead to a sampling error that is incorporated into analysis by estimating the standard error of the estimates. This phenomenon happens since a number of people refuse to respond or because not all the people are reachable or capable of responding (especially when they are not included in the LightspeedGMI panel).

Due to this limitation, hard quotas concerning the gender and age of respondents were implemented as a remedy, based on the US Census data (2010). The following table presents the hard quota for each age group (Table 3.2).

Table 3.2: Hard quotas

Age groups	**Required responses (%)**	**Required responses (count)**	**Gender distribution (%)**
18-24 years old	18.2%	109	Male: 48% Female: 52%
25-34 years old	19%	114	Male: 48% Female: 52%
35-44 years old	17.4%	104	Male: 48% Female: 52%
45-54 years old	17.1%	103	Male: 48% Female: 52%
55-64 years old	13.7%	82	Male: 48% Female: 52%
65+ years old	14.1%	88	Male: 48% Female: 52%
Total	100%	600	Male: 48% Female: 52%

Lastly, the income level, educational level and annual mileage of the survey respondents were compared with current US Census (2010) and/or NHTS (2017) data for LA and the results of comparisons are presented in Appendix B3.

3.5 Data Preparation

The survey data was analyzed and screened to ensure that there will not be any issues that may negatively influence the research results. Besides the issue of selection bias that was previously discussed, measurement errors are also part of the non-sampling errors (i.e. errors that cannot be attributed to the sample-to-sample variability (Lohr, 2009). Although the measurement error is a concern in all surveys that should be minimized in the design stage of the survey, sometimes is unavoidable. The reasons for this phenomenon are various: people sometimes do not tell the truth, do not always understand the questions, do not always answer all questions, questions may be misleading or wrongly displayed etc. (Lohr, 2009). Due to this danger, after the data collection, data preparation should follow, taking always into account the desired sample size.

Prior to modeling, cases of over-coverage should be removed. Over-coverage can occur when people not in the target population are not screened out of the sample (Lohr, 2009). Thus, data screening must be performed in terms of this problem, meaning that people that are under 18 years old or are not LA residents should be excluded from the analysis. An initial screen question was included in the survey, asking each respondent whether they are under or over 18 years old and whether they live in Los Angeles Metropolitan area. However, all the responses were tested again after the data is collected and the responses presenting the aforementioned problem were excluded.

Another issue that may occur is related to incomplete responses and missing values (Lohr, 2009). Failing to obtain all the information needed per respondent may distort the results and introduce many errors in the analysis. Regarding this, there are mainly three ways to follow (Raaijmakers, 1999; Bennett, 2001). The first option is to leave the data with the missing values in place, especially when the number of missing data is small. The second option is to delete the subjects for every missing value in the dataset. The third option is to replace the missing values using different estimation methods. The second option is usually chosen and thus, the responses that are not complete, meaning that over 10% of the questions are not answered were removed from the dataset, ensuring each time that there is enough number of observations in the data set.

The data set should also be checked for passive or unengaged responses (Lohr, 2009). This means that respondents give passive, “straight-lined” or “patterned” responses to the survey’s questions, reducing the variability of them. Through data cleaning, the responses that are extreme cases of this phenomenon can be discovered and removed; however, the researcher should be careful so as to not influence the level of objectivity that the survey should contain. In this thesis, there was evidence of passive or unengaged responses that were carefully removed from the data set.

Furthermore, outliers in the data set should be identified through an exploration of the descriptive statistics of the variables during data preparation. Outliers are those observations that are distant from other observations mainly due to experimental errors (Washington et al., 2011). There are two main schools of thought when it comes to the treatment of outliers (Osborne & Overbay, 2004; Zijlstra et al., 2011): those who treat outliers as outlaws and thus argue that outliers should be identified and kept out of the model; then there are those who argue that outliers may be telling something revealing and thus they should be kept and included in the model as long as they do not exceed a certain number. In this thesis, cases that were suspicious were removed from the data set.

4. MARKET ADOPTION ANALYSIS

This chapter describes the methodology used for the analysis and also, presents the estimation results for the short-term and long-term intention to drive on ERs or purchase an EV, the adoption rates and market segments. A detailed explanation of the methodology followed to answer each research question is provided in Sections 4.1.1 and 4.2.1. In short, the methodology that is used to identify the factors that affect the adoption of ERs has the ultimate goal to examine the influence of "time" in individual's decision to use the new technology. Thus, this approach introduces a "time" dimension into the analysis by providing the factors that affect the early and late intention to use ERs. The market segmentation analysis is a parallel procedure that can capture the "current/static" trend in the market. It can shed light on the characteristics and distribution of the different groups that may be potential users of the technology.

4.1 Short-term and Long-term Intention Models

The first objective of this thesis is to evaluate the factors affecting respondents' intention to drive on ERs as soon as ERs become available and their intention to purchase an EV, knowing that ERs are currently available (short-term intention model). In addition, the factors that affect respondents' long-term intention to drive on ERs and purchase an EV knowing that ERs will be available in the future will also be assessed (long-term intention model). The methodology used, the data analyzed and the estimation results are presented in the following sections. The two models are discussed in terms of their parameter estimates, goodness-of-fit and the implications of their results.

4.1.1 Modeling Technique

The questions used for the short-term intention model are the following: *"I intend to drive my EV on electric roadways as soon as electric roadways become available"* and *"I intend to purchase an EV, knowing that electric roadways are currently available"*. The corresponding questions for the long-term intention model are: *"I intend to drive my EV on electric roadways in the foreseeable future"* and *"I intend to purchase an EV, knowing that electric roadways will be available in the foreseeable future".* For both cases, the questions constitute the dependent variables of the modeling that are expressed in a 5 Likert-type scale: 1-strongly disagree, 2-disagree, 3-neutral, 4-agree, 5-strongly agree. It is also acknowledged that the question on the intention to drive an EV assumes that EVs will be WPT-enabled.

The short- or long-term intention to drive on ERs and the short- or long-term intention to purchase an EV knowing about ERs may raise concerns about potential correlation between them. This is because the EV purchase intention, as it is evident from the respective survey questions, is directly related to the existence of ERs. In particular, there is a reasonable assumption that the potential of using the ERs acts as a motive to purchase an EV and drive on this system. Hence, it is hypothesized that the intention to drive on ERs is a reflection of the reason why a customer would purchase an EV.

This assumption can also be supported by quantitative evidence. Indeed, it was found that the ER usage and EV purchase intentions are strongly related with a correlation greater than 0.6 (threshold established) based on the correlation matrix (Table 4.1). In addition, it is assumed that the intention to drive on ERs and the intention to purchase an EV, knowing about the existence of ERs share unobserved characteristics, leading to the correlation of their error terms. Therefore, it can be concluded that the dependent variables of the problem can be modeled as a system.

Table 4.1: Correlation matrix of dependent variables

	Short-term Intention	
	Intention to purchase an EV	Intention to drive on ERs
Intention to purchase an EV	1	0.74
Intention to drive on ERs	0.74	1
	Long-term Intention	
	Intention to purchase an EV	Intention to drive on ERs
Intention to purchase an EV	1	0.77
Intention to drive on ERs	0.77	1

The response data on the short- and long-term intention related to ERs is discrete and ordered. For this purpose, ordered probability models have been developed and usually address the problem of ordered discrete data. Standard multinomial discrete-outcome modeling methods such as the multinomial logit model (MNL) or nested multinomial discrete models are also a possibility and can be tested but such models do not account for the ordinal nature of the discrete data and thus, all information reflected by the ordering is lost (Washington et al, 2011). As stated in Amemiya (1985), if an unordered model (such as the MNL) is used to model ordered data, the model parameter estimates remain consistent but there is loss of efficiency.

Nevertheless, there are cases where an unordered probability model may provide a superior fit to ordered data. Such cases arise because ordered probability models place a restriction on how the independent variables affect outcome probabilities. In the process of selecting a model, a tradeoff is inherently being made between recognizing the ordering of responses and losing the flexibility in specification offered by unordered outcome models (Washington et al, 2011).

In order to simultaneously model the dependent variables as a system, a bivariate ordered probit model is used for each case: short-term and long-term intention. According to Greene & Hensher (2010) and Anastasopoulos et al. (2012), the structure of the model considering two outcomes (1 and 2) for each observation i of ordinal data y can be derived as follows:

First step

$$y_{i,1} = \beta'_1 X_{\iota,1} + \varepsilon_{\iota,1}, \;\; y_{i,1} = j \; if \; \mu_{j-1} < y_{i,1} < \mu_j, j = 0, \dots J_1,$$

$$y_{i,2} = \beta'_2 X_{\iota,2} + \varepsilon_{\iota,2}, \;\; y_{i,2} = j \; if \; \theta_{j-1} < y_{i,2} < \theta_j, j = 0, \dots J_2 \qquad \text{Equation 4.1}$$

with

$$\binom{\varepsilon_{\iota,1}}{\varepsilon_{\iota,2}} \sim N \left[\binom{0}{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \qquad \text{Equation 4.2}$$

where X is the vector of independent variables used to explain the dependent variables yi

β represents the vector of estimable parameters

ε denotes the vector of the random error terms, assuming that they are normally distributed with zero mean and variance equal to one

j are indices symbolizing the integer choice ordering (it corresponds to zero to 4)

μ and θ denote the estimable threshold parameters

ρ is the cross-equation correlation coefficient of the error terms

N stands for the normal distribution

Second step

The joint probability for $y_{i,1} = j$ and $y_{i,2} = k$ can be defined as:

$$P\left(y_{i,1} = j, y_{i,2} = k \left| X_{i,1,} X_{i,2} \right|\right) =$$

$$\begin{pmatrix} \Phi_2[(\mu_j - \beta'_1 X_{\iota,1}),(\theta_\kappa - \beta'_2 X_{\iota,2}),\rho] \\ - \Phi_2[(\mu_{j-1} - \beta'_1 X_{\iota,1}),(\theta_\kappa - \beta'_2 X_{\iota,2}),\rho] \end{pmatrix} - \begin{pmatrix} \Phi_2[(\mu_j - \beta'_1 X_{\iota,1}),(\theta_{\kappa-1} - \beta'_2 X_{\iota,2}),\rho] \\ - \Phi_2[(\mu_{j-1} - \beta'_1 X_{\iota,1}),(\theta_\kappa - \beta'_2 X_{\iota,2}),\rho] \end{pmatrix} \qquad \text{Equation 4.3}$$

where Φ [.] is the standard normal cumulative distributive function:

$$\Phi(\mu) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\mu} EXP\left[-\frac{1}{2}\omega^2\right] d\omega \qquad \text{Equation 4.4}$$

In the above model, the positive value of the parameter β indicates that the probability of higher responses increases with an increase in variable X. On the other hand, the probability of lower responses decreases with an increase in X. The opposite relationships apply for the case of a negative value of β.

One practical difficulty associated with ordered probit models is the interpretation of interior/intermediate categories. This difficulty could be attributed to the location of the thresholds where the areas between the shifted thresholds may cause probabilities to increase or decrease after shifts to the right or to the left. Marginal effects analysis is conducted to acquire a good sense of the direction of the influence on the interior categories. Each subject will have their own marginal effect and hence, the values of marginal effects are the average marginal effects over the population for each category (Greene, 2007; Washington et al., 2011).

$$\frac{P(y=j)}{\partial X} = \left[\varphi\left(\omega_{j-1} - \beta X\right) - \varphi\left(\omega_j - \beta X\right)\right] \beta \qquad \text{Equation 4.5}$$

where $P(y = j)$ is probability of outcome of level *j*

ω are thresholds, and

φ(.) is probability mass function of the standard normal distribution.

In the current thesis, all the questions of the survey are tested for their significance as independent variables. Among the survey questions, there are questions based on topics directly or indirectly related to the use of ERs (innovativeness, subjective and personal moral norms, environmental concerns, sustainability, car use habits, potential benefits and concerns of ERs). Each topic consists of a number of questions constituting a group of opinions or a variable. The responses to these questions were treated in a separate way compared to the other questions of the survey. More specifically, the average of responses to each of these variable-groups was computed for each observation, resulting to an index:

$$A_j = \frac{\sum_{i=1}^{n} a_i}{n} \qquad \text{Equation 4.6}$$

where A_j represents the attitude of each observation toward the variable or group of opinions *j*

a_i represents the rating on question *i*

n represents the number of questions included in each group

Since this index is based on questions with answer categories following the 5 Likert type scale, its value ranges from 1 to 5. The index was then used to create indicator variables and assess their significance as factors affecting respondents' usage intention.

However, the new dummy variables created are expected to be endogenous in the model, because of their correlation with the error terms that capture unobserved characteristics related to the short-term or long-term intentions. In order to address this limitation, binary probit models were estimated with each of these variables constituting the dependent variable and other exogenous variables being the independent variables. This way, the model would predict and replace those variables with their respective probabilities that would be then used to the initial bivariate ordered models as independent variables.

As far as the independent variables are concerned, new combined variables were created by analyzing the data set and by testing them in each model. For the variables that might be endogenous, separate binary probit models were estimated and they were replaced with their respective probabilities. For each created variable, it was ensured that there is an adequate number of observations (at least 10 to 15 observations or about 10% of the total sample), by developing histograms for the independent variables. Correlation matrices for dependent and independent variables were developed and also reviewed.

The selection of the model variables was mainly based on pre-processing data as well as on making educated assumptions regarding their association with the intention to drive on ERs and purchase an EV, knowing that ERs are or will be available. Through an iterative process of trial-and-error, significant variables were found based on a one-tailed hypothesis test at a significance level of 10% (t-critical =1.28) and were included in each model.

The assessment of overall model fit was based on the Likelihood Ratio test statistic, the McFadden ρ^2 statistic and adjusted McFadden ρ^2 (Washington et al., 2011). These measures are calculated in order to evaluate the quality of the model.

The Likelihood Ratio test is calculated as follows:

$$-2[\mathrm{LL}(\beta_R) - \mathrm{LL}(\beta_u)] \qquad \text{Equation 4.7}$$

Where $\mathrm{LL}(\beta_R)$ is the log-likelihood at zero of the restricted model and $\mathrm{LL}(\beta_u)$ is the log-likelihood at convergence of the unrestricted model.

The Likelihood Ratio test is calculated as follows:

$$-2[\mathrm{LL}(\beta_R) - \mathrm{LL}(\beta_u)] \qquad \text{Equation 4.8}$$

If the value of the Likelihood Ratio test is higher that the critical value $X^2_{\alpha,df}$ -where α the significance level and df the degrees of freedom-, the unrestricted model can be supported.

The ρ^2 statistic provides a measure of the overall model fit and is estimated as follows:

$$\rho^2 = 1 - \frac{\mathrm{LL}(\beta_u)}{\mathrm{LL}(\beta_R)} \qquad \text{Equation 4.9}$$

The adjusted ρ^2statistic reduces the log-likelihood at convergence of the unrestricted model, considering the number of parameters k in the model and is calculated as follows:

$$adjusted\ \rho^2 = 1 - \frac{\mathrm{LL}(\beta_u) - k}{\mathrm{LL}(\beta_R)} \qquad \text{Equation 4.10}$$

The values of McFadden ρ^2 and adjusted McFadden ρ^2 indicate the percentage of the variance explained. Thus, the model quality is higher when the values of these measures are close to 1.

The count R^2 is also a measure that indicates the predictive power of the model and is given by the following equation:

$$count\ R^2 = \frac{Number\ of\ observations\ correctly\ predicted}{Total\ count\ of\ observations} \qquad \text{Equation 4.11}$$

4.1.2 Data Analysis

Prior to starting the modeling procedure to identify the factors that affect the intention to drive on an ER and purchase an EV, the histograms of the short-term and long-term intention were reviewed to examine if there are enough observations in each category. Figures 4.1 and 4.2 show that each answer category seems representative with at least 10% of responses. Hence, there was no need to merge any categories. Similar figures were created to investigate how the short- or long-term intention to drive on ERs varies between respondents with EV experience or not (Figures C1.1 and C1. 2 in Appendix C1).

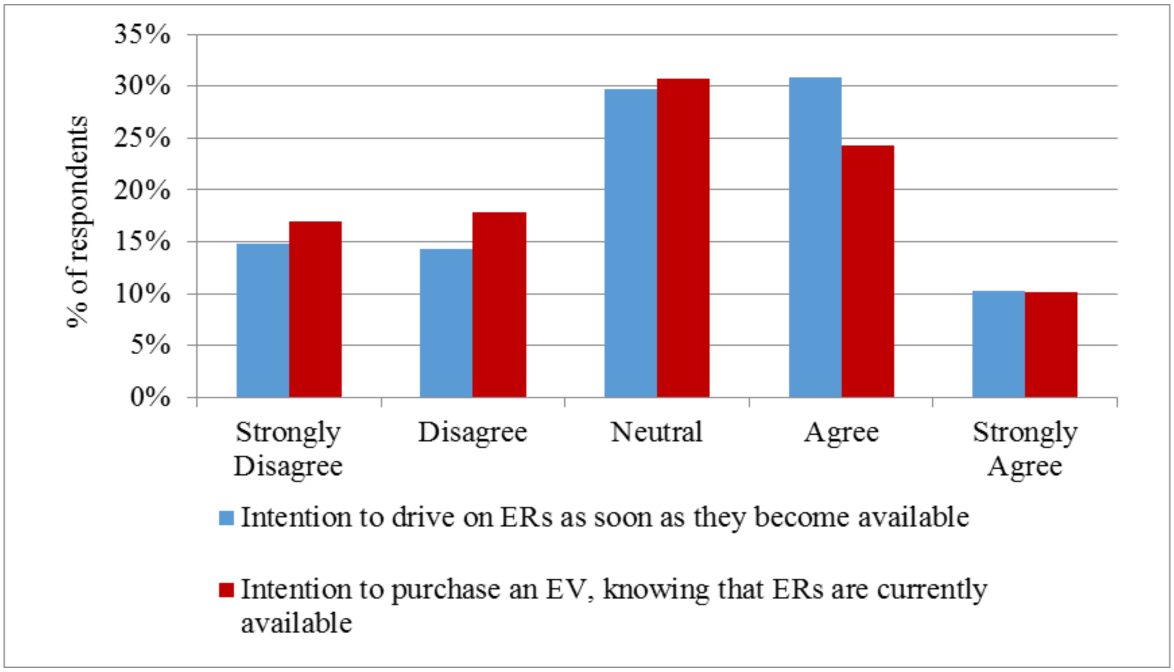

Figure 4.1: Descriptive statistics of the short-term intentions

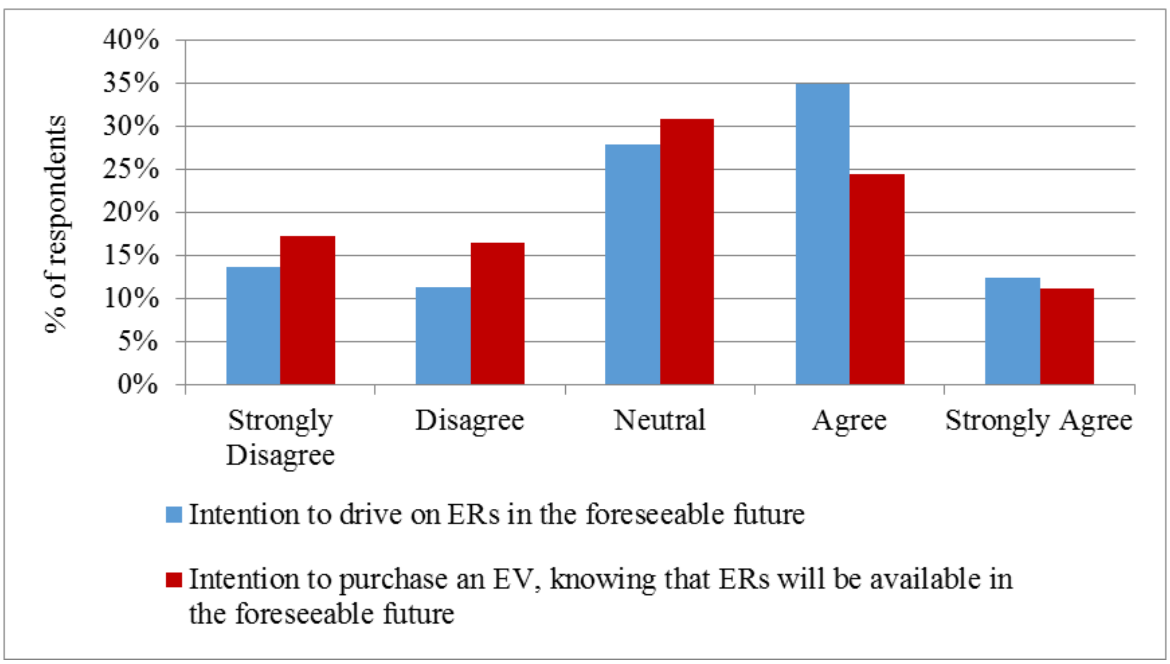

Figure 4.2: Descriptive statistics of the long-term intentions

Table 4.2 shows the descriptive statistics of the variables included in the model in addition to sociodemographic variables. It is important to mention that this table includes the statistics for the indicator variables that were used in the models. The only exception is the variable related to the mode choice per trip purpose that is provided with more details in the following table in order to avoid any confusion. An analytical table with the detailed answer breakdown per associated question is presented in Appendix C1 (Table C1.1).

Table 4.2: Descriptive statistics of the survey responses

Variable	Description	Response Frequency
Gender	1: Male 2: Female	1: 47% 2: 53%
Age	1: 18-24 years old 2: 25-34 years old 3: 35-44 years old 4: 45-54 years old 5: 55-64 years old 6: 65 years or older	1: 18.17% 2: 19% 3: 17.33% 4: 17.17% 5: 13.67% 6: 14.67%
Education	1: Grade school 2: Some high school 3: High school graduate 4: Technical training beyond high school 5: Some college 6: College graduate 7: Graduate school	1: 0% 2: 2.5% 3: 15.17% 4: 5.67% 5: 27% 6: 34.17% 7: 15.5%
Income	1: Less than $25K 2: $25K to less than $50K 3: $50K to less than $75K 4: $75K to less than $100K 5: $100K to less than $150K 6: $150K to less than $200K 7. $200K or more	1: 18.8% 2: 23.2% 3: 18.3% 4: 15.8% 5: 14.7% 6: 4.7% 7: 4.5%

Table 4.2 continued

Employment Situation	1: Full time 2: Part time 3: Unemployed 4: Student 5: Retired 6: Homemaker 7: Other	1: 45.5% 2: 13.7% 3: 9% 4: 9% 5: 14.8% 6: 6.5% 7: 1.5%
Household Size	1: One 2: Two 3: Three 4: Four 5: Five or more	1: 25.17% 2: 30.17% 3: 18.5% 4: 17.33% 5: 8.83%
Number of Children	1: None 2: One 3: Two 4: Three 5: Four	1: 65.83% 2: 16.33% 3: 13.67% 4: 2.83% 5: 1.33
Respondents who typically travel medium distances (10-50 miles) a few times per week or almost every day.	1: Yes 2: No	1: 32% 2: 68%
Respondents who agreed or strongly agreed on average that ERs are compatible with their lifestyle, daily needs or personal values and attitudes.	1: Yes 2: No	1: 85.5% 2: 14.5%
1 if respondent rated driving range as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 68.67% 2: 31.33%
Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation.	1: Yes 2: No	1: 84.83% 2: 15.17%

Table 4.2 continued

Respondents who agreed or strongly agreed on average that they have safety concerns about ERs.	1: Yes 2: No	1: 77.67% 2: 22.33%
Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations.	1: Yes 2: No	1: 71.17% 2: 28.83%
1 if respondent rated charging time as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 69.67% 2: 32.33%
1 if respondent rated financial incentives/rebates provided (such as subsidies) as very or extremely important factor when they think of purchasing an EV, 0-otherwise	1: Yes 2: No	1: 57.33% 2: 42.67%
1 if respondent rated operational cost/ cost to charge the EV (cost per mile) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 66.17% 2: 33.83%
1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 32.17% 2: 67.83%
1 if respondent rated safety as very or extremely important factor when planning their commute route, 0-otherwise.	1: Yes 2: No	1: 73.83% 2: 26.17%
Respondents who agreed or strongly agreed on average that ERs would offer more advantages compared to driving on non-electric (conventional) roadways.	1: Yes 2: No	1: 86.5% 2: 13.5%

Table 4.2 continued

1 if respondent rated EV's purchase cost as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 66% 2: 34%
1 if respondent rated environmental benefits as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 55.33% 2: 44.67%
1 if respondent owns an EV and their vehicle's driving range is 150 miles or below.	1: Yes 2: No	1: 8% 2: 92%
1 if respondent rated vehicle performance as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Yes 2: No	1: 68.5% 2: 31.5%
1 if respondent indicated that they typically charge their EV in DC Fast charging stations regardless of the location (either at home or at work or at public/private charging stations) 0-otherwise.	1: Yes 2: No	1: 20.17% 2: 79.83%
Primary mode of travel for trips for work/school.	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 12.84% 2: 3.21% 3: 0.51% 4: 68.07% 5: 5.07% 6: 7.77% 7: 1.86% 8: 0.68%

Table 4.2 continued

Primary mode of travel for trips for grocery and shopping.	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 10.4% 2: 3.02% 3: 1.51% 4: 72.99% 5: 6.38% 6: 3.52% 7: 1.68% 8: 0.5%
Primary mode of travel for trips for personal business (e.g., errands, trips to medical/dental facilities, banks, etc.).	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 5.21% 2: 2.02% 3: 1.51% 4: 73.28% 5: 5.88% 6: 7.73% 7: 3.53% 8: 0.84%
Primary mode of travel for trips for social/recreational activities (e.g., trips to gym, church, parks, theaters, etc.)	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 7.54% 2: 3.35% 3: 1.51% 4: 69.35% 5: 7.04% 6: 6.2% 7: 4.36% 8: 0.67%

4.1.3 Short-term Intention Estimation Results

The estimation results of the bivariate ordered model for the short-term intention to drive on ERs and purchase an EV, knowing that ERs are available are presented in Table 4.3. For the statistical analysis of the problem, NLOGIT6 was used as software. There was no correlation issue for the variables used in each model (Correlation matrix of variables used is presented in Appendix C2). The established threshold is 0.6.

Table 4.3: Estimation results (short-term intention)

Short-term intention		**Intention to drive on ERs**		**Intention to purchase an EV**	
Variable code name	**Description**	**Estimated parameter (St.Error)**	**t-value (p-value)**	**Estimated parameter (St.Error)**	**t-value (p-value)**
CONST	Constant	-1.237 (0.337)	-3.67 (0.0002)	-1.691 (0.262)	-6.44 (0.000)
MEDDIST	1 if respondents travel medium distances (10-50 miles) a few times per week or almost every day, 0-otherwise	0.157 (0.081)	1.93 (0.0268**)	-	-
PCOMP	Respondents who agreed or strongly agreed on average that ERs are compatible with their lifestyle, daily needs or personal values and attitudes. (*)	1.669 (0.370)	4.51 (0.000)	1.952 (0.381)	5.12 (0.000)
IMPRANGE	1 if respondent rated driving range as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	0.187 (0.083)	2.25 (0.012**)	-	-
PSUST	Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation. (*)	2.096 (0.356)	5.89 (0.000)	1.684 (0.360)	4.68 (0.000)
PSAFE	Respondents who agreed or strongly agreed on average that they have safety concerns about ERs. (*)	-0.670 (0.440)	-1.52 (0.064**)	-	-

Table 4.3 continued

PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	0.764 (0.429)	1.78 (0.038**)	1.067 (0.441)	2.42 (0.008**)
RICH1	1 if respondent has income of $100,000 or higher annually, 0-otherwise.	-	-	0.186 (0.083)	2.24 (0.0126**)
IMTIME	1 if respondent rated charging time as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	-0.235 (0.091)	-2.60 (0.009)
INCENT	1 if respondent rated financial incentives/rebates provided (such as subsidies) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	0.154 (0.083)	1.85 (0.032**)
COSTMILE	1 if respondent rated operational cost/cost to charge the EV (cost per mile) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	0.134 (0.08828)	1.52 (0.064**)
INFLU	1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	0.225 (0.0864)	2.61 (0.005**)
Threshold 1		0.586 (0.063)	9.36 (0.000)	0.694 (0.625)	11.10 (0.000)
Threshold 2		1.432(0.078)	18.37 (0.000)	1.606 (0.080)	20.10 (0.000)
Threshold 3		2.590 (0.101)	25.73 (0.000)	2.624(0.105)	24.95 (0.000)

Table 4.3 continued

Cross-equation correlation coefficient (ρ)	Estimated parameter (St. error): 0.74155 (0.01996) z-value (p-value): 37.16 (0.000)
McFadden pseudo ρ^2	0.1038562
Count R^2	60.7%
Log-likelihood	-1497.04712
Log-likelihood at zero	-1670.54335
Number of observations	600

**Predicted probability generated from an estimated binary probit model*

*** p-values were calculated and rounded using on-line calculator for one-tailed test and 0.10 significance level*

4.1.3.1 Model Goodness-of-fit

The Likelihood Ratio test statistic, the McFadden ρ^2 statistic and adjusted McFadden ρ^2 are calculated in order to evaluate the quality of the model. Using equations 4.7, the Likelihood Ratio test value is 346.99246. The statistic χ^2 is distributed with 23 degrees of freedom (23 parameters in the unrestricted model and 0 parameters in the restricted) and is equal to 32.0069 at a 10% confidence level, providing evidence to support the model. The ρ^2 statistic and the adjusted ρ^2 statistic are shown in the table and are calculated using equations 4.9 and 4.10, respectively. These measures indicate that approximately 10.39% of the variance is explained by the model. The values of McFadden ρ^2 and adjusted McFadden ρ^2 are lower than the desirable value of 1, but were the highest of all the various models attempted. The low values of these measures may be attributed to the quality of the data and the survey (missing data, selective bias) and the potential need for more specific questions in the questionnaire or the need for additional variables to account for unobserved factors.

Additionally, the count R^2 was also calculated to assess the predictive power of the model, using equation 4.11. It was found that the model shows a high predictive power (count R^2 = 60.7%). Lastly, the cross-equation correlation coefficient (ρ) is found to be statistically significant at a significance level of 0.10 (p-value <0.0001). This provides evidence for the correlation between the short-term intention to drive an ER and the short-term intention to purchase an EV, when ERs become available. Therefore, modeling the ER usage and EV purchase intentions as a system seems appropriate and reasonable in an attempt to identify the factors that affect short-term intention.

4.1.3.2 Interpretation of the Results

The final model includes variables related to travel patterns, opinions on EVs and ERs as well as some socioeconomic information. Since this is the first study related to the adoption of ERs, there is no literature to use so as to directly compare the results. However, there is sufficient literature on EV adoption which has been taken into consideration for the analysis of the results.

While evaluating and explaining the influence of the estimated parameters in ordered probit models, the signs of the coefficients are useful for determining the increase or decrease in the probability for the extreme categories (Washington et al., 2011). More specifically, it was found that respondents who frequently travel medium distances (10-50 miles) would strongly agree with the intention to drive on ERs as soon as the technology is available. A possible explanation for this result is that medium distance drivers may be more familiar with the issue of limited driving range. Thus, they may envision greater benefits by using the ERs due to the increased driving range of EVs that can operate on the system. A similar finding concerning the relationship of travel distance and EV orientation was found at Diamond (2009) and Hidrue et al. (2011) where the more frequent the trips or the longer the distance traveled, the more likely for respondents to be EV-oriented.

In addition, it was found that compatibility has a statistically significant positive relationship with the attitudes towards driving on ERs or purchasing an EV given that ERs are currently available. This is because respondents that believe that the concept of ERs is compatible towards their values, lifestyle and needs have higher intention to drive on them or purchase an EV that operates on them as soon as this technology is provided. It is important to mention that the influence of this variable is stronger for the intention to purchase an EV, by examining the corresponding parameter estimates. This finding can be generally connected to the work of Brown et al. (2014) where individuals’ decisions concerning their mode choice was found to be affected by their lifestyle needs.

For respondents who answered that the driving range of an EV is a very or extremely important factor, the likelihood that they would strongly agree with the intention to drive on ERs when they are available was high and the likelihood that they would strongly disagree with the intention to drive on them was low. This can be explained by the fact that range anxiety is considered an essential barrier for adopting electro-mobility. However, ERs could potentially deal with this issue, increasing this way people's intention to drive on them. There have been numerous studies indicating that driving range is an important factor affecting EV purchasing decisions (Hidrue et al., 2011; Carley et al., 2013; Wilmink, 2015; Diamond, 2009; Chorus et al. 2013; Hackbarth & Madlener 2013; Helveston et al., 2015; Valeri & Danielis, 2015).

Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation show a higher intention to drive on ERs or purchase an EV to drive on them. This is reasonable since people that have a general preference for sustainable modes of transport would opt for alternative and environmentally friendly ways to travel such as an EV that can operate on ERs. These results can be linked with other studies which generally found that respondents who were more concerned about environmental sustainability and fuel efficiency were more willing to adopt electro-mobility or purchase an EV (Axsen & Kurani, 2011; Brown et al., 2014; Burgess et al., 2013; Hidrue et al., 2011).

People that are concerned about the safety of the dynamic charging system may feel suspicious to drive on them and this is why this variable is negatively associated with the intention to drive on ERs as soon as they are available. In the beginning of the system implementation, safety concerns are a natural consequence for the majority of the people that are not familiar with this emerging concept. This finding is in line with other studies about different technologies where safety concerns negatively impact people's behavioral intention to adopt a technology (Musselwhite & Haddad, 2007, Musselwhite 2004).

There is a positive relationship between whether an individual supports innovativeness and intention to drive on ERs. People who are more innovative are more willing to try new technologies and thus have a higher intention to drive on ERs. Similarly, innovative individuals show stronger intention to purchase an EV, knowing that ERs are currently available. According to a number of studies, innovativeness has a positive influence on behavioral intention and is a common characteristic of early adopters of a new technology (Egbue & Long, 2012; Edison & Geissler, 2003; Moons & De Pelsmacker, 2015; Rogers, 2003; Heffner et al., 2007a, 2007b).

The short-term intention to purchase an EV, knowing that ERs are currently available is also influenced by respondents' income level and some characteristic of EVs. In particular, respondents with higher annual income levels (more than $100,000) are more likely to purchase an EV, knowing that ERs are currently available because they are less price-sensitive and thus, they can afford purchasing and operating an EV. This is in line with the existing literature (Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Hess et al., 2012; Diamond, 2009; Mabit & Fosgerau, 2011; Molin et al., 2012; Potoglou & Kanaroglou, 2007; Valeri & Danielis, 2015). In addition, people with higher income seem to show pro-environmental attitudes and are more interested in new "greener" technologies, indicating their positive attitudes toward purchasing an EV (Söderholm & Ek, 2010; Wu et al. 2010; Tran et al., 2013).

As far as the EV's characteristics are concerned, respondents who ranked charging time higher, the likelihood that they would purchase an EV, knowing that ERs are currently available is low. This is because potential buyers usually make rational choices and may prefer vehicles that do not require time to be recharged/refueled (e.g., ICEs). Even in the case of the ER, they may believe that this solution would only be complementary to the existent charging options for an EV, so it may not offer a significant advantage. This finding can be aligned with the results of the majority of the studies related to EVs and charging time (Hidrue et al., 2011; Carley et al., 2013; Wilmink, 2015; Bockarjova et al., 2014; Chorus et al., 2013; Hackbarth & Madlener, 2013; Hoen & Koetse, 2014; Rasouli & Timmermans, 2013).

Respondents who believe that the operational cost (cost of EV charging) is important when purchasing an EV would strongly agree with the intention to purchase an EV, knowing that ERs are currently available. This can be justified by the fact that people realize that an EV operating on an ER would have the benefit of lower fuel costs (Hidrue et al., 2011; Wilmink, 2015; Musti & Kockelman, 2011; Molin et al., 2012; Hackbarth & Madlener, 2013; Rasouli & Timmermans, 2013). Financial incentives or rebates seem to also have a substantial effect on people's purchasing decisions. In particular, respondents who answered that this factor is very or extremely important have a high intention to purchase an EV, knowing that ERs are currently available, since they can rip the benefits of rebate programs. The significance of policy attributes and incentives in promoting EV adoption has been acknowledged by different studies (Hess et al., 2012, Gallagher & Muehlegger, 2011; Potoglou & Kanaroglou, 2007; Glerum et al., 2014; Mau et al., 2008; Chorus et al., 2013; Hackbarth & Madlener, 2013; Hoen and Koetse, 2014; Horne et al., 2005 etc.).

Respondents who answered that social/family influence is very important or extremely important as a factor when they think of purchasing an EV have a higher intention to purchase an EV. This can be explained by the fact that a “greener” lifestyle associated with the usage of EVs is an important factor that positively affects people’s purchasing decision. This can also be supported by literature (e.g., Axsen and Kurani, 2011; Axsen et al, 2009; Rasouli & Timmermans 2013; Kim et al. 2014; Kahn, 2007; Lane & Potter, 2007; Heffner et al., 2007a).

The marginal effects for the short-term intention to drive on ERs and purchase an EV, knowing that ERs are available were computed to acquire a good sense of the direction and magnitude of each variable’s influence on the interior categories. The marginal effects for each category are interpreted as a change in the outcome probability of each threshold category P(y=j) given a unit change in an independent variable x (Washington et al., 2011). For indicator variables, the change in category probabilities is the outcome of the variable changing from zero to one. A positive marginal effect for a specific state indicates an increase in the probability for that state, while a negative value corresponds to a decrease in probability for that state in response to an increase in the explanatory variable. A large marginal effect indicates that the variable, expressed in the given units, has a relatively large effect on a respondent’s rating, while a relatively small marginal effect indicates a relatively minimal effect (Washington et al., 2011).

The results are presented in Tables 4.4 and 4.5. Table 4.4 shows that for one unit increase in the participants who frequently travel medium distances (10-50 miles), the probability of indicating a strong intention (“strongly agree”) or an intention (“agree”) to drive on ERs as soon as they become available increases on average by 0.02935 and 0.04941, respectively. The marginal effects of the other variables can be interpreted in a similar way.

Table 4.4: Computed marginal effects for intention to drive on ERs (short-term intention)

Short-term intention	**Intention to drive on ERs**					
Variable code name	**Variable Description**	**Str. Disagree [Ψ=1]**	**Disagree [Ψ= 2]**	**Neutral [Ψ=3]**	**Agree [Ψ=4]**	**Str. Agree [Ψ=5]**
MEDDIST	1 if respondents travel medium distances (10-50 miles) a few times per week or almost every day, 0-otherwise	-0.03804	-0.02589	-0.01483	0.04941	0.02935
PCOMP	Respondents who agreed or strongly agreed on average that ERs are compatible with their lifestyle, daily needs or personal values and attitudes (*)	-0.31902	-0.20749	-0.10196	0.40516	0.22330
IMPRANGE	1 if respondent rated driving range as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.02766	-0.01733	-0.00750	0.03438	0.01811
PSUST	Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation.(*)	-0.41505	-0.26994	-0.13265	0.52713	0.29052
PSAFE	Respondents who agreed or strongly agreed on average that they have safety concerns about ERs. (*)	0.02733	0.01778	0.00874	-0.03471	-0.01913
PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	-0.15437	-0.10040	-004934	0.19605	0.10805

**Predicted probability generated from an estimated binary probit model*

Table 4.5**:** Computed marginal effects for intention to purchase an EV, knowing that ERs are currently available (short-term intention)

Short-term intention	**Intention to purchase an EV**					
Variable code name	**Variable Description**	**Str. Disagree [Ψ=1]**	**Disagree [Ψ= 2]**	**Neutral [Ψ=3]**	**Agree [Ψ=4]**	**Str. Agree [Ψ=5]**
RICH1	1 if respondent has income of $100,000 or higher annually, 0-otherwise.	-0.03493	-0.02642	-0.00380	0.04226	0.02289
IMTIME	1 if respondent rated charging time as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	0.07984	0.06191	0.01264	-0.09781	-0.05657
INCENT	1 if respondent rated financial incentives/rebates provided (such as subsidies) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.03622	-0.02499	-0.00021	0.04119	0.02022
COSTMILE	1 if respondent rated operational cost/cost to charge the EV (cost per mile) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.03745	-0.02520	0.00072	0.04187	0.02005
INFLU	1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.07241	-0.05580	-0.01057	0.08843	0.05034
PCOMP	Respondents who agreed or strongly agreed on average that ERs are compatible with their lifestyle, daily needs or personal values and attitudes. (*)	-0.39849	-0.28142	-0.01064	0.46061	0.22994

Table 4.5 continued

PSUST	Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation. (*)	-0.33406	-0.23592	-0.00892	0.38613	0.19276
PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	-0.23592	-0.16661	-0.00630	0.27269	.13613

**Predicted probability generated from an estimated binary probit model*

By comparing the marginal effects associated with the common variables across the ER usage and EV purchase intentions, conclusions can be made on the magnitude of influence some parameters exert on the short-term intention to drive on an ER or purchase an EV, knowing that ERs are currently available. In particular, the variable indicating respondents who agreed on average that ERs are compatible with their needs appears to be more influential on the intention to purchase an EV, as shown by the larger value of the corresponding marginal effect. The same applies in the case of the variable that represents respondents who are positive towards trying new innovations. As such, it seems that compatibility and innovation are more important factors in affecting the decision to purchase an EV than the decision to drive on an ER. This may have implications in terms of the market acceptance of ERs. More particular, it could be assumed that even if a customer is innovative or believes that the new technology is compatible with his/her needs, purchasing an EV would be the first step to become familiar with the new concept. As is has been shown in studies related to public acceptability of innovative finance strategies or technologies (e.g., Jones, 2003; Ricci et al., 2008; Yetano Roche et al., 2010), familiarity with the proposed technology is a key factor in increasing public acceptance.

4.1.4 Long-term Intention Results

The estimation results of the bivariate ordered model for the long-term intention to drive on ERs and purchase an EV, knowing that ERs will be available in the foreseeable future are presented in Table 4.6. No correlation issue was identified for the variables used in each model, based on a 0.6 threshold (Correlation matrices of variables used in Appendix C3).

Table 4.6: Estimation results (long-term intention)

Long-term intention		Intention to drive on ERs		Intention to purchase an EV	
Variable code name	**Description**	**Estimated parameter (St.Error)**	**t-value (p-value)**	**Estimated parameter (St.Error)**	**t-value (p-value)**
CONST	Constant	-1.128 (0.308)	-3.66 (0.003)	-0.880 (0.319)	-2.76 (0.006)
COLLEGE	1 if respondent's highest level of education is some college or graduate college or graduate school.	0.200 (0.074)	2.71 (0.007)	-	-
SROUTE	1 if respondent rated safety as very or extremely important factor when planning their commute route, 0-otherwise.	0.282 (0.104)	2.72 (0.007)	0.244 (0.104)	2.35 (0.009**)
PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	1.840 (0.411)	4.47 (0.000)	1.870 (0.463)	4.03 (0.000)
PRELA	Respondents who agreed or strongly agreed on average that ERs would offer more advantages compared to driving on non-electric (conventional) roadways. (*)	1.198 (0.445)	2.69 (0.007)	0.734 (0.485)	1.51 (0.066**)
PCOST	1 if respondent rated EV's purchase cost as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.134 (0.072)	-1.88 (0.030**)	-	-
ENVBEN	1 if respondent rated environmental benefits as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	0.356 (0.105)	3.39 (0.001)	0.398 (0.115)	3.47 (0.001)
SRANGE	1 if respondent owns an EV and their vehicle's driving range is 150 miles or below.	0.356 (0.114)	3.12 (0.002)	-	-
YOUNG	1 if respondent is 34 years old or younger, 0-otherwise.	-	-	0.161 (0.082)	1.95 (0.026**)

Table 4.6 continued

VEHPERF	1 if respondent rated vehicle performance as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	-0.273 (0.087)	-3.13 (0.002)
DCCHARGE	1 if respondent indicated that they typically charge their EV in DC fast charging stations regardless of the location (either at home or at work or at public/private charging stations) 0-otherwise.	-	-	0.341 (0.116)	2.94 (0.003)
INFLU	1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-	-	0.246 (0.082)	3.00 (0.003)
WBIKE	1 if respondent indicated that their primary mode of travel is walking or biking (conventional bike or electric bike) for each of the trip purposes (work/school, grocery and shopping, personal business, social/recreational)	-	-	0.198 (0.073)	2.72 (0.007)
Threshold 1		0.521 (0.070)	7.50 (0.000)	0.615 (0.060)	10.17 (0.000)
Threshold 2		1.327 (0.082)	16.10 (0.000)	1.503 (0.079)	18.95 (0.000)
Threshold 3		2.510 (0.102)	24.72 (0.000)	2.481 (0.105)	23.62 (0.000)
Cross-equation correlation coefficient (ρ)		Estimated parameter (St. error): 0.80139 (0.01682) z-value (p-value): 47.66 (0.000)			
McFadden pseudo ρ^2		0.1279834			
Count R^2		62.5%			
Log likelihood		-1460.399999			
Log-likelihood at zero		-1674.73885			
Number of observations		600			

**Predicted probability generated from an estimated binary probit model*

*** p-values were calculated and rounded using on-line calculator for one-tailed test and 0.10 significance level*

4.1.4.1 Model Goodness-of-fit

The selection of the final model was based on the Likelihood Ratio test statistic, the McFadden ρ^2 statistic and adjusted McFadden ρ^2. By calculating the aforementioned measures as in the short-term intention model, the χ^2 value for the Likelihood Ratio Test value is 428.6779 which is greater than the critical value $X^2_{0.10,25} = 34.38159$. The McFadden ρ^2 statistic is 0.1279834 and the adjusted McFadden ρ2 is 0.11305, indicating that the model explains around 12.8% of the variance.

Furthermore, the count R^2 was calculated and showed a high predictive power of 62.5% (375 correctly predicted observations). The intention to drive on an ER in the foreseeable future and the intention purchase an EV, knowing that ERs will be available in the foreseeable future seem to be highly correlated, due to the statistical significance of the cross-equation correlation coefficient (ρ) (significance level of 10%; p-value <0.0001).

4.1.4.2 Interpretation of the Results

As far as the factors affecting the long-term intention are concerned, it was found that education level is positively associated with the intention to drive on ERs in the foreseeable future. Respondents that have a higher level of education (some college, graduate college or graduate school) usually are more open-minded, willing to try and confident with the adoption of a new technology. Prior research to different fields has shown that highly educated individuals tend to have a higher intention to adopt new technologies compared to less educated individuals (Welch, 1973; Wozniak, 1984; Lleras-Muney & Lichtenberg, 2002; Kennickell & Kwast, 1997). In addition, there are studies which have found that education level is an important factor influencing EV preferences (Hidrue et al., 2011; Kim et al. 2014; Potoglou & Kanaroglou, 2007; Wu et al, 2010b; Söderholm & Ek, 2010).

Respondents that rated safety as very or extremely important factor when planning their commute route are more likely to ride on ERs and purchase an EV in the foreseeable future. The safety of the commute route is positively associated with the intention to drive on ERs, since respondents may think that the system's safety will be optimized in the foreseeable future. Although safety concerns were found to negatively influence the intention to drive on ERs in the model of short-term intention, in the foreseeable future these concerns may be non-existent potentially due to the wider implementation of the system. The safety of the commute route is also positively associated with the intention to purchase an EV, knowing that ERs will be available in the foreseeable future but with a lower coefficient compared to the coefficient in the intention to drive on ERs. Similarly, respondents who consider the safety of their route as an important factor may feel confident that driving an EV on an ER will be safe and the technology could be mature enough in the foreseeable future.

Respondents who agreed or strongly agreed, on average, that they are positive towards trying new innovations may have a higher intention to drive on ERs and purchase an EV, knowing that ERs will be available in the foreseeable future. This shows that innovativeness was found to be a significant factor for both the short- and long-term intention to use the ER technology. In addition to innovativeness, the perceived relative advantage that ERs may have compared to other technologies positively affects people's intention to purchase an EV and drive on ERs in the foreseeable future. Past studies have shown that relative advantage can form positive attitudes towards the use of a new technology (Moons & De Pelsmacker, 2015; Rogers, 2003; Rogers, 1995).

Purchase cost is also an essential factor affecting the intention to drive on ERs in the foreseeable future. More specifically, for respondents who answered that the purchase cost of an EV is very or extremely important, the likelihood that they would agree with the intention to drive on ERs in the foreseeable future is low. A possible explanation for that is that people consider that driving on an ER would require a specialized vehicle that may be expensive but they would prefer lower cost vehicles. This finding is aligned with the results of some studies that have explored EV preferences and have found that EV purchase cost is a factor of greater importance (Hidrue et al., 2011; Carley et al., 2013; Wilmink, 2015; Musti & Kockelman, 2011; Molin et al., 2012; Hackbarth & Madlener, 2013; Rasouli & Timmermans, 2013).

Another factor that can influence the intention to drive on ERs in the foreseeable future is the one related to the environmental benefits of ERs. Respondents that consider the environmental aspect of using an EV as an essential factor when making purchasing decisions, may have increased likelihood of choosing environmentally friendly modes of transport. Thus, they have a higher intention to drive on ERs that are expected to reduce traffic emissions even more in the foreseeable future. Similarly, because of the perceived environmental benefits that EVs have, respondents have higher intention to purchase an EV, knowing that ERs will be available in the future. These results can also be supported by the existing literature regarding the relationship of

EV adoption and the perceived environmental friendliness of these vehicles (Kahn, 2007; Axsen & Kurani, 2009; Hidrue et al., 2011; Kim et al., 2014; Burgess et al., 2013).

People who own an EV and their vehicle's driving range is 150 miles or below seem to have a higher intention to drive on an ER in the foreseeable future. This is because EV owners with a limited range may be more likely to choose a charging solution that can address the barrier of range anxiety and thus, have a higher intention to drive on ERs in the foreseeable future. This finding can be linked with studies that have found either that driving range is an important factor in electro- mobility (Hidrue et al., 2011; Carley et al., 2013; Wilmink et al., 2015; Diamond, 2009; Chorus et al. 2013; Hackbarth & Madlener 2013; Helveston et al., 2015; Valeri & Danielis, 2015) or that EV experience plays a major role in forming positive attitudes related to EVs (Skippon & Garwood, 2011; Jabeen et al., 2012).

Younger individuals (34 years old or below) usually have a tendency towards "greener" or innovative transportation modes. As a result, the likelihood to purchase an EV, knowing that ERs will be available in the future appears to be high. This finding is in line with previous research on Millennials' intention to purchase EVs (Wu et al., 2010a; Polatoglu & Ekin, 2001; Morris et al. 2005; Hidrue et al., 2011). The vehicle performance as a factor of purchasing an EV is negatively associated with the intention to purchase an EV, knowing that ERs will be available in the foreseeable future. One possible explanation for that is that conventional vehicles are considered to have a stronger performance (engine power, acceleration time or maximum speed) compared to EVs. Consumers may value these characteristics more and hence they have a low intention to purchase an EV. Generally, vehicle performance is a factor that has found to be significant in past studies associated with EV purchase intentions (Graham-Rowe et al., 2012; Lieven, 2011; Hidrue et al, 2011; Burgess et al., 2013). EVs' performance has been reported as a barrier to adoption in the studies of potential buyers' intentions to adopt EVs (Egbue and Long, 2012; Graham-Rowe et al., 2012), indicating that consumers may prefer better performance.

People who typically charge their EV in DC fast charging stations regardless of the location (either at home or at work or at public/private charging stations) may value charging time and efficiency more than other factors. Thus, the likelihood of purchasing an EV, knowing that ERs will be available in the foreseeable future is high given that ERs have the potential to reduce charging times. In line with the short-term intention model, social/family influence plays an important role in the intention to purchase an EV; however, by comparing the corresponding coefficients, it seems that this factor has less impact on the short-term intention model.

Respondents who indicated that their primary mode of travel is walking or biking (conventional bike or electric bike) for each of the trip purposes would strongly agree with the intention to purchase an EV, knowing that ERs will be available in the foreseeable future. This may be explained by the fact that people who prefer non-motorized modes of transport for every trip purpose usually exhibit a more environmentally friendly behavior and thus, they would be more likely to choose a cleaner car for their daily trips.

The marginal effects for the long-term intention to drive on ERs and purchase an EV, knowing that ERs will be available were estimated. The same rationale is used to explain the results in the current model of long-term intention. The marginal effects are presented in Tables 4.7 and 4.8.

A trend may be revealed by comparing the marginal effects of the common variables of the short-term and long-term intention models. In particular, it is observed that the variable indicating the respondents who are innovative has a larger effect in the long-term (Tables 4.7, 4.8) than in the short-term intention to drive on ERs (Tables 4.4, 4.5). Similarly, the variable that represents the importance of social/family influence and the variable of innovativeness have a stronger association with the intention to purchase an EV in the foreseeable future compared to the short-term intention.

This result may show that the probability of using the new technology or purchasing an EV, being aware of ERs, depends on the implementation time of this technology. In particular, individuals may feel more confident to try a new technology if it has been studied and tested for a certain time period. This is why the same factors are less influential in the short-term intention model.

Table 4.7: Computed marginal effects for intention to drive on ERs in the foreseeable future (long-term intention)

Long-term intention	**Intention to drive on ERs**					
Variable code name	**Variable Description**	**Str. Disagree [Ψ=1]**	**Disagree [Ψ= 2]**	**Neutral [Ψ=3]**	**Agree [Ψ=4]**	**Str. Agree [Ψ=5]**
COLLEGE	1 if respondent's highest level of education is some college or graduate college or graduate school.	-0.04464	-0.02481	-0.01919	0.05368	0.03496
SROUTE	1 if respondent rated safety as very or extremely important factor when planning their commute route, 0-otherwise.	-0.06012	-0.03279	-0.02446	0.07158	0.04579
PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	-0.33661	-0.20299	-0.18581	0.41851	0.30690
PRELA	Respondents who agreed or strongly agreed on average that ERs would offer more advantages compared to driving on non-electric (conventional) roadways. (*)	-0.21466	-0.12945	-0.11849	0.26689	0.19572
PCOST	1 if respondent rated EV's purchase cost as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	0.03993	0.02356	0.02078	-0.04910	-0.03516
ENVBEN	1 if respondent rated environmental benefits as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.06924	-0.04019	-0.03482	0.08409	0.06016
SRANGE	1 if respondent owns an EV and their vehicle's driving range is 150 miles or below.	-0.08105	-0.06262	-0.09204	0.09708	0.13863

**Predicted probability generated from an estimated binary probit model*

Table 4.8: Computed marginal effects for intention to purchase an EV, knowing that ERs will be available in the foreseeable future (long-term intention)

Long-term intention	**Intention to purchase an EV**					
Variable code name	**Variable Description**	**Str. Disagree [Ψ=1]**	**Disagree [Ψ= 2]**	**Neutral [Ψ=3]**	**Agree [Ψ=4]**	**Str. Agree [Ψ=5]**
YOUNG	1 if respondent is 34 years old or younger, 0-otherwise.	-0.07936	-0.05414	-0.01219	0.08644	0.05925
SROUTE	1 if respondent rated safety as very or extremely important factor when planning their commute route, 0-otherwise.	-0.06243	-0.03585	0.00198	0.06171	0.03460
VEHPERF	1 if respondent rated vehicle performance as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	0.09201	0.06578	0.02042	-0.10253	-0.07567
DCCHARGE	1 if respondent indicated that they typically charge their EV in DC Fast charging stations regardless of the location (either at home or at work or at public/private charging stations) 0-otherwise.	-0.05016	-0.037	-0.01235	0.05731	0.0422
INFLU	1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.08605	-0.06090	-0.01761	0.09551	0.06904
PINNOV2	Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations. (*)	-0.31467	-0.20213	-0.02155	0.33291	0.20544
ENVBEN	1 if respondent rated environmental benefits as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	-0.08787	-0.05366	-0.00291	0.08981	0.05464

Table 4.8 continued

PRELA	Respondents who agreed or strongly agreed on average that ERs would offer more advantages compared to driving on non-electric (conventional) roadways. (*)	-0.25238	-0.16212	-0.01729	0.26701	0.16477
WBIKE	1 if respondent indicated that their primary mode of travel is walking or biking (conventional bike or electric bike) for each of the trip purposes (work/school, grocery and shopping, personal business, social/recreational).	-0.02749	-0.01848	-0.0033	0.02985	0.01945

**Predicted probability generated from an estimated binary probit model*

4.2 Market Segmentation

One of the objectives of the current thesis is to find the level of adoption of the ERs technology. The survey of general population was used as a tool to extract the data needed for the market segmentation analysis. Multidimensional statistical methods were used in order to create groups of respondents based on their similarities among the different opinions examined through the questionnaire.

4.2.1 Modeling Technique

The data obtained from the questionnaire was processed by means of two multivariate statistical analysis methods: Principal Component Analysis (PCA) and Cluster Analysis (CA).

Principal Component Analysis

PCA is an explanatory factor procedure commonly used in market research (Henson & Roberts, 2006; Tabachnick & Fidell, 2007; Thompson, 2004). The objective of this method is to reduce the initial number of variables into a new set of items, called principal components. If the initial variables are not correlated, this method does not achieve remarkable results (Washington et al., 2011). Observational data typically contain a large number of correlated variables and thus

PCA can be successful. In particular, this technique uses the potential correlations among different items to estimate independent factors that best represent the items they include and thus, they best describe the research question of the technology adoption (Mooi & Sarstedt, 2011). The fact that the obtained factors are not correlated is an important aspect of this analysis, since they can be used in regression analysis without collinearity issues (Mooi & Sarstedt, 2011).

Each principal component resulted from PCA is a linear weighted combination of the initial variables and can be described by the following equation (Vyas & Kumaranayake, 2006):

$$P\,C_m = \alpha_{m1}X_1 + \alpha_{m2}X_2 + +\alpha_{mn}X_n \qquad \text{Equation 4.12}$$

where PC_m represents the m^{th} principal component extracted, α_{mn} denotes the weight for the m^{th} principal component and the n^{th} variable and X_n stands for the n^{th} variable. The weights for each component are given by the eigenvectors of the correlation matrix or the co-variance matrix in the case where the data is standardized (Vyas & Kumaranayake, 2006). The combination of various variables under different components is based on the variables' observed variance (O'Rourke & Hatcher, 2013). This variance is described by the eigenvalue of the corresponding eigenvector (Vyas & Kumaranayake, 2006). The components are presented in order from the component that explains the greatest percentage of the total variation to the one that explains the least variation (Vyas & Kumaranayake, 2006).

In order to conduct the PCA, the following steps have to be taken, according to Mooi & Sarstedt (2011) and Williams et al. (2010):

- Evaluation of the assumptions of PCA and data appropriateness for the analysis

The assumptions are related to the nature of the data (internal or ratio scale level), the sufficient correlation between the items (correlation matrix, Kaiser–Meyer–Olkin (KMO) statistic and the Bartlett's test of sphericity), the sample size and the sample to variable ratio.

- Extraction of the factors

Since PCA is the extraction method, factors are extracted in a way that minimizes the difference between the initial and reproduced each time correlation matrix (Mooi & Sarstedt, 2011). In particular, a set of highly correlated variables are selected by the PCA and are related to a specific component. Then, another set of variables with high correlation are chosen and included in a second factor. This process is iterative until all the variables have been included (Mooi & Sarstedt, 2011). The overall objective though is to reduce the number of items through this factor extraction by extracting only a few factors that account for a high degree of the overall variation (Mooi & Sarstedt, 2011).

- Determination of the number of factors

There are certain criteria that can determine factor extraction. Among the various extraction rules and approaches are: the Kaiser's criterion (eigenvalue > 1) (Kaiser, 1960), the scree test (Cattell, 1966), the cumulative percent of variance extracted, the variable's variance that can be reproduced (called communality) and the parallel analysis (Horn, 1965). It is suggested that multiple approaches be used in factor extraction (Williams et al., 2010). The selection of the rotation method is also included in this step and it can facilitate the interpretation of the results. Rotation offers a more simplified solution, since it maximizes high item loadings and minimizes low item loadings (Williams et al., 2010). There are two common rotation techniques: orthogonal rotation and oblique rotation. The orthogonal rotation is used when the factors produced should not be correlated. The orthogonal Varimax rotation is the most common technique in PCA (Thompson, 2004) and aims at maximizing the dispersion of loadings within factors (Mooi & Sarstedt, 2011). The varimax rotation is also recommended to be used to enhance the interpretability of the results (Mooi & Sarstedt, 2011). The oblique rotation is used when the factors produced do not need to be uncorrelated and should be used only if the results are different to interpret (Mooi & Sarstedt, 2011). Direct oblimin is the most commonly used oblique rotation technique (Mooi & Sarstedt, 2011).

- Interpretation of the results

This step involves labeling of the factors based on the variables assigned to each factor. The labeling of factors is a subjective, theoretical, and inductive process (Pett et al., 2003) and thus, it is challenging. The resulted factor loadings describe the association between variables and factors and this is why higher loadings are desired. However, it is also reasonable to assign a variable to a factor, despite the fact that the variable does not load highly on the specific factor (Mooi & Sarstedt, 2011); as long as the variable's factor loading is above an acceptable level, depending on the number of factors in general and on the number of variables in each factor. In any case, the factors' eigenvalues (eigenvalue>1), the difference between the observed and reproduced correlation coefficients (residuals>0.05), the cumulative variance explained (total variance>50-60%) and the communalities of each variable (communality>0.30) should be checked compared to their acceptable levels (Mooi & Sarstedt, 2011).

All the above steps are presented in more detail in the section of the PCA results (Section 4.2.2).

Cluster Analysis

The new set of components found from PCA was used as an input to cluster analysis (CA). Cluster analysis is a method that examines the similarity of multidimensional objects and then identifies homogenous groups of these objects called clusters (Mooi & Sarstedt, 2011). The objects that are in the same cluster have the maximum similarity but also the maximum dissimilarity with objects not belonging in that cluster. The initial step of CA is to decide which characteristics or in other words clustering variables will be used to segment the sample. Given that a PCA has been conducted, the clustering variables are considered to be the principal components extracted from PCA. It is important to mention that the selection of the clustering variables in general should be such that they provide sufficient differentiation between segments (Mooi & Sarstedt, 2011). In addition, if there are collinearity-correlation issues between the clustering variables, they are not considered sufficiently unique to identify distinct clusters, since specific aspects covered by these variables will be over-presented in the clustering solution (Mooi & Sarstedt, 2011). This is the reason why the PCA using the Varimax rotation method can handle this issue and is the first step before the CA.

There are different approaches to measure the level of similarity between objects or to form clusters and thus, there are different clustering procedures. The usual differentiation is between hierarchical and partitioning methods. There is also the two-step clustering that constitutes a combination of hierarchical and partitioning methods (Mooi & Sarstedt, 2011). Hierarchical methods are based on clustering algorithms that use distance measures to create clusters while partitioning methods use the within cluster variation as a measure and require a pre-specified number of clusters (Mooi & Sarstedt, 2011).

Hierarchical methods can be agglomerative or divisive. The agglomerative clustering starts with each object being an individual cluster. Then, the individual clusters are merged, depending on their similarity, in order to successively form new clusters. Each new cluster is linked to a higher level of hierarchy from the bottom up. The opposite procedure is the divisive clustering. In this method, there is one initial cluster that includes all the objects of the analysis and this cluster is gradually divided from the top down. In both techniques, the assignment of an object to a cluster means that this object cannot be reassigned to any other cluster; a characteristic that distinguishes hierarchical and partitioning methods. There is a variety of measures of similarity to be used in these methods. Examples are the Euclidean distance, the city-block distance (Manhattan metric), the Angular, Canberra or Mahalanobis distance (Mooi & Sarstedt, 2011). Among the most popular clustering algorithms that exist for the hierarchical methods are: nearest neighbor (single linkage), furthest neighbor (complete linkage), average linkage, centroid and Ward's method (Mooi & Sarstedt, 2011).

The two-step cluster analysis is based on two steps: first, a procedure similar to k-means takes place by forming pre-clusters. Then, the hierarchical clustering algorithm is applied on the pre-clusters to combine the objects and form final homogenous clusters (Mooi & Sarstedt, 2011). This method can result in solutions based on a mix of both continuous and categorical variables and for different number of clusters. This is the advantage of this method compared to the other clustering procedures.

As far as the partitioning methods are concerned, the k-means procedure is one of the simplest non-hierarchical clustering methods (Mooi & Sarstedt, 2011). This is the method that this thesis followed. The k-means algorithm-where k the number of pre-determined clusters-aims at segmenting the data in a way that within-cluster variation is minimized (Steinley, 2006). The initial step of this algorithm is the random assignment of all the projects to different clusters. As a next step, successive reassignments of the objects to other clusters take place. The criterion for an object reassignment is the squared distance of each case to the center (cluster mean) of the associated cluster (Mooi & Sarstedt, 2011). This procedure is repeated until all cases are allocated to the cluster for which their distance to the cluster mean is the shortest.

The cluster centers are found by computing the mean values of the objects contained in the corresponding cluster concerning each of the variables (Mooi & Sarstedt, 2011). The k-means algorithm starts with an initial set of centers and classifies the observations based on their distances from the centers. The cluster means are computed again and iteratively, every time the objects are reallocated to other clusters until the cluster affiliation does not change between successive steps or the maximum number of iterations is reached. After iteration stops, all the objects are assigned to clusters and the cluster centers are computed for a last time (final cluster centers). Based on the final cluster centers, the results of the clustering solution can be interpreted.

An important characteristic of this method is that the researcher has to pre-specify the number of clusters to be obtained. Due to this issue, different approaches exist and can offer help.

Some researchers use the variance ratio criterion introduced by Calinski & Harabasz (1974) (Milligan & Cooper, 1985) or apply a hierarchical procedure to determine the appropriate number of clusters and then the k-means procedure (Punj & Stewart, 1983). Another approach is to try different number of clusters using k-means and examine which solution is best, based on certain validation criteria (Mooi & Sarstedt, 2011). In general, k-means is considered a superior method compared to hierarchical methods based on (Mooi & Sarstedt, 2011), since "it is less affected by outliers and the presence of irrelevant clustering variables and also can be applied to large datasets".

The interpretation of the cluster solution is made by defining and labeling the obtained clusters. This can be achieved by examining the clustering variables' mean values and comparing the average score of each cluster compared to the average scores of each clustering variable. The label of each cluster should reflect its objects and demographic variables can be used to profile the retained segments.

The validation of the cluster solution is also an essential step. The solution should be evaluated with respect toward its stability, reliability and validity (Mooi & Sarstedt, 2011; Dibb 1999; Tonks 2009; Kotler & Keller, 2009). In order to assess the solution's stability, examining the output regarding its metrics and statistics is important. In addition, different clustering procedures, algorithms or distance measures can be used to re-run the analysis and review the results. In order to evaluate the solution's reliability, it is suggested to replicate the analysis using a separate collected dataset (Mooi & Sarstedt, 2011). Finally, the solution's validity can be examined by exploring the significance of the differences between the segments with regard to some criterion variables or by exploring whether the segments are: substantial, accessible, differentiable, actionable, stable, parsimonious, familiar and relevant, based on Dibb (1999), Tonks (2009), Kotler & Keller (2009). The obtained clusters should exhibit high degree of within-homogeneity and between segment heterogeneity (Mooi & Sarstedt, 2011).

The following sections provide the results of the PCA and the CA used to estimate the adoption rates and conduct market segmentation analysis. In particular, the specific settings and methods utilized in each case are discussed and the final clusters are analyzed in terms of their size and characteristics.

4.2.2 Principal Component Analysis (PCA) Results

A PCA was conducted in this section in order to identify which variables are the most salient and capture important information to be used for the clustering process. For this purpose, the IBM SPSS Statistics software, version 22 was used.

Ofthe total number of variables of the survey (228 variables), the variables related to general thoughts and opinions on ERs (70 variables, third section of the survey) were used in the analysis. This decision was made based on a process of trial and error. In particular, all the variables of the survey were tested in the PCA analysis but the results indicated that the validity of the analysis was ambiguous, the variance explained was minimum and the interpretation of the results was not reasonable. Since, there was an idea of the factor structure that could be helpful in evaluating the research question of the ER technology adoption, the factor solution can be adjusted (Mooi & Sarstedt, 2011). Hence, the focus was on the variables-questions associated with the intention to use ERs that had also the advantage of being expressed on the same scale (Likert scale of 5 point ordinal scale: 1-strongly disagree to 5-strongly agree).

Prior to starting the analysis, the assumptions of PCA should be studied. Although there are different opinions in the appropriate sample size for this type of analysis, there is the general view that over 500 observations denotes an adequate size (Comrey & Lee, 1973) as cited by Gorsuch, 1983; Hair et al., 1995; Pett et al., 2003; Thompson, 2004). Thus, the sample of 600 responses can be considered sufficient. Additional rules have been stated and are related to the ratio of the number of observations to the number of variables. Examples of these rules mention that this ratio ranges from 3:1, 6:1, 10:1, 15:1 or 20:1 (Gorsuch, 1983; Hair et al., 1995; Pett et al., 2003; Thompson, 2004; as cited by Williams et al., 2010). In the current work, there are 600 responses and 70 variables. However, there are studies that have shown that there is not a specific ratio to determine the level of success of the analysis (Hogarty et al., 2005; MacCallum et al., 1999; as cited by Williams et al., 2010). Thus, this rule seems ambiguous. As a next step, the variables should be examined for potential correlation issues through their correlation matrix and the significance levels of their correlation. Since there were some variables that were highly correlated (above absolute 0.3), the PCA can be used a solution that would result in independent factors which are suitable for being used in grouping the respondents in distinct clusters (Mooi & Sarstedt, 2011).

Further measures used to test for the appropriateness of this method are the Kaiser–Meyer–Olkin (KMO) statistic and the Bartlett's test of sphericity (Lattin, 2005; Field, 2005). The KMO index, also called the measure of sampling adequacy, ranges from 0 to 1, with 0.50 considered suitable for factor analysis (Hair et al., 1995; Tabachnick & Fidell, 2007). This test explains whether other variables in the dataset can explain the correlations between a pair of variables (Mooi & Sarstedt, 2011).

Bartlett's test of sphericity was used to test whether the correlation matrix is diagonal (null hypothesis indicating that non-diagonal elements are zero) (Mooi & Sarstedt, 2011). The desired result is to reject the null hypothesis, since high correlations are needed in PCA. Thus, this test should be significant ($p< 0.05$) for factor analysis to be suitable (Hair et al., 1995; Tabachnick & Fidell, 2007). Both tests gave satisfactory results and confirmed that all the variables are related and can be used in the PCA.

In order to extract the principal components, the criteria that will assist in the determination of the factors should be assumed. The rotation method selected was the Varimax method (orthogonal method) (O'Rourke & Hatcher, 2013), which forces the factor solution to be uncorrelated. In other words, through this procedure the variables that are highly correlated are selected to factor, constituting a component that is not associated with the other components. This characteristic is important for the use of the factor solution in the CA that requires the independence of the clustering variables.

The extraction method was based on Kaiser's criteria (components' eigenvalues>1), the scree plot test that shows the correct number of factors and the cumulative percent of variance explained (Kaiser, 1960; Cattell, 1966). As far as the settings are concerned, the minimum correlation between a factor and each variable (factor loading) was set as 0.3. Thus, any coefficient with an absolute value below this value was ignored (Tabachnick & Fidell, 2014). In addition, every retained component must include at least three variables to be reliable. Also, in order to avoid multicollinearity issues between the factors, every variable should appear in only one component. If the previous conditions are not met, the corresponding variables removed from the analysis and the PCA should re-run (Samuels, 2017). Furthermore, the determinant of the correlation matrix should be ensured that it is greater than 0.00001. A value lower than the suggested one indicates high inter-correlations among variables.

Another important aspect of the analysis is each variable's communality that can indicate how well this variable is represented or captured by the extracted components (Mooi & Sarstedt, 2011). Communalities are usually indicators of the solution's goodness-of-fit but there is not a commonly used threshold for them. As a rule of thumb, the variable's variance should be explained by at least 30% through the components extracted and thus, the communalities should be above 0.3 (Mooi & Sarstedt, 2011).

Based on the aforementioned guidelines, the PCA was conducted. This led to a solution comprising of four factors and 22 variables in total. Table 4.9 shows the KMO and Barlett's test as well as the value of the determinant, indicating that the respective conditions mentioned previously were met.

Table 4.9: KMO statistic, Barlett's test and determinant

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.884
Bartlett's Test of Sphericity	**Approx. Chi-Square**	6609.948
	df	231
	Significance	.000
Determinant		0.000014

Table 4.10 illustrates that around 62% of the observed variance has been accounted for. As general rule, the total variance explained should be at least 50-60% (Streiner, 1994) and thus, using this criterion the solution seems valid. In contrast with other components, eigenvalues of the first four components are above one, validating Kaiser's criterion, and therefore confirming the assumption that the proportion of the variance explained by each component is acceptable.

Table 4.10: Final components and eigenvalues

Component	Eigenvalue	% of Variance explained	Cumulative % of variance explained
1	6.978	31.719	31.719
2	2.714	12.338	44.057
3	2.380	10.819	54.876
4	1.582	7.192	62.069

The scree plot can also be used to confirm the suitable number of extracted factors. According to Williams et al. (2010), interpreting the scree plot is made in two steps: first, a straight line can be drawn through the smaller eigenvalues where a departure from this line occurs, indicating where a break occurs; second, the point beyond the break can show the number of components retained. Figure D1.1 in Appendix D1 indicates that 4 factors are to be retained.

The groups of variables retained for the PCA are indicated on the summary table below (Table 4.11). In particular, this table shows the adopted name for each component *("Component name")*, the variables-questions of the survey assigned in each component *("Variables included")*, the code name of each variable ("*Code name*"), the variables' loadings to each component *("Loadings to each component")* and the communality estimates *("Communalities")*.

Based on the table (Table 4.11), the four factors extracted are: opinions on ERs, environmental consciousness, safety concerns and habits towards driving a car. More specifically, opinions on ERs (first component) reflect ten variables-questions of the survey: two behavioral intention questions (intention to drive on ERs), two questions of attitudes towards the use of ERs, one question of personal moral norms, two questions of self-efficacy, two questions from perceived behavioral control and one question from the innovation category. All these questions are related to the section of opinions on ERs, as explained in the survey design (Section 3.3), and this is why this component was labeled accordingly. The second component contains questions from the general environmental concerns' subsection of the survey while the third component includes questions related to the safety concerns concerning the ER technology. The last component consists of one question from the sustainability subsection and two from the subsection of the habits towards the use of cars. All the four components are positively associated with the corresponding questions they include. Finally, all factor loadings are high and above 0.3 increasing the results' face validity (Mooi & Sarstedt, 2011).

Table 4.11: PCA analysis

Component name	Variables included	Code name	Loadings to each component				Communalities
			1	2	3	4	
Opinions on ERs	I intend to drive my EV on electric roadways as soon as electric roadways become available.	IntRideERs1	0.825				0.688
	I intend to drive my EV on electric roadways shortly after electric roadways become available.	IntRideERs2	0.812				0.662
	For me, driving on electric roadways would be__Undesirable: Desirable	AttERs7_1	0.764				0.665
	Because of my own principles, I would feel an obligation to drive on electric roadways because electric vehicles can be charged more efficiently.	PerMorNor1	0.724				0.596
	When electric roadways become widely available, I would know enough to drive on one.	SelfEff3	0.724				0.614

Table 4.11 continued

	When electric roadways become widely available, I would have the ability to drive on them if I want to.	PercBehCont2	0.719				0.593
	I would have the necessary knowledge to drive on electric roadways.	SelfEff1	0.717				0.595
	Driving on electric roadways sounds _____ to me. Stupid:Smart	AttERs4_1	0.714				0.611
	I believe that the sales of conventional (internal-combustion) vehicles may be banned in the future.	PercBehCont4	0.584				0.421
	I am willing to be an early adopter of new technologies, but prefer to follow the lead of others and to ensure there is a clear benefit to me before doing so.	EarMaj1	0.458				0.393
Environmental consciousness	I think that cars are negatively impacting air quality.	EnvConc4		0.816			0.683
	I think that trucks are negatively impacting air quality.	EnvConc5		0.788			0.628
	I believe that transportation can have an important impact on the environment and our ability to be sustainable.	EnvConc6		0.764			0.648

Table 4.11 continued

	I think we are not doing enough to save scarce natural resources from being used up.	EnvConc2		0.754			0.635
	I think air pollution is becoming more and more serious in recent years.	EnvConc3		0.716			0.588
	I think individuals have a responsibility to protect the environment.	EnvConc1		0.707			0.583
Safety concerns	I would have safety concerns about driving on electric roadways.	Safety1Rev			0.873		0.779
	On-road charging on electric roadways would cause me safety concerns.	Safety3Rev			0.780		0.633
	I would have safety concerns about driving on electric roadways if trucks are not banned from these roads.	Safety2Rev			0.854		0.751
Habits towards driving a car	Driving a car is one of my habits.	HAB2				0.814	0.704
	No matter how convenient and sustainable the travel options are, I will always prefer to drive my personal vehicle.	SUS2				0.812	0.685
	Not driving a car is something I would not feel comfortable with.	HAB1				0.780	0.637

As a last step, the goodness-of-fit of the factor solution was also evaluated by ensuring that the proportion of cases where differences (residual) between the correlation coefficients in the data (observed) and the correlation coefficients from the factors (reproduced) are greater than 0.05 is as small as possible (Mooi & Sarstedt, 2011). There is no rule of thumb regarding the maximum proportion of residuals greater than 0.05 but in general a proportion of more than 50% can be problematic (Mooi & Sarstedt, 2011). It should be noted that this issue would also appear in the stage where the assumptions of the PCA are checked. In particular, low correlations and an unsatisfactory KMO test would have raised concerns. In the PCA conducted, the solution is considered sufficient since there are only 57 (27% which is < 50%) non-redundant residuals with absolute values greater than 0.05.

4.2.3 Cluster Analysis (CA) Results

In this section, the sample of 600 LA residents was clustered by applying the k-means cluster method on four clustering variables found from the Principal Component Analysis (PCA): opinions on ERs (factor 1), environmental consciousness (factor 2), safety concerns (factor 3) and habits towards driving a car (factor 4). The CA was conducted using IBM SPSS Statistics software, version 22. The methodology was based on the book of Mooi & Sarstedt (2011), on software tutorials and on studies that have used the same software (Chawla & Joshi, 2017; Carvalho, et al., 2015).

4.2.3.1 Clustering Procedure

Before conducting the CA, a one-way analysis of variance (ANOVA) was used in order to assess whether the means of the four principal components vary across different demographic variables: gender, age, employment situation, household income level, educational level, household size, number of children, vehicle ownership. The ANOVA was used, since it can analyze multiple differences comparing three or more means (Mooi & Sarstedt, 2011). After testing the homogeneity of variances, Levene’s test showed that population variances are homogenous and thus, the F-statistic is used to estimate the p-value (significance level) according to F-distribution. The F-statistic gives the ratio of factor variance to the error variance in ANOVA and tests the null hypothesis that there is no difference in the means of the factors across the different testing variables. Using a significance level of 0.05, if the p-value is less than or equal to 0.05, the null hypothesis can be rejected and thus, the means of the factors (*dependent variables in SPSS)* vary across the demographic variables (*factors in SPSS).*

The results are reported in Table 4.12. As can be seen, the opinions on ERs vary across all demographic variables except vehicle ownership. Environmental consciousness vary across educational level; safety concerns vary across age and household size; habits towards driving a car vary across age, employment situation, income level, household size and vehicle ownership. Since each principal component varies across at least one demographic variable, the respective principal component can be used as a clustering variable. The aforementioned results support the decision to use these four factors in the analysis.

Table 4.12: One-way ANOVA with principal components and demographic variables

Principal Component	Demographic variable	F-value	Significance
Opinions on ERs	Gender	17.309	0.000
	Age	12.783	0.000
	Employment situation	7.744	0.000
	Household income	2.709	0.013
	Educational level	2.324	0.042
	Household size	6.542	0.000
	Number of children	9.845	0.000
	Vehicle ownership	1.600	0.173
Environmental consciousness	Gender	8.681	0.003
	Age	0.644	0.666
	Employment situation	0.196	0.964
	Household income	0.312	0.931
	Educational level	3.110	0.009
	Household size	0.044	0.996
	Number of children	0.331	0.857
	Vehicle ownership	1.465	0.211
Safety concerns	Gender	0.226	0.635
	Age	2.515	0.029
	Employment situation	0.733	0.599
	Household income	0.697	0.653
	Educational level	0.995	0.420
	Household size	3.596	0.007
	Number of children	2.187	0.069
	Vehicle ownership	0.728	0.573

Table 4.12 continued

Habits towards driving a car	Gender	1.932	0.165
	Age	2.696	0.020
	Employment situation	3.695	0.003
	Household income	3.899	0.001
	Educational level	0.983	0.427
	Household size	3.033	0.017
	Number of children	0.885	0.473
	Vehicle ownership	10.779	0.000

The k-means method was then used to group respondents into clusters. This method was chosen because of its superiority compared to other clustering techniques. In particular, k means technique is claimed to be less influenced by outliers or irrelevant variables (Mooi and Starstedt, 2011). In addition, the nature of the thesis' data is ordinal and k-means is routinely used on ordinal data. Furthermore, this nonhierarchical clustering procedure is suggested for large sample sizes, over 500 responses (Mooi & Sarstedt, 2011). Thus, k means method seemed to be more suitable.

The data of the analysis did not need to be standardized in SPSS, since the range or scale of one clustering variable is not larger or different from others. The method of iterate and classify was used to define the successive iterations and how the final process will be carried out. The maximum number of iterations until convergence was set as 10 (default value) and the convergence criterion as 0 (default value). The squared Euclidean distance is used for the divergence measure between units (Chawla & Sondhi, 2016).

4.2.3.2 Number of Clusters

In order to determine the appropriate number of clusters, different numbers of clusters were deployed and the results were reviewed to determine the robustness of the clustering algorithm. It was found that three clusters can offer the best solution. The final decision on the number of clusters was based on the examination of the stability, reliability and validity of the cluster solution and also the clarity in interpreting the results. For this purpose, the SPSS output was carefully examined.

The k-means clustering starts with an initial set of centers. Each observation is assigned to the closest cluster, based on the distance from all the cluster centers. When all the cases have been allocated to the clusters, new cluster centers are estimated and the assignment process is made again, based on the updated clusters. This process is iterative and cluster centers and assignments are modified until the convergence criterion is satisfied. This iteration process and progress of each cluster is part of the software's output and is presented in Table D1.1 in Appendix D1. As can be observed, the cluster centers change less over time until iteration 9^{th} where there is no change and the solution converges. Thus, the cluster solution can be claimed strong and stable.

The analysis of variance of the four components of the analysis can indicate the impact of each one of them on determining which observation is allocated to each cluster. The results reported in Table 4.13 show that the average scores for the four dimensions used are significantly different among the three clusters because of the large F-statistics and the low p-values (at a 5% significance level). As a result, the principal components included indeed contribute to the separation of clusters; the largest the F-value the greatest the contribution of the factor to the cluster solution.

Table 4.13: One-way ANOVA results

ANOVA/Principal components	Cluster		Error		F	Significance
	Mean Square	df	Mean Square	df		
Opinions on ERs	108.55	2	0.64	597	169.69	0.000
Environmental consciousness	179.169	2	0.403	597	444.457	0.000
Safety concerns	25.04	2	0.919	597	27.233	0.000
Habits towards driving a car	27.091	2	0.913	597	29.685	0.000

The final cluster centers are estimated as the mean for each factor within each final cluster and reflect the characteristics of each respondent for each cluster. This in conjunction with the output of the Euclidean distances between the clusters centers can indicate the level of similarity or dissimilarity among clusters. In particular, a graph is generated by the software and shows the final cluster centers (Figure D1.2 in Appendix D1). This graph can show whether the resulted clusters are different by each factor. On the Y-axis there is the Euclidean distance from the cluster center for each factor and the X-axis includes the three clusters. Using this graph, the factors that seem not to be very different across different pairs of clusters can be visually identified. Based on this figure (Figure D1.2), safety concerns (factor 3) seemed to have similar values for clusters 1 and 2.

To test if this factor (safety concerns) is statistically significant across the two clusters and to generally verify that each pair of clusters is different by every factor, a one-way ANOVA is conducted. More specifically, a post hoc test is used to evaluate whether the difference between the average scores of the factors between the cluster pairs is different. The four factors are used as dependent variables and the cluster membership is used as factor in the software. The Fisher's Protected Least Significant Difference (PLSD) test was used, since it is less conservative and it is more likely to identify at least one significant pairwise comparison, given a significant ANOVA (Howell, 2014). The results are presented in Appendix (Table D1.2 in Appendix D1) and clearly show that the difference of mean values is statistically significant (significance ≤ 0.05), providing more evidence that the cluster solution is valid.

The number of cases assigned in each cluster is also reported and can be used as an additional way to evaluate the cluster solution. There were no missing values while the clusters seem to be well-sized, meaning that no cluster was under-represented and thus, the results can be claimed meaningful (Table 4.14).

Table 4.14: Number of cases in each cluster

Cluster	**1**	166
	2	143
	3	291
Valid cases		600
Missing values		0

A diagnostic graph with vertical box plots was also created to identify outliers within each of the clusters. The figure shown in Appendix D1 (Figure D1.3) reveals that there are eight outliers in cluster 1 and one outlier in cluster 3. The lines in the middle of the boxes represent the median. These observations can be claimed slightly outliers, since all the distances are within reason. In particular, the length of each box is the interquartile range (IQR) computed from Tukey's hinges, representing the 25th and 75th percentile of data (Nuzzo, 2016). Values more than three IQR's from the end of the box are labeled as extreme, denoted with an asterisk in the figure (*). Values more than 1.5 IQR's but less than 3 IQR'S from the end of the box are labeled outliers (o) (Nuzzo, 2016). Since there are no extreme values in the figure, it was decided to retain the outliers. In general though, when there are many outliers, different number of clusters should be tested. However, this cluster solution gave the minimum number of outliers.

It is important to mention that the solution's stability and reliability was evaluated by also using different clustering procedures on the data set and testing whether the results are the same. More specifically, a hierarchical cluster analysis and a two-step cluster analysis were attempted, indicating that three clusters provide a sufficient solution. In addition, potential changes in the clusters' composition were examined by critically revisiting and replicating the results of k-means algorithm many times (Mooi & Sarstedt, 2011). Based on these evaluations, the three cluster solution was more effective and efficient.

4.2.3.3 Cluster Labeling

As a next step, the cluster mean values were computed across the four factors/clustering variables in order to assign appropriate labels to each of the three clusters. More specifically, the initial steps taken are the following:

1) For each observation/respondent, his/her average "score" (average value of answers) in the questions that are included in each component was calculated (average values by respondent by component).

2) For each cluster, the observations that are included in it were isolated. Then, the averages of mean responses (from the previous step) of all the respondents in each cluster were estimated by each component (average values by cluster by component).

The results can be shown in the following table (Table 4.15) that shows the average or "score" of each cluster in each component. The last row presents the overall mean score in each component by all respondents, regardless of the cluster membership.

According to the table (Table 4.15), the clusters seem to be conceptually distinguishable. Taking into account that the scale (Likert scale of 5 point ordinal scale: strongly disagree to strongly agree) and direction of the answers is the same: from 1 (least positive opinions to each factor) to 5 (most positive opinions to each factor), Cluster 3 (291 respondents) has the highest mean values compared to the other clusters on three out of four components indicating that this group of respondents may be more positive towards the adoption of ERs.

Table 4.15: Average score of each cluster across the principal components

Principal components/ Clusters		Average values by cluster by component			
		Opinions on ERs*	**Environmental consciousness***	**Safety concerns***	**Habits towards driving a car ***
Clusters	1	3.087	3.069	2.552	3.394
	2	2.849	4.376	2.338	3.107
	3	3.952	4.295	2.838	3.800
Overall mean score		3.446	3.975	2.640	3.522

Scale of answers:
-Opinions on ERs: 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, 5. Strongly Agree
-Environmental Consciousness: 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, 5. Strongly Agree
-Safety concerns: 1. Strongly Agree (= I have safety concerns), 2. Agree, 3. Neutral, 4. Disagree, 5. Strongly Disagree (=I do not have safety concerns)
-Habits towards driving a car: 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, 5. Strongly Agree

According to the meaning of each component, respondents of this cluster agreed the most to the thought of driving on ERs and had the fewest safety concerns regarding the use of ERs. As far as the car usage is concerned, the average of responses leaned toward the agree options concerning the habit of driving the car and this average was higher compared to the other clusters. Therefore, this group of respondents which scored the highest value related to habits towards driving a car, seem to be more positive on embracing the concept of ERs and using the technology installed in passenger electric cars. However, this cluster appears to have the second highest value in terms of the environmental consciousness, standing after cluster 2 with a slight difference. Regardless of this characteristic, cluster 3 seems to be generally more likely to adopt the technology first. In addition, by comparing with the overall mean scores, this cluster has higher than average mean values in all components. Thus, the users in this cluster can be labeled as “early adopters”.

Cluster 2 (143 respondents) has the lowest values across three out of four components (opinions on ERs, safety concerns, habits towards driving a car) showing that this group may have concerns regarding the adoption of ER technology. In addition, the cluster’s values in these three components are lower than the overall mean. The average of responses concerning the opinions on ERs and safety concerns is less than 3 which represented the “neutral” option. Thus, cluster 2 seems to disagree with driving on ERs and has less trust of the safety of the technology. However, this cluster appears to agree with the need to protect the environment more than any other cluster and this can be corroborated by the fact that it has the least tendency towards using the car (fourth principal component). This result may be an indication that respondents of this cluster cannot perceive and they are skeptical towards the fact that this new technology can potentially have a greater environmental benefit than EVs already have. Although one could claim that this cluster shows a greater appreciation toward the environmentally friendly technologies, the difference with cluster 3 (early adopters) is marginal. Thus, no clear consensus can be emerged for the cluster labeling based only on this factor. To conclude, the respondents included in this cluster can be labeled as "late adopters", mainly based on the lowest values in general.

Cluster 1 (166 respondents) comprises of respondents whose mean score is slightly below "early adopters" and seem to be more skeptical of adopting the technology compared to "early adopters". More specifically, cluster 1 appears to have less pessimistic answers compared to "late adopters" on ERs and safety concerns and less optimistic responses on all the four components compared to early adopters. It has also the second highest score in the factor of habits towards driving a car, after early adopters. This cluster though has the lowest score in the environmental factor, possibly meaning that they are less environmentally concerned. As with cluster 1, this cluster's labeling can be based on a general review of the factors included in the analysis. From this perspective, cluster 1 has mostly lower values than early adopters and higher values than late adopters. In addition, cluster 1 has average scores close to 3 (neither agree nor disagree) and it appears that are somehow skeptical and indecisive. Thus, this cluster can be labeled as "mid-adopters".

In conclusion, clusters 2 and 3 can be treated as extreme behaviors while cluster 1 includes values that usually stand somewhere in between the two. Thus, "early adopters" have the most optimistic attitude toward ER technology followed by "mid-adopters" and "late adopters".

The following graph shows the distribution of the aforementioned clusters (Figure 4.3).

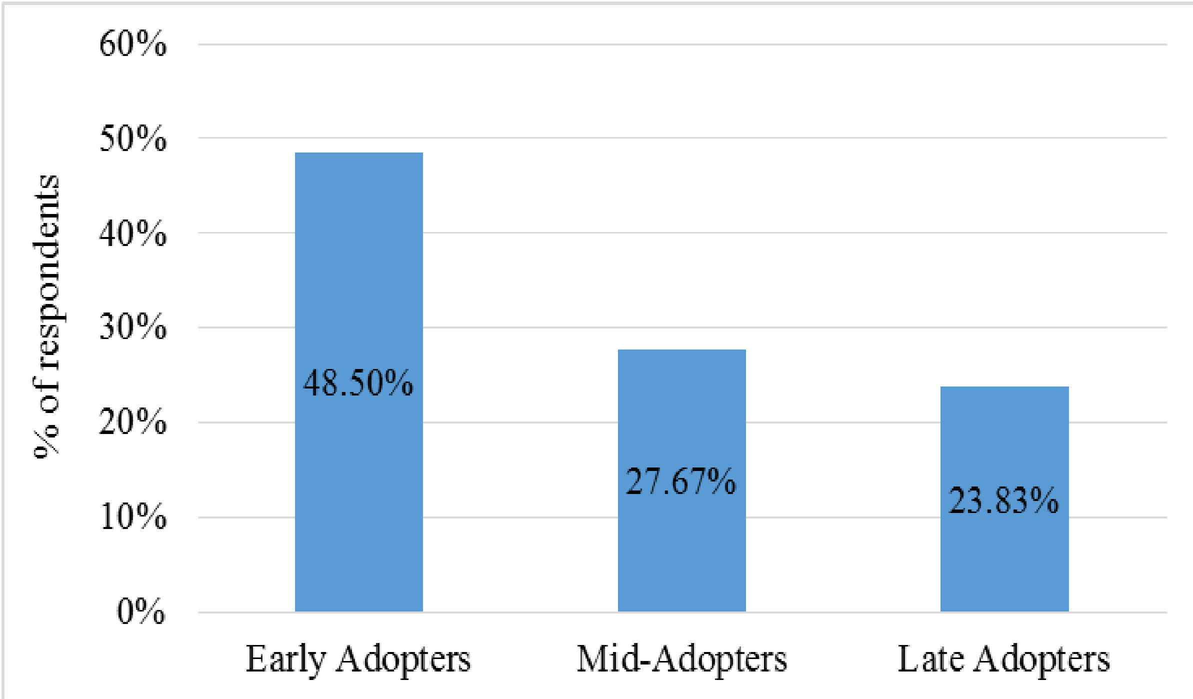

Figure 4.3: Distribution of clusters (adoption rates)

The interpretation of the results in terms of the adoption of the technology can also be supported by examining each cluster's responses to the short-term and long-term intention questions. In particular, the majority of "agree" and "strongly agree" responses come from the cluster labeled early adopters (cluster 3) followed by mid-adopters (cluster 1) and late adopters (cluster 2) (Figures D2.1-D2.8 in Appendix D2).

The potential gap between stated attitudes of respondents and the hypothetical nature of the topic of interest is worth to be acknowledged at this point (Kaufmann & Panni, 2017; Kaufmann et al., 2012). From a general perspective, it can be easily understood that the two factors that are directly connected to ERs are the factor of opinions on ERs and the factor of safety concerns on ERs compared to the other two factors (environmental consciousness and habits towards driving a car.) The other two factors are also statistically important but from a behavioral point of view their interpretation of the results can be ambiguous. This in conjunction with the survey limitations and the cluster solution stability can lead to the conclusion that the cluster labeling provided is as much representative as possible.

4.2.3.4 Clusters' Characteristics

After identifying the clusters, the objective is to describe the characteristics of each cluster and how they differ on relevant dimensions. Data that is not included in the cluster procedure is used to profile the characteristics of each cluster and thus, gain more insights on the ER adoption pattern. The three clusters derived from cluster analysis were described with respect toward their most important characteristics.

In an attempt to identify the most important characteristics to be discussed by cluster, the relationship between the obtained clusters and basic sociodemographic, travel and EV charging related variables was evaluated. A χ^2 analysis was conducted for this purpose at a 5% significance level. Tables D2.1 and D2.2 in Appendix D2 present a summary of the results by providing the χ^2 statistics by each variable ("*Variable categories*" column) and the profile of each cluster. It was evident that all the variables-except for household size, car ownership per fuel type and type of charger used-are associated with the adoption of ER technology, since the χ^2 test gives p-values lower than 0.05. This shows that the level of adoption significantly varies across these variables.

Based on the aforementioned results, the following characteristics were analyzed across clusters:

Demographics and socioeconomic characteristics

Among the respondents in the "early adopters" cluster, 23% belong to the age group of 25-34 years old. This age group is the dominant category in this cluster, indicating that early adopters would more likely be younger individuals (Millennials) who may have a greater tendency toward innovativeness. The majority of mid-adopters (20.5% of respondents) is between 35-44 years old, while late adopters are mostly 65 or above years old (24%). The results are shown in Figure 4.4. This result emphasizes the difference between younger and older generation in adopting new technologies. Older people are usually less familiar with newer technologies than younger generation. Overall, early and mid-adopters tend to be younger, a finding that is in line with the literature (Dubin et al., 2011; Morris et al., 2015).

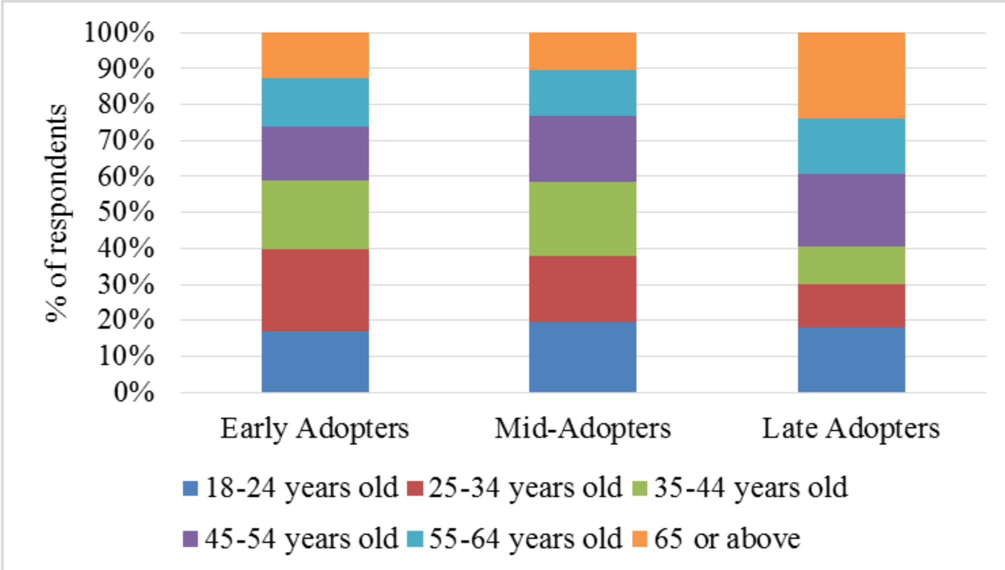

Figure 4.4: Age distribution across clusters

Early and mid-adopters have a similar gender distribution with male respondents constituting 54% and 52% respectively while female respondents are 46% and 48% respectively (Figure 4.5). On the other hand, “late adopters” include more female (73%) than male respondents (27%) (Figure 4.5).

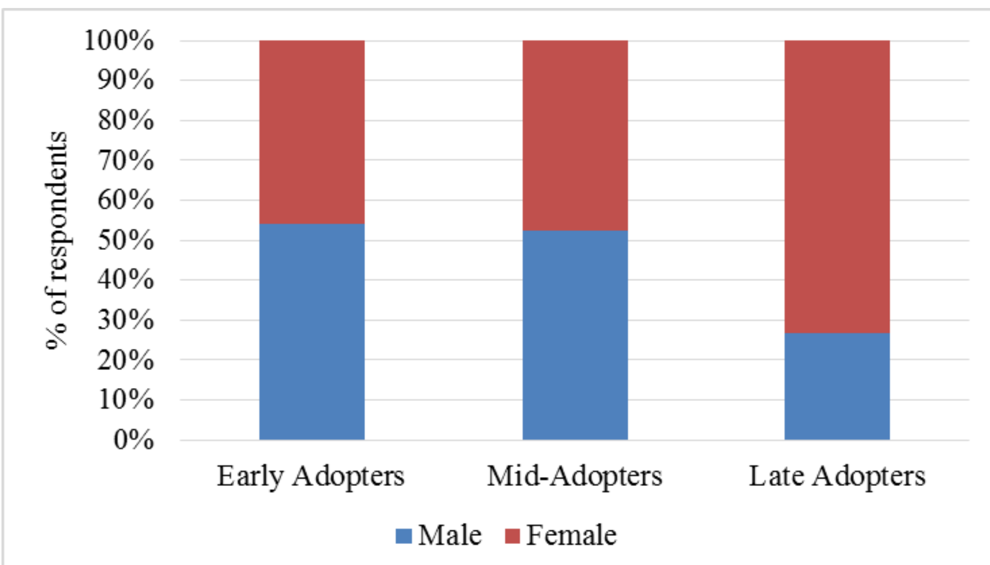

Figure 4.5: Gender across clusters

Early adopters have the highest percentage of respondents with annual income over $75,000 (48%) compared to mid-adopters (36%) and late adopters (28%). The dominant income category for mid-adopters and late adopters is $25,000-$50,000 while the majority of early adopters make

$75,000 to $100,000. A similar trend exists for the employment situation of respondents across clusters, since the percentage of people working full time from the "early adopters" cluster to the late adopters cluster drops from 53% to 32%. In addition, the highest percentage of unemployment was reported in the cluster of late adopters (12% of respondents compared to 8% in early adopters and 9% in mid-adopters). This may have implications for the relationship between income level and level of adoption. In particular, it seems that the earliest adopters may be described by a higher income and status while late adopters tend to have a mid-level socioeconomic status. Different studies in the past have found a positive association between income and level of innovativeness (Dickerson & Gentry 1983; Gatignon & Robertson 1991; Rogers 1995; Uhl et al., 1970; Im et al., 2003). The results are shown in Figures 4.6 and 4.7.

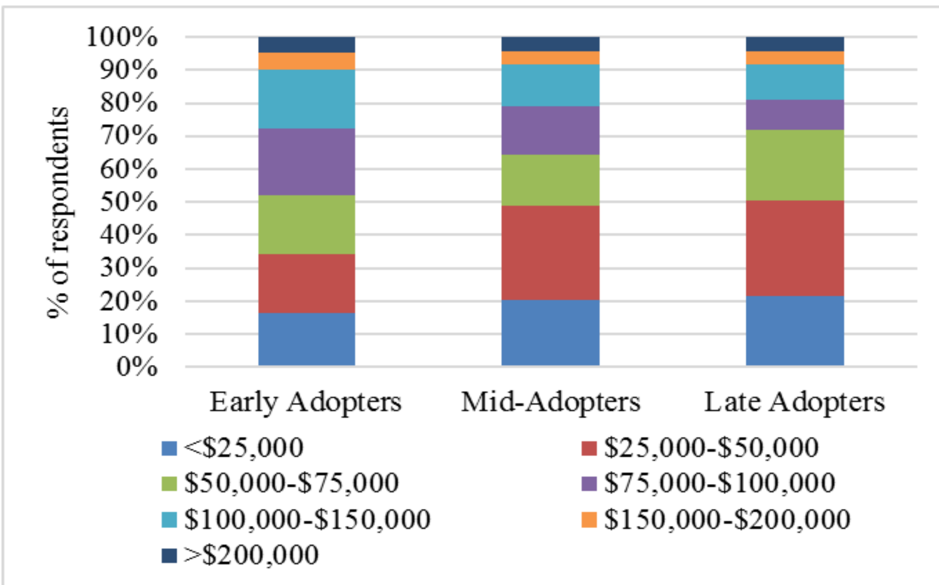

Figure 4.6: Income level across clusters

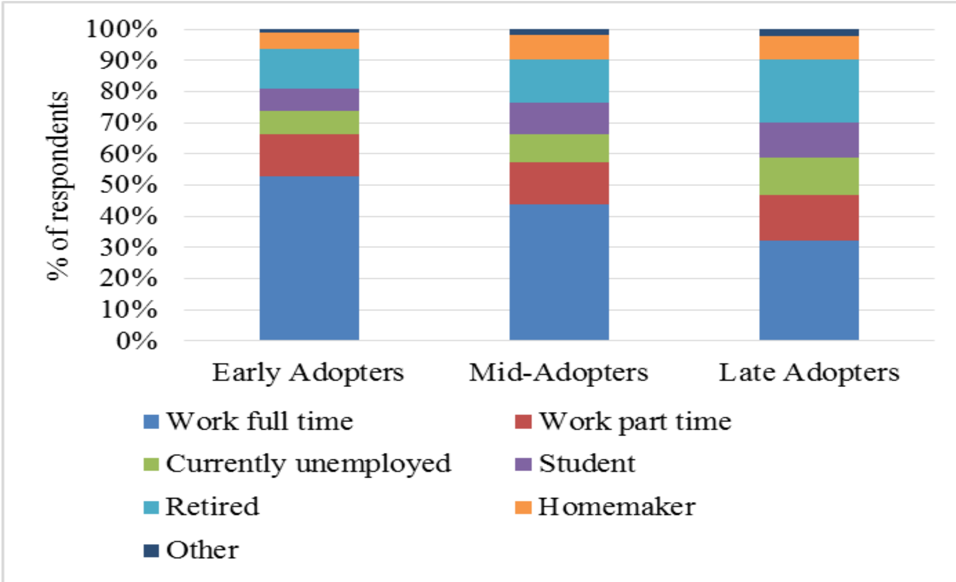

Figure 4.7: Employment situation across clusters

As far as the educational level is concerned, there were not significant differences across clusters (Figure 4.8). The vast majority of respondents in each cluster has a high educational level, meaning their highest level is some college or college graduate or graduate school (early adopters: 82%; mid-adopters: 69%; late adopters: 73%). However, it is noteworthy that early adopters have a considerably higher rate of graduate school attendants (20%) compared to 11% for mid-adopters and 12% for late adopters, indicating what was expected: early adopters may have a higher educational level.

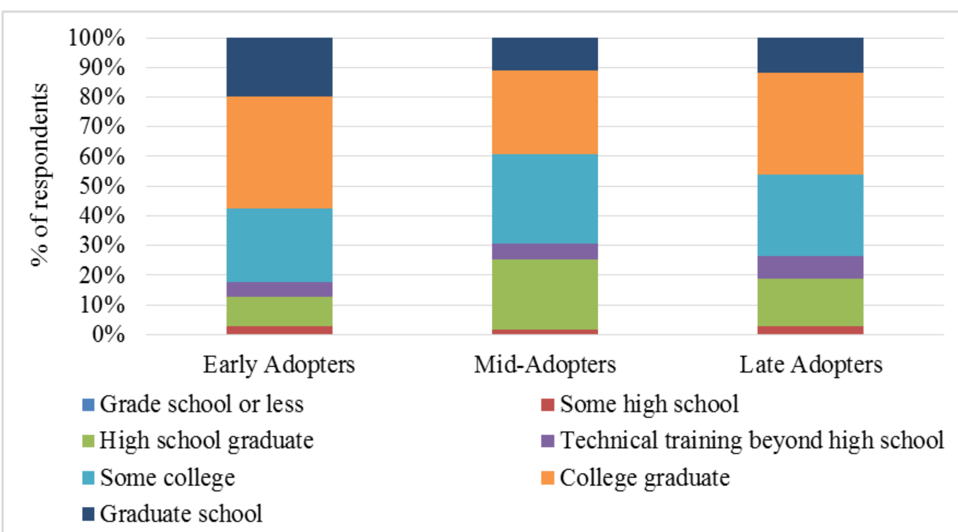

Figure 4.8: Educational level

The majority of respondents in each cluster do not have children. In particular, around 78% of late adopters do not have children while 66% of mid-adopters and 60% of earlier adopters also do not have children. The highest percentage of respondents with more than 2 children seems to be in the mid-adopters cluster (7%) followed by late adopters (5%) and early adopters (2%) (Figure 4.9).

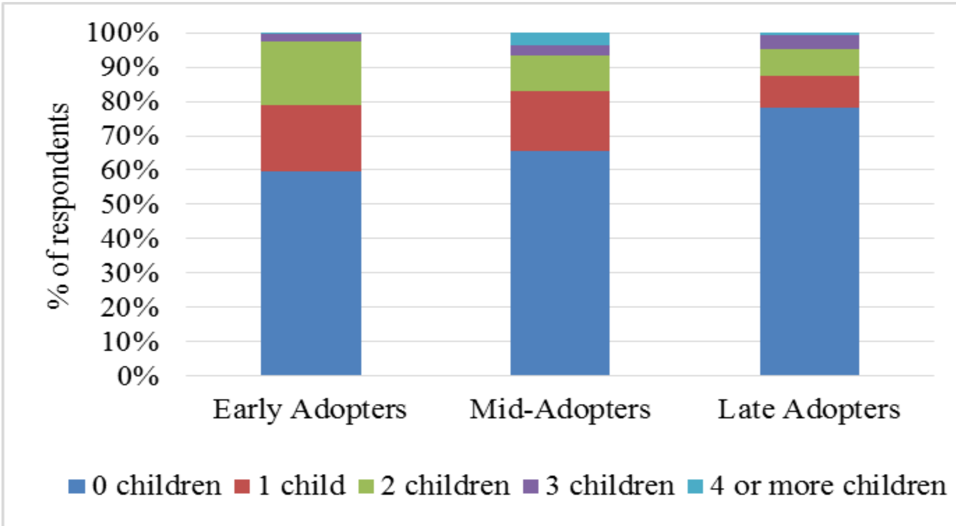

Figure 4.9: Number of children across clusters

It was also observed that around 94% of early adopters have a driver's license while this percentage drops for the mid-adopters (84.94%) and late adopters (84.62%). Thus, it seems that the people who would adopt this technology first would be drivers; a conclusion that is intuitive. The results are shown in Figure 4.10.

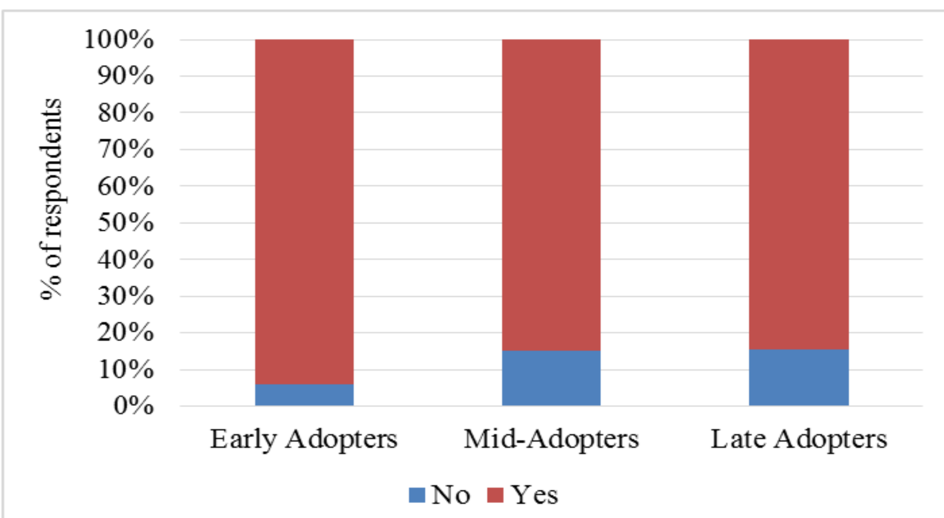

Figure 4.10: Driver's license ownership across clusters

Early adopters seem to have the least percentage of people that do not own a personal vehicle (4%) compared to mid-adopters (11%) and late adopters (12%) (Figure 4.11). 39% of early adopters, 35% of mid-adopters and just 19% of late adopters drove their personal vehicle more than 15,000 miles. The dominant answer category in the early and mid-adopters' clusters is driving 10,000 to 14,999 miles, while the category that had more responses for late adopters is driving less than 10,000 miles. This clearly illustrates that early to mid-adopters are people with a higher car use throughout the year; a finding that was also evident from their higher average score in the principal component of habits towards driving a car. The results are shown in Figure 4.12.

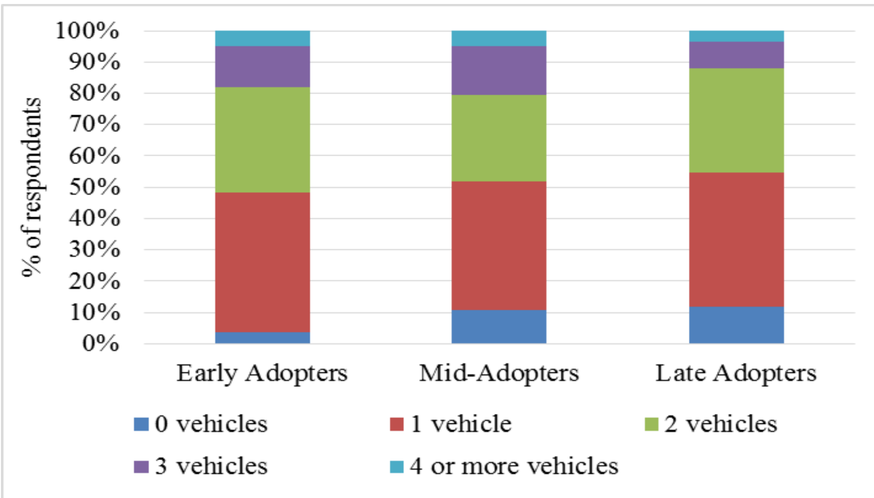

Figure 4.11: Car ownership across clusters

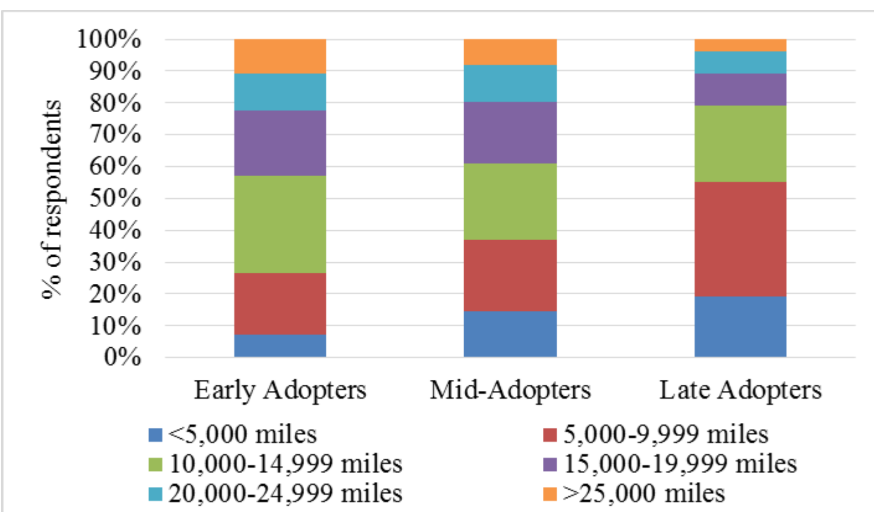

Figure 4.12: Mileage across clusters

Travel and EV charging characteristics

Car sharing or ride-hailing services appear to be more attractive to early adopters, since 34% of respondents are members of one of these or both services (Figure 4.13). Only 17% of mid-adopters and just 4% of late adopters are members of car-sharing or ride-hailing services. This shows that early adopters are willing to try innovative services compared to the other clusters and this is why they could adopt the ER technology more quickly.

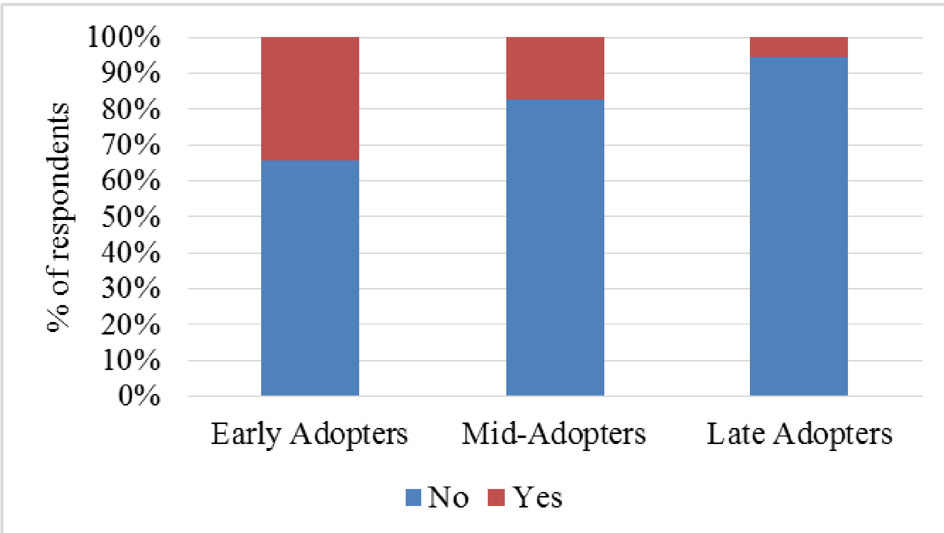

Figure 4.13: Car sharing or ride hailing membership across clusters

Even if the majority of respondents in each cluster does not own an EV, there are some respondents that have driven an EV in general (Figure 4.14). The highest percentage of respondents that have driven an EV appears in the early adopters' cluster (37%). On the other hand, 23% of mid-adopters and just 14% of late adopters have driven an EV. This might mean that if an individual has a more positive evaluation (perception, attitudes) of EVs from experiencing them, he or she will probably be more willing to purchase this kind of vehicle or generally try new technologies associated with the use of EVs. This finding is in line with other studies as well (e.g., Skippon & Garwood, 2011; Jabeen et al., 2012).

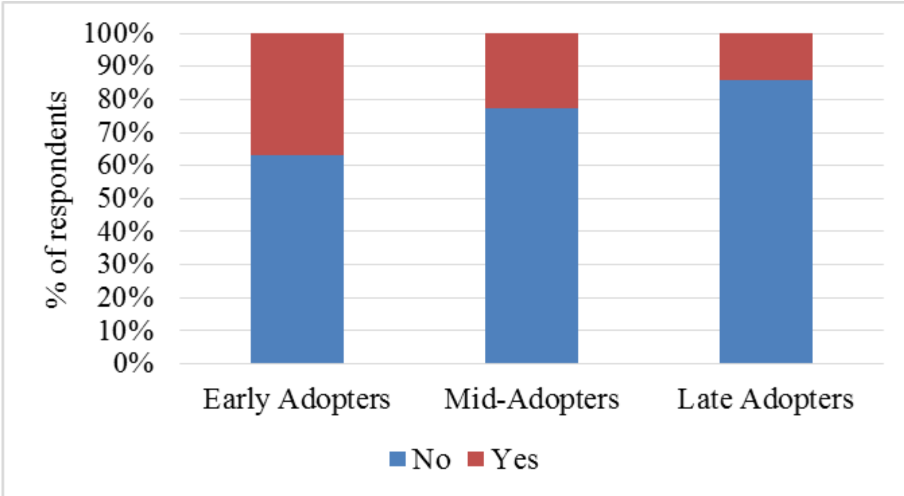

Figure 4.14: EV experience across clusters

Early adopters charge their EV more than the other clusters do. In particular, 21% of early adopters charge their EV at home at least a few times per week while this percentage drops to 16% for mid-adopters and 6% for late adopters. A similar trend exists for EV charging at work or public/private charging stations. This may indicate that early adopters have greater needs in terms of charging, since they use their EVs more and are concerned about their vehicle's range. In addition, the majority of early adopters seem to charge their EVs at home (21%) compared to the other locations. This finding may imply that early adopters who mostly charge their EVs at home seem to have invested more in this technology by purchasing the charging equipment needed. Thus, the technology of ER which overcomes range anxiety would seem more attractive to them compared to the other clusters. The results are shown in Figures 4.15-4.17.

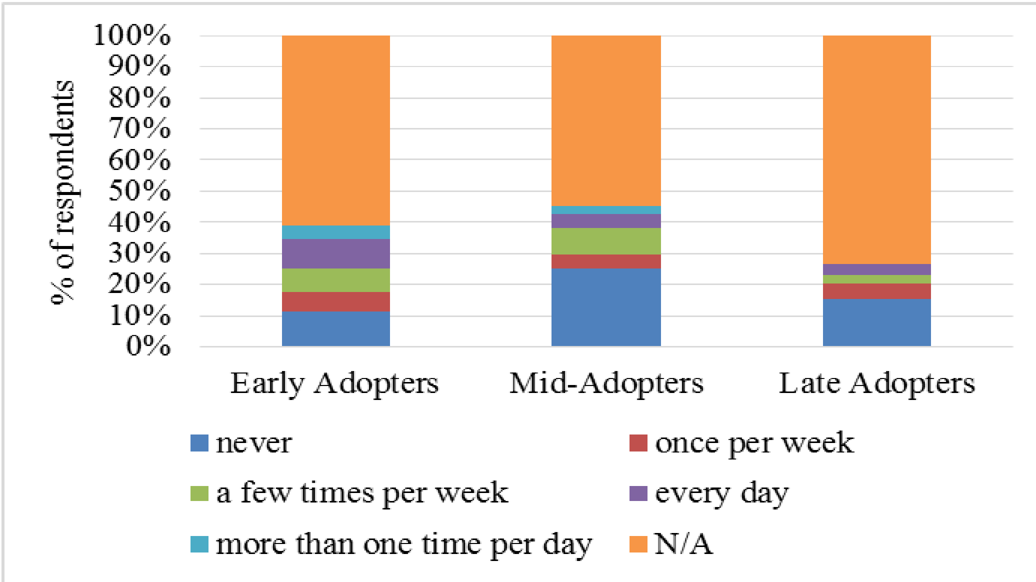

Figure 4.15: Charging frequency at home across clusters

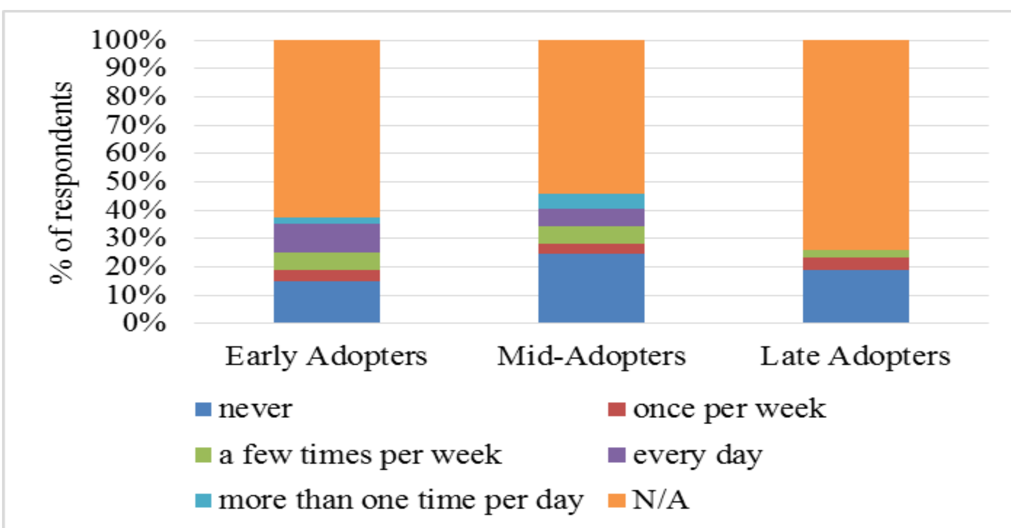

Figure 4.16: Charging frequency at work across clusters

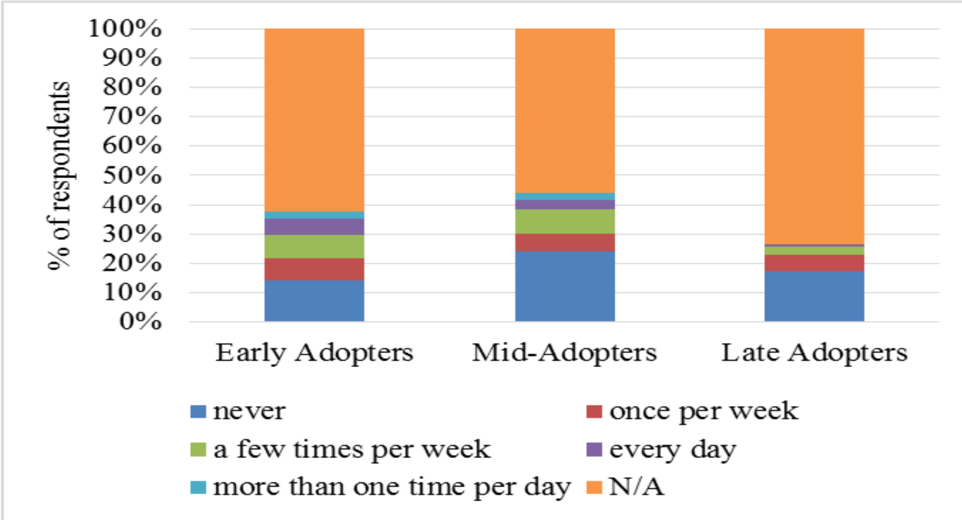

Figure 4.17: Charging frequency at public/private stations across clusters

When respondents were asked about their battery's level when they leave home, the majority of early adopters answered that their EVs are fully charged (26%) while this respondents' share drops for mid-adopters (16%) and late adopters (14%) (Figure 4.18). This may indicate that people who usually fully charge their EV before they leave home are more concerned about their vehicle's range and thus, a technology that overcomes a barrier like that would be appealing to them.

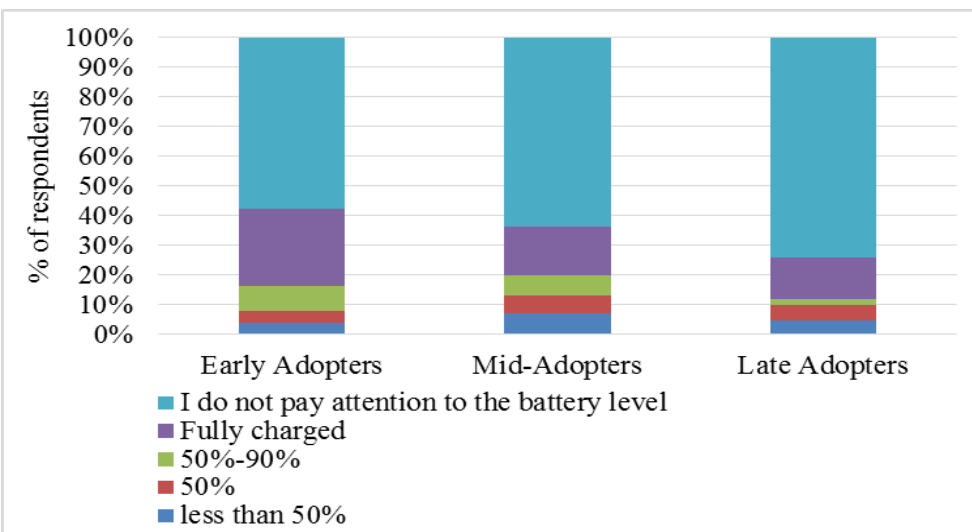

Figure 4.18: Battery level when they leave home across clusters

Level of awareness

Results indicate that early adopters have a higher level of awareness. On average 16% of early adopters indicated that they are following the news about the topics related to electro-mobility presented in the level of awareness section of the survey. The corresponding percentages for mid-adopters and late adopters are on average only 9% and 5% respectively. In addition, the cluster of early adopters has the highest average score in all the questions related to the level of awareness, followed by mid-adopters and lastly late adopters. The results are shown in Figures 4.19-4.22.

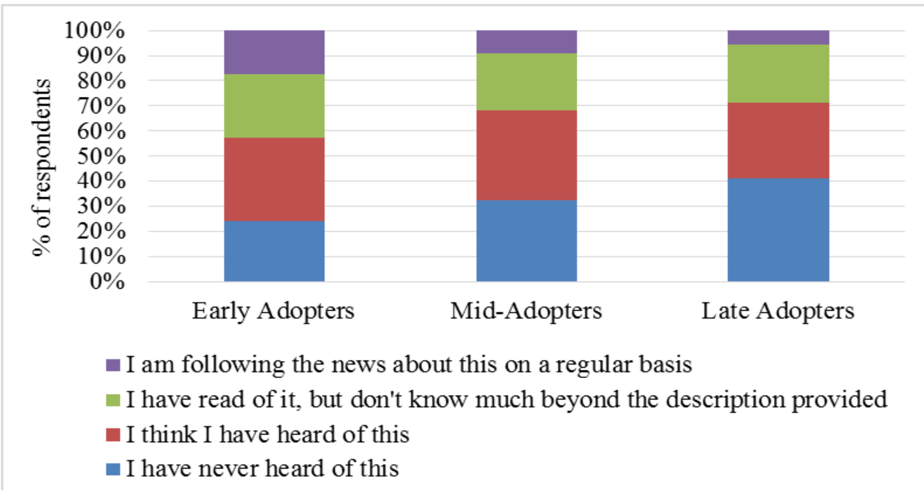

Figure 4.19: Level of awareness across clusters-1

("Are you aware of California's goal of getting 1.5 million zero-emissions vehicles on the states' roads by 2025"?)

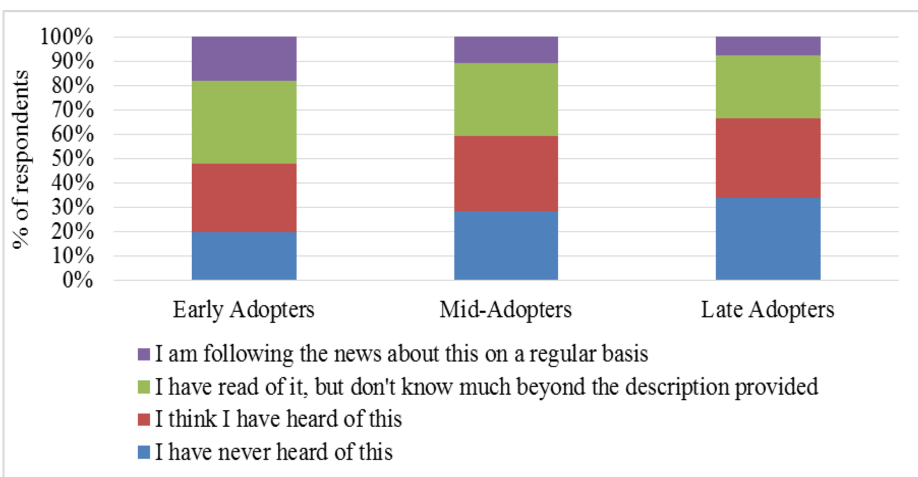

Figure 4.20: Level of awareness across clusters-2

("Are you aware that California has given tax rebates to buyers of new Zero Emissions Vehicles"?)

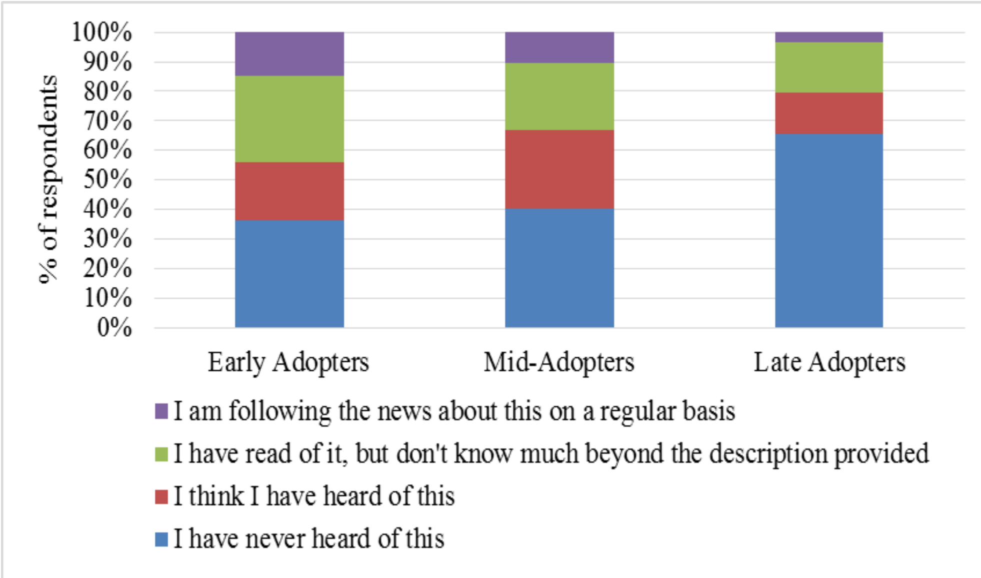

Figure 4.21: Level of awareness across clusters-3

(“Have you ever heard about on-road charging of EVs”?)

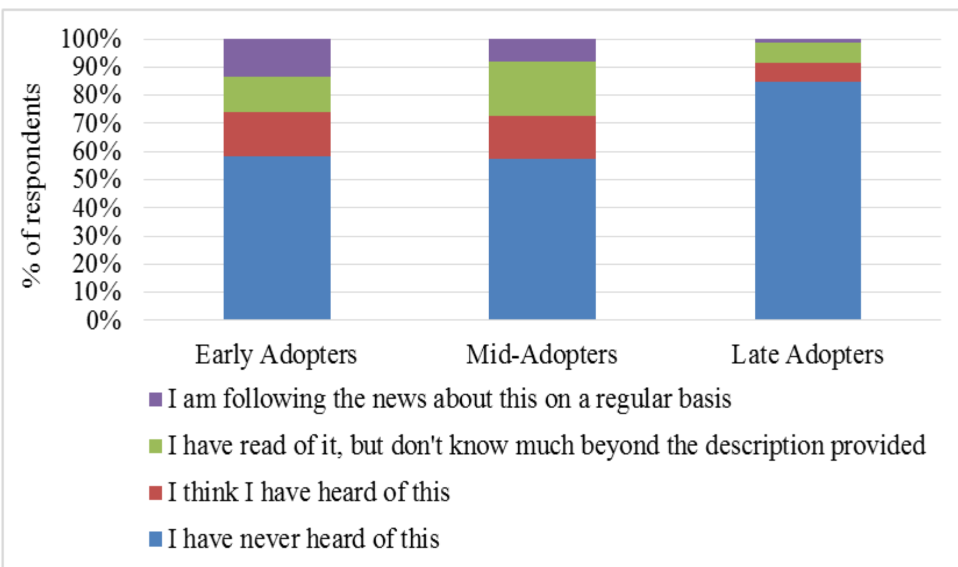

Figure 4.22: Level of awareness across clusters-4

(“Have you heard that there was a proposal to electrify a section of Interstate 710 with on-road charging”?)

The following table (Table 4.16) summarizes the main findings for early, mid- and late adopters.

Table 4.16: Summary of clusters characteristics – market segmentation analysis

Early Adopters	Mid-Adopters	Late Adopters
40% are Millennials (<34 years old)	Most dominant age category is people 35-44 years old (20%)	Most dominant category people 65 or above years old (24%)
48% have annual income over $75,000	Most dominant income category (28%) is annual income of $25,000-$50,000	50% have annual income less than $50,000
53% work full time (8% are currently unemployed)	44% work full time (9% are currently unemployed)	32% work full time (12% are currently unemployed)
45% own one vehicle, 18% own three or more vehicles and 4% do not own a vehicle. 39% drove more than 15,000 miles last year	41% own one vehicle, 20% own three or more vehicles and 11% do not own a vehicle. 20% drove between 5,000-10,000 miles last year	43% own one vehicle, 12% own three or more vehicles and 12% do not own a vehicle. 19% drove more than 15,000 miles and 17% less than 5,000 miles last year
34% use ride-hailing services	17% use ride-hailing services	4% use ride-hailing services
37% have driven EVs	23% have driven EVs	14% have driven EVs
Most dominant category is charging their EVs every day and the most usual charging location is at home	Most dominant category is charging their EVs few times per week and the most usual location is at work	Most dominant category is charging their EVs once per week and the most usual location is at home
Higher level of awareness on topics related to electro-mobility	Average level of awareness on topics related to electro-mobility	Lower level of awareness on topics related to electro-mobility

4.2.3.5 Cluster Solution Validation

As a last step, a discriminant analysis was conducted to validate the results obtained from the CA. Through this procedure, a predictive model is built for group membership. Discriminant functions are generated from a sample of cases with known cluster membership and low correlation. The process is effective if group membership is based on values of a categorical variable and predictor variables are continuous following a normal distribution. An additional assumption of the procedure is that the smallest group should be greater in size than the number of predictor variables (Bian, 2012).

This procedure is a case of reversed ANOVA, the predictors (average scores of the factors) are used as independent variables and the group membership is used as dependent variable. After ensuring that all the assumptions are met, the four components were used to classify respondents in relation to the three groups established in the cluster analysis. The independent variables were entered together for the analysis. The prior probabilities of membership in the groups formed are calculated for each observation, using different group sizes.

Table 4.17 illustrates the results of the discriminant analysis. According to the table, overall 94.2% of original grouped cases was correctly classified. In particular, the table shows the level of accuracy with which respondents were classified into the three groups. It can be read as follows: 89.2% of cluster 1 (mid-adopters), 88.1% of cluster 2 (late adopters) and 100% of cluster 3 (early adopters) were correctly classified. The rest 10.8% of mid-adopters was classified to early adopters and the remaining 11.9% of late adopters was classified to early adopters.

Table 4.17 shows that the model does a satisfactory job of classifying the survey respondents by showing a high level of classification accuracy. Thus, the cluster analysis results can be claimed as credible and can confirm the existence of three well discriminative groups of respondents with respect toward the four factors that are strongly associated with the ER technology.

Table 4.17: Classification results

Cluster Number of Case		Predicted Group Membership			
		Cluster 1 (Mid-Adopters)	**Cluster 2 (Late Adopters)**	**Cluster 3 (Early Adopters)**	**Total**
Count	Cluster 1 (Mid-Adopters)	148	0	18	166
	Cluster 2 (Late Adopters)	0	126	17	143
	Cluster 3 (Early Adopters)	0	0	291	291
%	Cluster 1 (Mid-Adopters)	89.2	0	10.8	100.0
	Cluster 2 (Late Adopters)	0	88.1	11.9	100.0
	Cluster 3 (Early Adopters)	0	0	100.0	100.0
Overall accuracy of classification		94.2%			

5. IMPACT ON CRITERIA POLLUTANTS AND GREENHOUSE GAS EMISSIONS

This chapter describes the model used to assess the impact of ERs on criteria pollutants and greenhouse gas (GHG) emissions as well as the data used and assumptions made for the analysis. The results regarding the emissions change due to the implementation of the ERs are presented, considering the scenarios of early (optimistic) and late (pessimistic) adoption. A sensitivity analysis with respect to speed is also conducted to account for the effect of different traffic conditions on the emissions related to ERs.

5.1 Model Presentation

Vehicle emissions and criteria pollutants resulted from the dynamic charging are calculated using California Air Resources Board's (CARB) 2017 EMissions FACtor model (EMFAC). EMFAC2017 estimates tailpipe (or tank-to-wheel) emissions and supports air quality planning and state implementation plans. This model includes the latest emissions inventory model that calculates mobile emissions of motor vehicles operating on roads in California (California Air Resources Board [CARB], 2017b).

This model was selected because it includes the latest and most accurate data on California's car and truck fleets and travel activity, supporting air quality and state implementation plans and rulemaking (California Air Resources Board [CARB], 2017a). The model reflects CARB's current understanding of vehicle's way of travel and emissions production (California Air Resources Board [CARB], 2017b) and thus, it can be generally used to show emission changes over-time as well as future projections (California Air Resources Board [CARB], 2017b). This way CARB can assess potential control programs and proposals with the view to shielding the environment (California Air Resources Board [CARB], 2017b).

The modeling is based on two main processing steps. The first step includes the determination of the emission factors that state the rate at which the emissions are produced and in the second step, estimates of vehicle activity are calculated. Then, the emissions are found using the following relationship:

Emissions= emissions rates x vehicle activity data from motor vehicles Equation 5.1

where emissions rates are expressed in mass of pollutant (grams) emitted per mile traveled, per vehicle per day or per trip made and vehicle activity data is data from all motor vehicles, from passenger cars to heavy duty cars operating on highways, freeways and local roads in California (California Air Resources Board [CARB], 2017b). A list of all the vehicle classifications that are available in EMFAC2017 is presented in Appendix E (Table E.1).

The pollutants that are modeled in EMFAC are presented in Table 5.1 (California Air Resources Board [CARB], 2017b). The same table also presents the types of emission processes that are available for the analysis (California Air Resources Board [CARB], 2017b). The emission processes account for the daily emissions of a vehicle regardless of its condition (in-motion or otherwise).

Table 5.1: Primary pollutants and emissions processes in EMFAC2017

Primary Pollutants and GHGs	Carbon monoxide (CO)
	Nitrogen oxides (NO_x)
	Hydrocarbons (HC): HC can be expressed as TOG (total organic gases), ROG (reactive organic gases), THC (total hydrocarbon), or CH_4 (methane). According to the Environmental Protection Agency, ROG is a fraction of TOG and can represent Volatile Organic Compounds (VOC), because of their similarity
	Particulate matter (PM): particulate matters 10 microns or less in diameter (PM_{10}), and particulate matters 2.5 microns or less in diameter ($PM_{2.5}$)
	Sulfur oxides (SO_x)
	Fuel: fuel consumption based on the tailpipe emissions of CO, CO_2 and THC using the carbon balance equation
	Greenhouse Gases (GHG): CO_2, Nitrous Oxide (N_2O) and Methane (CH_4)

Table 5.1 continued

Emissions Processes	Running Exhaust Emissions (RUNEX): while the vehicle is traveling on the road
	Idle Exhaust Emissions (IDLEX): while the vehicle is operating but not traveling significance distances (e.g., during loading or unloading of HDVs)
	Start Exhaust Tailpipe Emissions (STREX): when the vehicle is starting to work
	Diurnal Evaporative HC Emissions (DIURN): when increased ambient temperatures lead to fuel evaporation due to the vehicle being inactive
	Resting Evaporative Losses (RESTLOSS): when fuel permeation occurs through rubber and plastic vehicle components while the vehicle is inactive
	Hot Soak Evaporative HC Emissions (HOTSOAK): when fuel heating or vapor losses occur after a trip is made
	Running Loss Evaporative HC Emissions (RUNLOSS): when hot fuel vapors are released from the vehicle's fuel system
	Tire Wear Particulate Matter Emissions (PMTW): due to wear of tires
	Brake Wear Particulate Matter Emissions (PMBW): due to break usage

There are different tools for different types of emissions analyses and purposes in EMFAC. The run modes that are offered are the following: the emissions mode (Custom or Default Activity) and the emissions rate mode (Project Level Analysis-PL). These modes are included in the full version of the model. The web database option is also an alternative and provides the ability for analyses using both emission rates and emissions.

The emissions mode of the full model version is proposed for regional analyses and is based on travel activity data (California Air Resources Board [CARB], 2017b). The vehicle activity data are either default to facilitate fuel-based inventory analyses or customized by the user in order to include regional travel activity data of local transportation agencies. The researcher can define the level of detail of the output using a variety of options, depending on his /her needs. In particular, the emissions mode provides the ability to conduct emissions analysis by area, calendar year, vehicle type, vehicle model year or aggregated, speed or aggregated, pollutant and process. The area types provided for selection are: Statewide, Air Basin, Air District, MPO, County, Sub-area and specific geographic areas.

The default activity mode offers the capability of specifying emissions by vehicle model year and also for EVs. These two features are not available in the custom activity mode and constitute the main difference between the two run types. The custom activity mode is usually proposed when the goal is to estimate on-road emissions for State Implementation Plans (SIPs) (California Air Resources Board [CARB], 2017b). This type of modeling can also generate an output for natural gas heavy duty vehicles.

The emissions rate mode (Project Level Analysis) is used for generating emission rates for a Project-Level assessment using specific data (California Air Resources Board [CARB, 2017b). This mode is more data intensive, since local meteorological and activity data are needed. Another major difference compared to the emissions mode is that in the emissions rate mode, the emission rates can be generated using the aggregate option for the vehicle technology type. Although in the emissions mode the analysis by speed is optional, in the project level mode speed bins must be selected in order to estimate the emissions rates.

The EMFAC Web database option is an on-line platform that provides an easy way to conduct emissions analysis without the need for installing the full version of the model. The user specified conditions are the same with the aforementioned modes with the difference that the Web Database can provide spatially aggregate data without accepting user activity inputs during modeling. In addition, it currently does not include hourly emissions data or emission rates data by temperature and humidity.

In conclusion, different data types provide different levels of detail. The following table (Table 5.2) provides a summary of the features that are available (√) or not (X) so far in the three aforementioned tools (California Air Resources Board [CARB], 2017a).

Table 5.2: Model features across EMFAC mode tools

(California Air Resources Board [CARB], 2017a)

Tools/Features	**Full model version**			**Web Database**
	Emission Mode Default Activity	**Emission Mode Custom Activity**	**Emission Rate Mode**	
Aggregated Area	X	X	X	√
Model Year	√	X	√	√
Aggregated Vehicle Class	X	X	√	X
Temperature/Relative Humidity	Default only	Default only	Users specific	Default only
Hourly Emissions/Emission Rates	√	√	√	X
Emissions/Emission Rates for EVs	√	X	√	√
Emissions/ Emission Rates for Natural Gas Vehicles	X	√	√	X
Emissions/Emission Rates for all pollutants	√	√	√	No Total Hydrocarbon (THC), No Total Particulate Matter (TPM)
Daily emissions/Emission Rates by calendar year or season, speed and process.	√	√	√	√

EMFAC modeling uses vehicle population, in-use emissions and travel activity data to calculate emissions. In particular, EMFAC2017 uses vehicle fleet characteristics based on 2013-2016 vehicle registration data from California Department of Motor Vehicles (DMV). For the heavy-duty vehicle population, the most recent International Registration Plan (IRP) Data is used as another source. California Highway Patrol (CHP) School Bus Inspections and National Transit Database (NTD) data are also used to characterize school buses and urban transit buses respectively (California Air Resources Board [CARB], 2017b).

Extensive emission testing (on-road and chassis dynamometer) of light duty and heavy-duty trucks provides the data for the necessary emission factors (California Air Resources Board [CARB], 2017b). More specifically for light duty vehicles (LDVs), the following data sources that are used for estimating the emission rates: new Federal Test Procedure (FTP) data from the US Environmental Protection Agency's In-Use Vehicle Program (IUVP), data from CARB's Vehicle Surveillance Program (VSP) and national fuel efficiency data on CO_2 rates from the official US government source for fuel efficiency information (www.fueleconomy.gov) (California Air Resources Board [CARB], 2017c). For the emissions and speed correction factors related to medium heavy-duty (MHD) and heavy heavy-duty (HHD) diesel trucks, EMFAC2017 utilizes data from a variety of sources such as: the UC Riverside testing project, CARB's Truck and Bus Surveillance Program (TBSP), CARB PEMS tests, Texas A&M Transportation Institute (TTI) idle testing projects, Integrated Bus Information System (IBIS) of West Virginia University (WVU), CARB's Transit Bus Tests of Valley Transit Agency (VTA) and bus data by Altoona Center.

The model also develops vehicles' profiles through the collection of vehicle activity characteristics that influence emissions production. The datasets used for the activity profiles of LDVs and HDVs include state Metropolitan Planning Organizations (MPOs), the Bureau of Automotive Repair (BAR) Smog Check Data (2001-2014), the 2010-2012 California Household Travel Survey and activity data from the study of the UC Riverside's College of Engineering-Center for Environmental Research & Technology (UCR CE-CERT) (California Air Resources Board [CARB], 2017c). However, depending on the mode selected, localized activity profiles developed by transportation agencies can be used to create regional emission inventories (California Air Resources Board [CARB], 2017c).

To determine the change of sales and VMT data over-time, EMFAC2017 relies on regression model forecasting techniques using the latest data from UCLA Anderson Forecast (UCLA), California Department of Finance (DOF), California Board of Equalization (BOE), California Energy Commission (CEC), US DOE Energy Information Administration (EIA), and US Bureau of Economic Analysis (BEA) (California Air Resources Board [CARB], 2017b). In particular, planning agencies use transportation models to estimate overall target VMT for a base year and predict VMT for the following years. These models are based on historical fuel sales and regression-based growth rates and estimate new future VMT as a function of socioeconomic indicators such as the gas price, the unemployment rate, disposable income, etc.

Finally, the regulations and policies related to air quality and reduction of greenhouse gases (GHG) emissions are based on Phase 2 GHG standards, the Road Repair and Accountability Act of 2017 (Senate Bill 1) and updates on Advanced Clean Cars (ACC) regulation based on the 2017 Midterm review (California Air Resources Board [CARB], 2017c). Emissions standards of these policies are used by the model to estimate the change in emission factors over time.

For more information on the data and methods used by EMFAC2017, the interested reader can refer to the technical documentation of the model that includes the necessary details (California Air Resources Board [CARB], 2017b).

5.2 Data and Methods

In order to estimate the on-road emissions that would occur as a result of the implementation of ERs, two scenarios will be considered. These scenarios are termed “without electrification” for the current condition in the study area and “with electrification” for the case in which the technology of ERs is implemented and localized data will be used for the analysis. The horizon year is the period 2018-2050 due to the availability of EMFAC resources. Overall, the steps followed for the analysis are: corridor selection, development of assumptions, data collection, EMFAC model application.

5.2.1 Corridor Selection

The analysis was based on the I-710 corridor in LA (Port of Long Beach to Valley Blvd). I-710 is a north-south auxiliary freeway running for 22 miles through Los Angeles within the Southern California Edison (SCE) territory. Since it is a freeway corridor, the average speed of vehicles driving on this corridor depends on the traffic conditions each time of day. On average, speeds can vary from 30 to 70 mph, with the majority of traffic operating at 50-70mph throughout the day, based on PeMs (Performance Measurement) data. Different segments of I-210 have different number of lanes, ranging from three to six (including HOV lanes in some segments) (California Department of Transportation [Caltrans], 2013). Many segments of this corridor operate at level of service (LOS) E or F throughout the day (California Department of Transportation [Caltrans], 2012; City of Los Angeles, 2012) mainly due to the high average daily traffic and the aging infrastructure of the corridor. A summary table showing some basic geometric characteristics of I-710 is presented in Appendix E (Table E.2) (California Department of Transportation [Caltrans], 2013).

As a result, serious problems appear, including safety risks (e.g., damage on the freeway pavement), congestion and air pollution, mostly originating from diesel-fueled vehicles idling in rush-hour traffic congestion. Hence, the cities in the vicinity of these corridors deal with serious traffic issues and low air quality, putting the public health of LA residents in jeopardy. In response, government associations, LA residents and community groups are making efforts to improve air quality, mobility, congestion, safety and assess alternative, green goods movement technologies (LA Metro, 2018). More information on the corridor data used is presented at a summary data table later. Figure 5.1 shows the location of I-710 corridor.

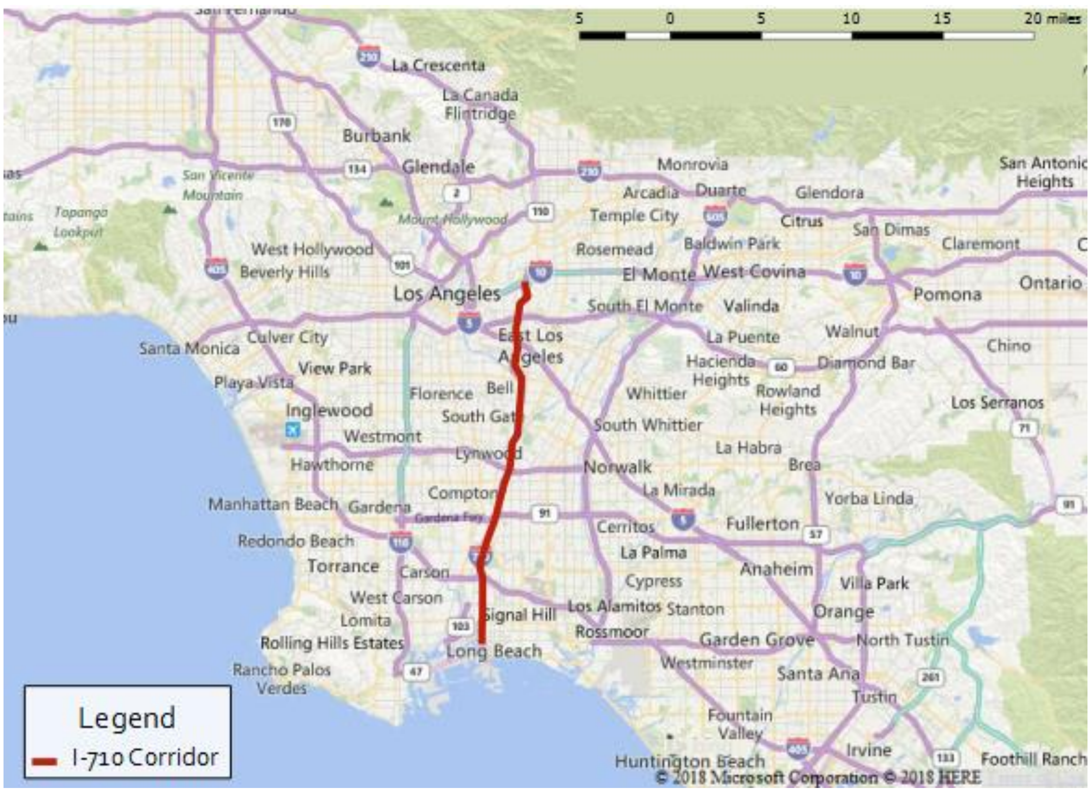

Figure 5.1: Overview of study corridor (I-710)

(Bing Maps)

5.2.2 Assumptions

The main initial assumptions made for the analysis are presented in the following table (Table 5.3) by subject of interest.

Table 5.3: Assumptions for emissions modeling

Subject	Assumptions
Corridor selected	It was assumed that both directions of the corridor will be electrified.
Type of emissions	The ER infrastructure or vehicle manufacturing emissions are not included in the analysis. Since the ER technology is about dynamic charging, the emissions analysis focuses on the emissions while the vehicle is traveling on the road. Thus, the running exhaust emissions are explored.
Vehicle types	Since the choice experiment was designed only for light-duty vehicles (the survey respondents did not include medium and heavy-duty vehicle owners or operators), it would be more effective to focus only on light duty vehicles for which the adoption rates were found. The category of light duty vehicles (LDV)–non-truck in EMFAC consists of the following vehicle types (EMFAC2007 Categories): -Passenger cars (LDA) -Light- duty vehicles with GVWR<6000lbs and ETW<=3750 lbs (LDT1) -Light-duty vehicles with GVWR<6000lbs and ETW 3751-5750lbs) (LDT2)
Pollutants and emissions	CO_2, CO, NO_x, ROG, $PM_{2.5}$, PM_{10}, N_2O, CH_4 and SO_x
Adoption rates	The adoption rate represents those who will adopt the technology including both EV owners or not. It shows the percentage of people who will use ERs, meaning that the diesel/gas vehicles and the corresponding VMT will be reduced by this percentage (VMT reduction due to the eVMT and the VMT of individuals who would adopt the ERs).
VMT	VMT per capita will remain the same between the “without electrification” and “with electrification” scenarios.

The previous table also includes the main settings used for the EMFAC2017 Web database model.

5.2.3 Traffic Data

In order to conduct the analysis, traffic related data on the I-710 corridor was necessary in order to construct the “without electrification” scenario. Average aggregate values were sought, since the analysis would constitute a high-level planning. The following table (Table 5.4) shows the data found for the conditions in I-710.

Table 5.4: I-710 traffic data

Type of data	Use	Value	Source
Average annual daily I-710 LDV VMT (2017-2018)	Estimation of aggregate I-710 VMT for “without electrification” scenario for year 2018	3,442,355 VMT (both directions)	PeMs version 18.00 (VMT aggregates for I-710: 2017-2018) Processed in excel: non-truck average annual VMT per direction of travel
Diesel/gas VMT per vehicle type in LA for each year	Estimation of I-710 VMT for “without electrification” scenario per fuel and vehicle type for year 2018	The proportion of diesel/gas VMT of I-710 is assumed to be the same for LA diesel/gas VMT	EMFAC2017 model data I-710 Energy technical report, 2017
Average speed in I-710	Setting for the model run. Use also for sensitivity analysis	65mph	PeMs version 18.00 (speed distribution across VMT in I-710) More than 48% VMT was observed in high speed bins (65mph)
Traffic growth for VMT	Estimation of the VMT change over the years for “without” electrification scenario and reduce 2018 VMT	The VMT growth in I-710 per vehicle/fuel type was assumed to be the same as this in LA per vehicle/fuel type	EMFAC2017 model data.

5.2.4 Adoption Rates Data

An important input for the emissions modeling is the market penetration rates of ERs found from the survey on general population. The accurate prediction of the rate of market penetration over the years includes great uncertainties and depends on a variety of influencing factors (i.e., fossil fuel price, national incentive schemes and new developments in EV technology). In this analysis, the rate of market penetration from 2018-2050 is estimated based on the assumption of a logistic S-curve. This methodology is in line with other studies, which have used S-curves to predict the market penetration of new technologies (Draper et al., 2008; Choi et al., 2013; Brady & O'Mahony 2011; Smith, 2010).

The logistic curve is determined by specifying two points (year, adoption rate) of the curve. Assuming that in 2018 the adoption will be 0%, two scenarios are explored: an "optimistic" scenario achieving 48.5% market adoption for ERs by 2050 and a "pessimistic" scenario indicating 23.8% adoption by 2050. These values correspond to the percentages of early and late adopters of the survey, respectively. The equation of the S-curve is given by the following:

$$f(x) = \frac{1}{1+e^{-x}} \qquad \text{Equation 5.2}$$

This equation is transformed by adding two parameters (α and T_0) in order to reflect the growth of adoption (Branderwinder, 2008; Humphrys, 1987):

$$f(x) = \frac{1}{1+e^{-\alpha(t-T_0)}} \qquad \text{Equation 5.3}$$

where f(x) indicates the adoption rate value

t indicates the time (year)

α is a parameter that stretch or compress time

T_0 is a parameter and shift the timeline of the curve

By applying and calibrating the parameters of s curve function, the values shown in Figure 5.2 were obtained.

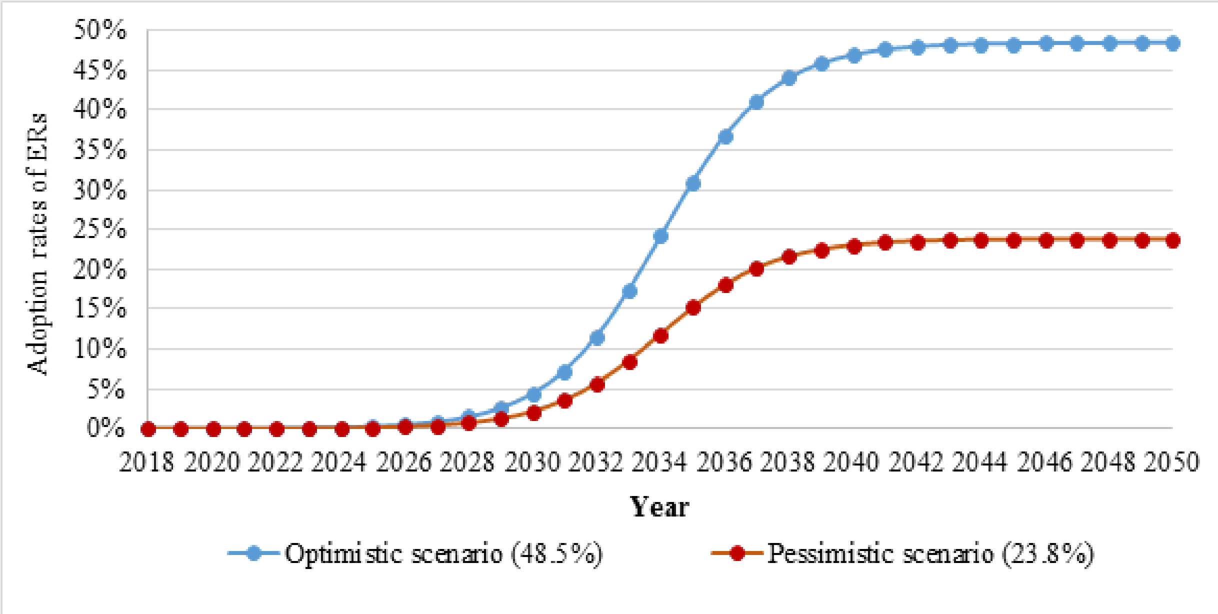

Figure 5.2: Projected ER penetration under two scenarios: "optimistic" (48.5% by 2050) and "pessimistic" (23.8% by 2050)

5.2.5 Methods

Based on the aforementioned assumptions, the EMFAC2017 Web Database model was run for the general LA area and for speed of 65 mph generating the emissions rates regarding the travel activity of light duty vehicles in the area. The data for I-710 described in the previous section was used to obtain the current situation (VMT and emissions) in the corridor (without electrification scenario), since EMFAC2017 Web database does not provide the ability for a corridor analysis.

The calculated emission rates and I-710 VMT are found only for the diesel and gas LDVs operating in the specific speed chosen (65mph). More specifically, EMFAC model generates an output with LA VMT for diesel and gas vehicles operating at 65mph and the proportion of diesel and gas VMT by vehicle type in LA is estimated for 2018. By assuming that the fuel type share remains constant, the I-710 VMT found from PeMs database are multiplied by each percentage to obtain the gas and diesel VMT by vehicle type in the corridor.

The future VMT for the "without electrification" scenario were based on VMT growth models and vehicle profiles of EMFAC, as described in Section 5.1. The adoption rates were used to appropriately reduce the VMT in the existing situation and produce the "without electrification" scenario. The emission rates of pollutants were estimated for light-duty vehicles and converted into emissions based on the VMT levels. The following figure (Figure 5.3) shows the aggregate method used to estimate the impact of ERs on emissions.

It is important to mention that the majority of the assumptions developed (the VMT per capita remains the same before and after the electrification of I-710, the proportion of diesel/gas vehicles and traffic growth in I-710 will be the same as in the LA, the ER adoption rates correspond to the VMT reduction that includes both eVMT and "ER VMT") are attributed to data limitations but also due to the high-level nature of the analysis. Future research can work on finding more detailed data on the related topics.

5.3 Results

Based on the VMT and adoption rate change over the years, it is expected that total emissions would decrease on some order of magnitude. The emissions modeling results are presented in the following table (Table 5.5) which contains a summary of the comparisons of VMT and emissions levels between "without electrification" scenario and "with electrification" scenario, including the two cases of adoption rates. As mentioned in Section 5.1, emissions of the criteria pollutants (ROG, CO, NO_X, SO_X, PM_{10}, $PM_{2.5}$) and GHGs (CO_2, CH_4, N_2O) are computed. ROG is used to describe the VOC, since the model does not produce emissions rates for VOC.

The emissions estimates are presented separately for light duty diesel vehicles and light-duty gas vehicles (Table 5.5) summed over the 32-year analysis period (2018-2050). The analysis is not conducted by vehicle type (LDA, LDT1, LDT2), since the results were found to be similar for all the three types; thus, they were analyzed together based only on the fuel type difference. VMT are presented in average annual daily values and emissions are provided in grams. GHG emissions (CH_4 and N_2O) are converted into CO_2 equivalents so they can be compared. The 100-year global warming potential (GWP) of CH_4 compared to CO_2 is 28kg of CO_2 and the GWP of N_2O is 265kg of CO_2, according to the latest values from the Fifth Assessment Report (AR5) (Myhre et al., 2013).

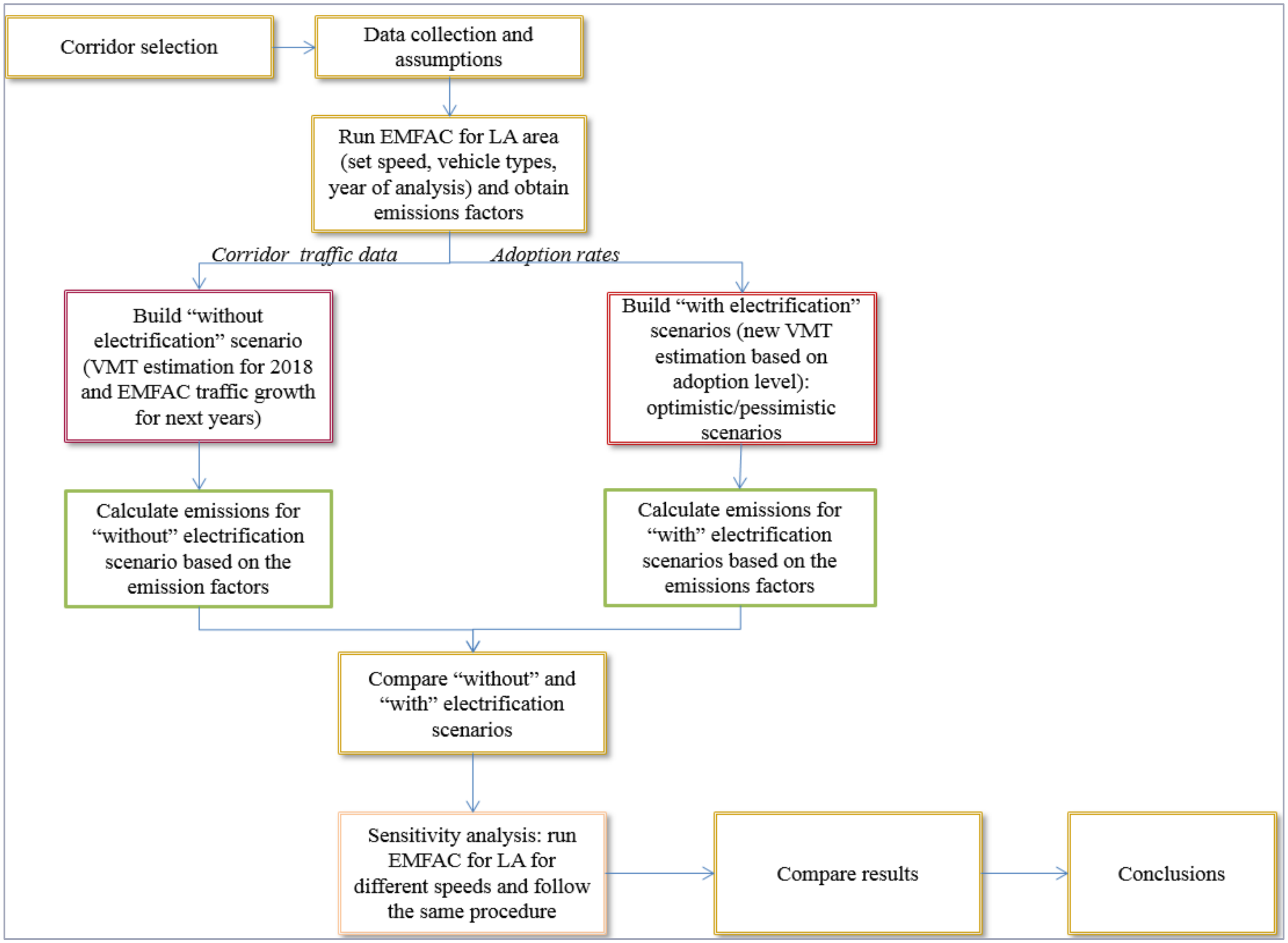

Figure 5.3: Emissions modeling methodology using EMFAC

Table 5.5: EMFAC results-emissions levels across scenarios (speed of 65 mph)

Vehicle type	Measure	Without electrification level	With electrification level-optimistic	With electrification level-pessimistic
LDV (DIESEL)	VMT*	1.04E+06	7.69E+05	9.05E+05
	ROG**	6.02E+03	5.15E+03	5.59E+03
	CO**	9.24E+04	7.41E+04	8.34E+04
	NO_X**	2.97E+04	2.70E+04	2.83E+04
	SO_X**	1.92E+03	1.47E+03	1.70E+03
	CO_2**	2.03E+08	1.55E+08	1.80E+08
	CH_4**	7.83E+06	6.69E+06	7.27E+06
	PM_{10}**	3.36E+03	3.01E+03	3.19E+03
	$PM_{2.5}$**	3.22E+03	2.88E+03	3.05E+03
	N_2O**	8.48E+09	6.46E+09	7.49E+09
LDV (GAS)	VMT*	1.07E+08	8.17E+07	9.44E+07
	ROG**	6.07E+05	5.55E+05	5.81E+05
	CO**	4.16E+07	3.45E+07	3.81E+07
	NO_X**	3.58E+06	3.13E+06	3.36E+06
	SO_X**	2.51E+05	1.99E+05	2.25E+05
	CO_2**	2.54E+10	2.01E+10	2.28E+10
	CH_4**	4.48E+09	4.00E+09	4.24E+09
	PM_{10}**	9.22E+04	7.87E+04	8.56E+04
	$PM_{2.5}$**	8.48E+04	7.24E+04	7.87E+04
	N_2O**	1.09E+11	8.98E+10	9.96E+10

**VMT (Annual average daily vehicle miles traveled)*

***Pollutants in grams and GHGs (CO_2, CH_4, N_2O) in CO_2 equivalent grams*

The following figures (Figures 5.4-5.5) show the percent difference in emissions of the two scenarios of “with electrification” scenarios from the “without electrification” scenario. The aggregated results are presented for diesel and gas vehicles.

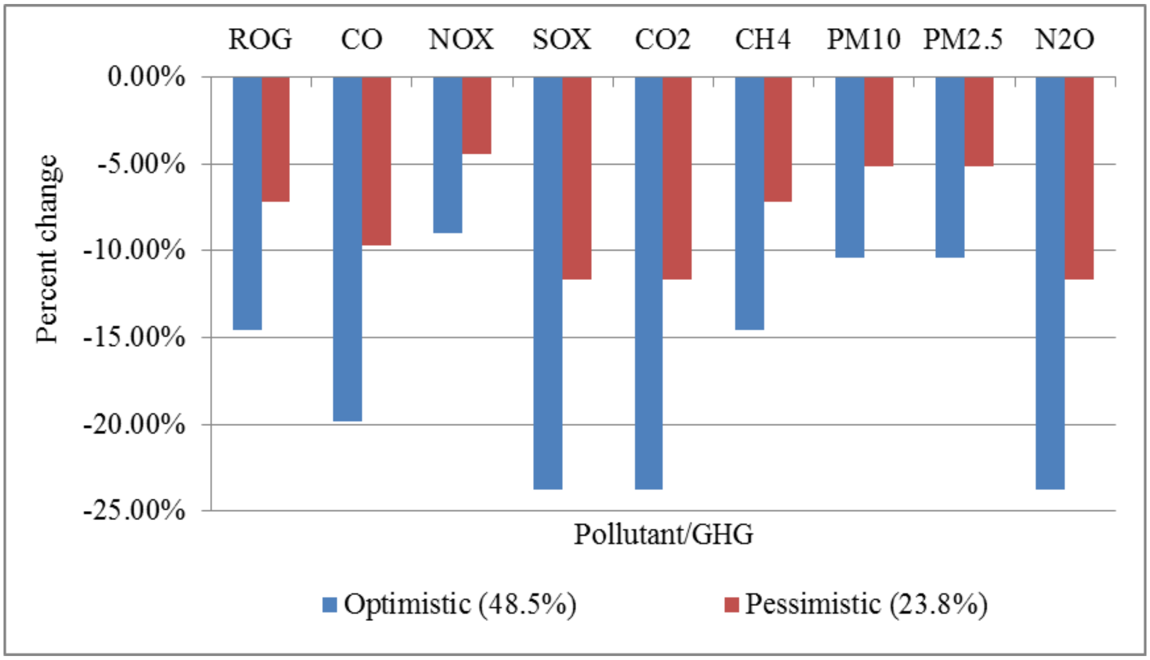

Figure 5.4: Total emissions change for diesel LDVs

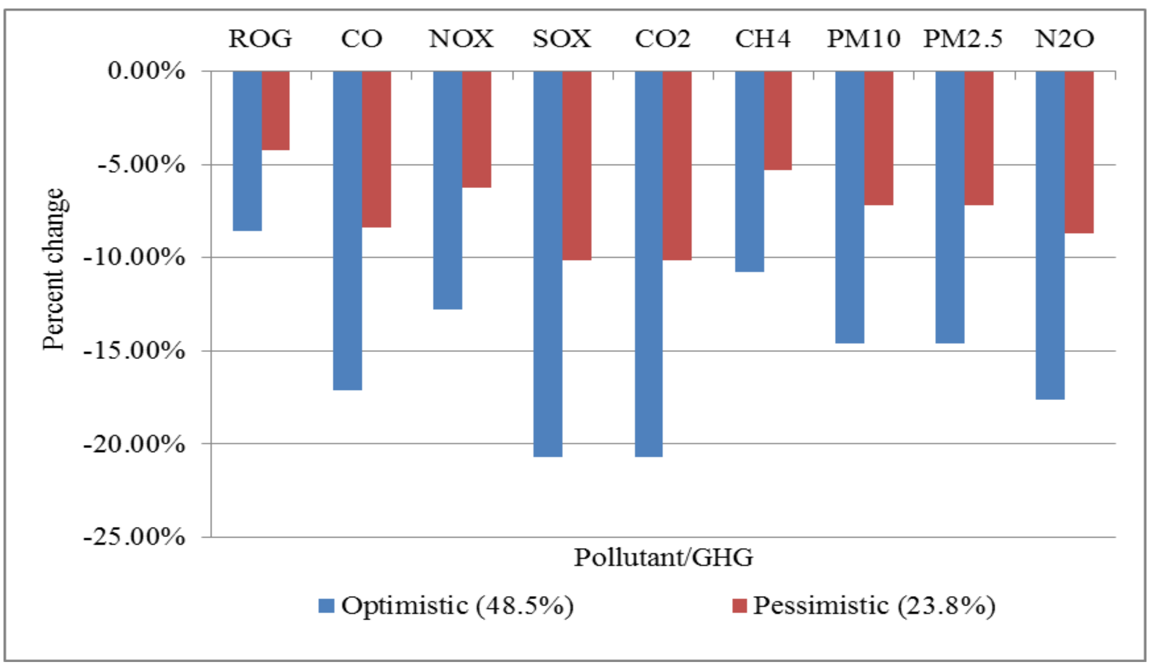

Figure 5.5: Total emissions change for gas LDVs

The results show that the use of ER technology will lead to significant savings with respect to diesel and gas fuel use and emissions, based on the two scenarios adopted. Overall, the emissions reduction for diesel vehicles ranges from 4.43% (pessimistic scenario) to 23.75% (optimistic scenario), while for gas vehicles varies from 4.21% (pessimistic scenario) to 20.68% (optimistic scenario), depending on the pollutant. As expected, the net emissions reduction is greater for all pollutants and greenhouse gases in the optimistic scenario compared to the pessimistic scenario. The resulted emissions reductions may overall reflect the fact that a) diesel and gas engines are certified to strict emissions standards since 2000 which are taken into consideration by the model in order to achieve future emissions reduction targets and b) the adoption of ER technology will lead to more changes with respect to all pollutants and gases.

For both scenarios, the greatest difference for diesel LDVs (24% for optimistic scenario/12% for pessimistic scenario) appears for CO_2, N_2O and SO_x, while the least reduction for the same fuel type comes from NO_x (9%/4%). For gas vehicles, CO_2 and SO_x show the greatest reduction (21%/10%) followed by N_2O (18%/9%) while ROG and CH_4 are close to their base case levels (without electrification scenario).

Turning to CO, while it is produced at a higher level by gas vehicles, diesel vehicles demonstrated greater reductions in both scenarios (20%/9%). In addition, gasoline engines are associated with a greater reduction in PM_{10} and $PM_{2.5}$ (15%/7% for each) compared to diesel engines. This was expected, since gas emission is the primary source of the particular matter pollutant (United States Environmental Protection Agency [EPA], 2002). The same applies for NO_x (13%/6% reduction for gas LDVs) whose levels appear higher for gas vehicles.

While at this study SO_x and PM show a decrease over time, other studies have found that the particular pollutants may increase with the implementation of dynamic charging (Nesbitt et al., 1990; Limb et al., 2017). Given that diesel vehicles constitute primary contributors to SO_x, this thesis' finding suggests that improvements in diesel engines are expected in LA. The model may account for other environmental factors or mandates regarding the transition to ultra-flow diesel fuel, according to the California diesel fuel program (California Air Resources Board [CARB], 2015). As a result, alternative fuel technologies (fuel cell vehicles, natural gas vehicles etc.) are being sought.

Comparing the order of the reduction for each pollutant within each scenario of adoption, it seems that it stays constant. For example, in both adoption scenarios the greatest reduction in emissions originates from SO_x and CO_2 for both fuel types and the lowest from NO_x in diesel LDVs. On the other hand, the emission reduction across the two scenarios is elastic to varying adoption estimates, reaching a maximum of around 15% difference between the two scenarios.

Table 5.6 below illustrates the latter findings including two columns that indicate the order of the reduction in each scenario for both fuel types.

Table 5.6: Order of emissions reduction by adoption scenario (1: greatest reduction-13: lowest reduction) and emissions reduction from current condition across scenarios by pollutant

Vehicle type	Measure	%Difference (optimistic)	Order	% Difference (pessimistic)	Order	% difference in emissions levels (optimistic-pessimistic)
LDV (DIESEL)	ROG	-14.55%	7	-7.15%	7	8.7%
	CO	-19.81%	3	-9.73%	3	12.6%
	NO_X	-9.02%	11	-4.43%	11	5.0%
	SO_X	-23.75%	1	-11.67%	1	15.8%
	CO_2	-23.75%	1	-11.67%	1	15.8%
	CH_4	-14.55%	7	-7.15%	7	8.7%
	PM_{10}	-10.41%	10	-5.12%	10	5.9%
	$PM_{2.5}$	-10.41%	10	-5.12%	10	5.9%
	N_2O	-23.75%	1	-11.67%	1	15.8%
LDV (GAS)	ROG	-8.57%	13	-4.21%	13	4.8%
	CO	-17.11%	5	-8.41%	5	10.5%
	NO_X	-12.75%	8	-6.26%	8	7.4%
	SO_X	-20.68%	2	-10.16%	2	13.3%
	CO_2	-20.68%	2	-10.16%	2	13.3%
	CH_4	-10.75%	9	-5.28%	9	6.1%
	PM_{10}	-14.59%	6	-7.17%	6	8.7%
	$PM_{2.5}$	-14.59%	6	-7.17%	6	8.7%
	N_2O	-17.65%	4	-8.67%	4	10.9%

The following figures (Figure 5.6-5.9) show the total reduction in criteria pollutants (ROG, CO, NO_x, SO_x, $PM_{2.5}$ and PM_{10}) and GHGs levels (CO_2, CH_4, N_2O) over the 32 years of analysis for diesel and gas LDVs. As can be seen from the graphs, the emissions reduction is more distinctive across the scenarios approximately after 2030 where a 4% of adoption in optimistic scenario and a 2% adoption in the pessimistic scenario are achieved. This may be related to the fact that California has established targets for emissions reduction by 2030 and 2050 (United States Environmental Protection Agency, 2018), meaning that the reduction would be more intense between these years. The pattern of reduction with respect to pollutants is the same between the gas and diesel fueled vehicles, while the reduction of GHGs shows a different pattern for the two fuel types.

In particular, the pollutants' change for both fuel types show a parabolic trend ending at a point that stands lower compared to the beginning of analysis period. The same applies for the case of gas GHG emissions curves. In contrast, the GHGs curves for diesel LDVs show that the total GHG emissions will increase until 2023. After this year, for the "without electrification" scenario a slight downward trend is evident but the emissions level in 2050 is predicted to be higher than that in 2018. For the "with electrification" scenarios, the GHG emissions substantially decrease from 2023 until 2043 when the reduction rate starts to be smaller. The slower rate at which GHGs are reduced in all the scenarios after a certain time may be attributed to the fact that the reductions from existing mobile source diesel regulations may have been already realized until then (Lyons et al., 2005).

In all the cases though, it seems that the implementation of ERs in I-710 will yield the greatest benefits in terms of emissions reduction under a 48% adoption by 2050.

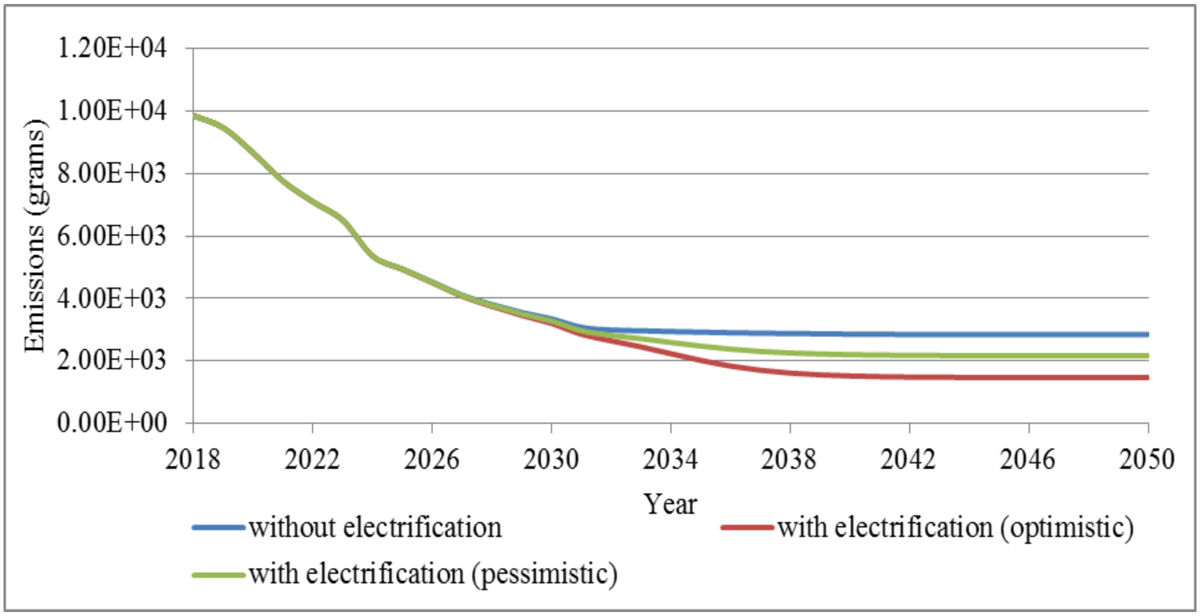

Figure 5.6: Total emissions change from 2018-2050 for diesel LDVs (criteria pollutants)

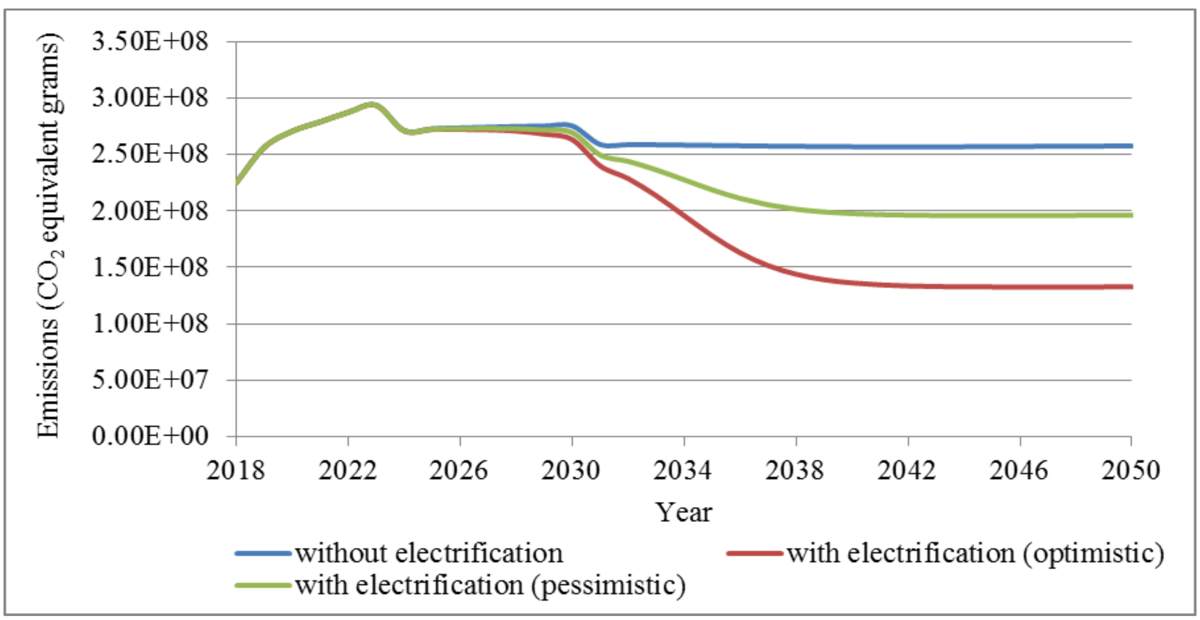

Figure 5.7: Total emissions change from 2018-2050 for diesel LDVs (GHGs)

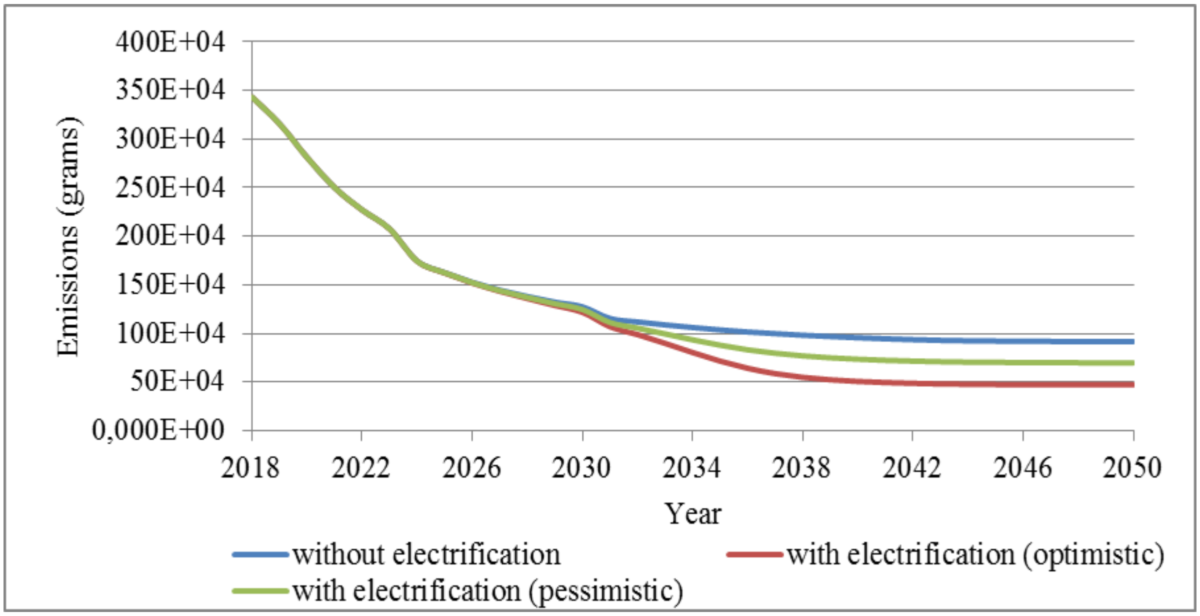

Figure 5.8: Total emissions change from 2018-2050 for gas LDVs (criteria pollutants)

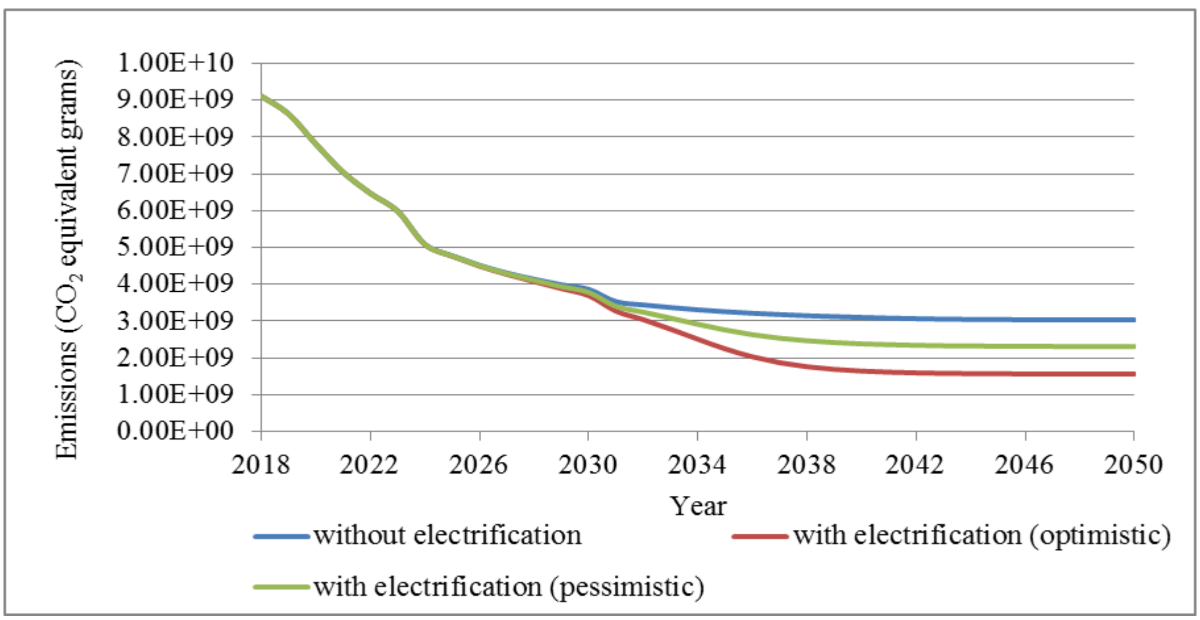

Figure 5.9: Total emissions change from 2018-2050 for gas LDVs (GHGs)

Sensitivity analysis

A sensitivity analysis was conducted in order to test the effect of speed on emissions levels or changes. The purpose of the specific analysis is to indirectly capture different traffic conditions of the corridor corresponding to more congested periods, such as during a peak period. The speed can be highly variable from time to time on the freeways. Based on PeMs data, speeds in I-710 vary on average from 50-70 mph throughout the day. Thus, the minimum speed of 50mph was chosen to be tested. By also considering the peak time periods, the speed under very congested traffic conditions varies from 15mph to 25mph (PeMs data). Thus, an average speed of 20mph was chosen to conduct the analysis (URS Corporation, 2009) and compare the results with those occurring using 65mph.

The emissions estimates for each speed are presented in the following figures (Table 5.7 and Tables 5.8). It is important to mention that by varying the speed, two separate runs were conducted for the two adoption scenarios; one at a time using the same base case of 2018.
Figures 5.10-5.11 show the percent change in emissions across the speeds tested (65mph, 50mph, 20mph) and are presented for gas and fuel LDVs.

As can be seen from the results (Tables 5.7-5.8), for 50mph the emissions levels of diesel and gas CO and diesel CH_4 increased while the emissions of all others decreased compared to these at 65mph. This is in line with other studies that have investigated the effect of speed on emissions, considering freeways (European Environment Agency, 2011; United States National Research Council, 1995; Newman & Kenworthy 1992). The level of emissions' change by pollutant due to the ER technology is higher for both scenarios using 50 mph. Judging by the figures showing the emissions change due to the ER technology (Figures 5.10-5.11) at 50mph, the trend is similar to this in Figures 5.4 and 5.5, regarding the greatest and least emissions reduction compared to the base case. The findings suggest that traveling at a speed that is 30% lower than the average in I-710 corridor and by implementing ERs, emissions can decrease anywhere from around 4.3% (lowest value at pessimistic scenario) and 24.12% (highest value at the optimistic scenario).

Table 5.7: EMFAC results-emissions (speed of 50 mph)

Vehicle type	Measure	Without electrification level	With electrification level-optimistic	With electrification level-pessimistic
LDV (DIESEL)	ROG**	6.39E+03	5.28E+03	5.85E+03
	CO**	1.02E+05	7.92E+04	9.09E+04
	NO_X**	2.92E+04	2.61E+04	2.77E+04
	SO_X**	1.56E+03	1.19E+03	1.38E+03
	CO_2**	1.65E+08	1.25E+08	1.46E+08
	CH_4**	8.32E+06	6.87E+06	7.61E+06
	PM_{10}**	3.14E+03	2.75E+03	2.95E+03
	$PM_{2.5}$**	3.01E+03	2.63E+03	2.82E+03
	N_2O**	6.89E+09	5.23E+09	6.07E+09
LDV (GAS)	ROG**	5.20E+05	4.74E+05	4.97E+05
	CO**	5.33E+07	4.37E+07	4.86E+07
	NO_X**	3.19E+06	2.76E+06	2.98E+06
	SO_X**	2.36E+05	1.86E+05	2.12E+05
	CO_2**	2.39E+10	1.88E+10	2.14E+10
	CH_4**	3.84E+09	3.41E+09	3.63E+09
	PM_{10}**	7.64E+04	6.50E+04	7.08E+04
	$PM_{2.5}$**	7.03E+04	5.98E+04	6.51E+04
	N_2O**	9.95E+10	8.13E+10	9.06E+10

***Pollutants in grams and GHGs (CO_2, CH_4, N_2O) in CO_2 equivalent grams*

Table 5.8: EMFAC results-emissions (speed of 20 mph)

Vehicle type	Measure	Without electrification level	With electrification level-optimistic	With electrification level-pessimistic
LDV (DIESEL)	ROG^{**}	2.57E+04	2.03E+04	2.30E+04
	CO^{**}	4.52E+05	3.38E+05	3.96E+05
	NO_X^{**}	4.61E+04	3.82E+04	4.22E+04
	SO_X^{**}	2.75E+03	2.07E+03	2.41E+03
	CO_2^{**}	2.91E+08	2.18E+08	2.55E+08
	CH_4^{**}	3.35E+07	2.63E+07	3.00E+07
	PM_{10}^{**}	6.00E+03	5.21E+03	5.61E+03
	$PM_{2.5}^{**}$	5.74E+03	4.99E+03	5.37E+03
	N_2O^{**}	1.21E+10	9.10E+09	1.06E+10
LDV (GAS)	ROG^{**}	1.40E+06	1.27E+06	1.34E+06
	CO^{**}	8.73E+07	7.10E+07	7.93E+07
	NO_X^{**}	4.42E+06	3.78E+06	4.11E+06
	SO_X^{**}	3.47E+05	2.71E+05	3.10E+05
	CO_2^{**}	3.51E+10	2.74E+10	3.13E+10
	CH_4^{**}	1.05E+10	9.23E+09	9.87E+09
	PM_{10}^{**}	2.15E+05	1.81E+05	1.98E+05
	$PM_{2.5}^{**}$	1.97E+05	1.66E+05	1.82E+05
	N_2O^{**}	1.40E+11	1.13E+11	1.27E+11

***Pollutants in grams and GHGs (CO_2, CH_4, N_2O) in CO_2 equivalent grams*

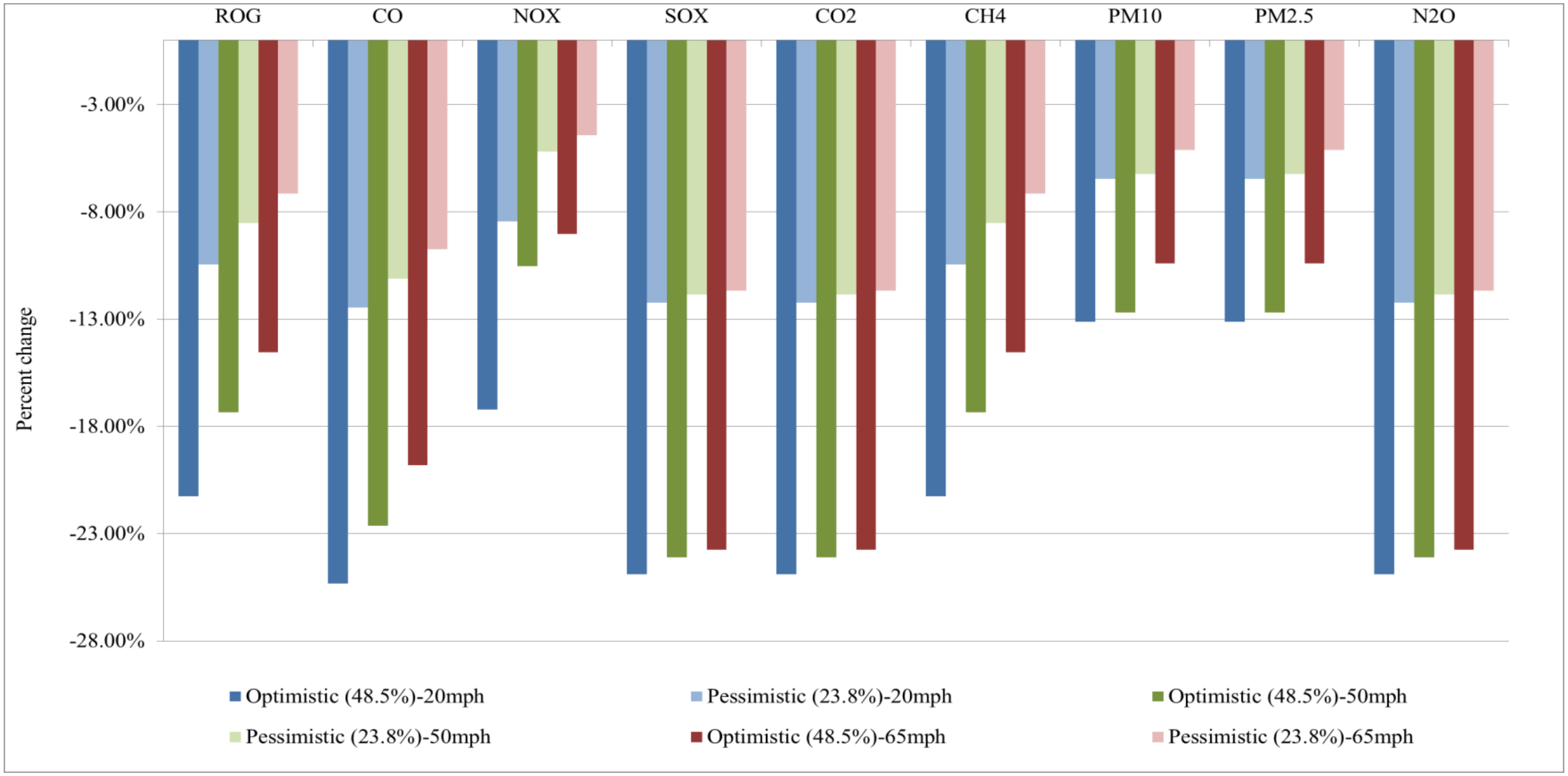

Figure 5.10: Total emissions reduction in with electrification scenario for diesel LDVs (65mph, 50mph, 20mph)

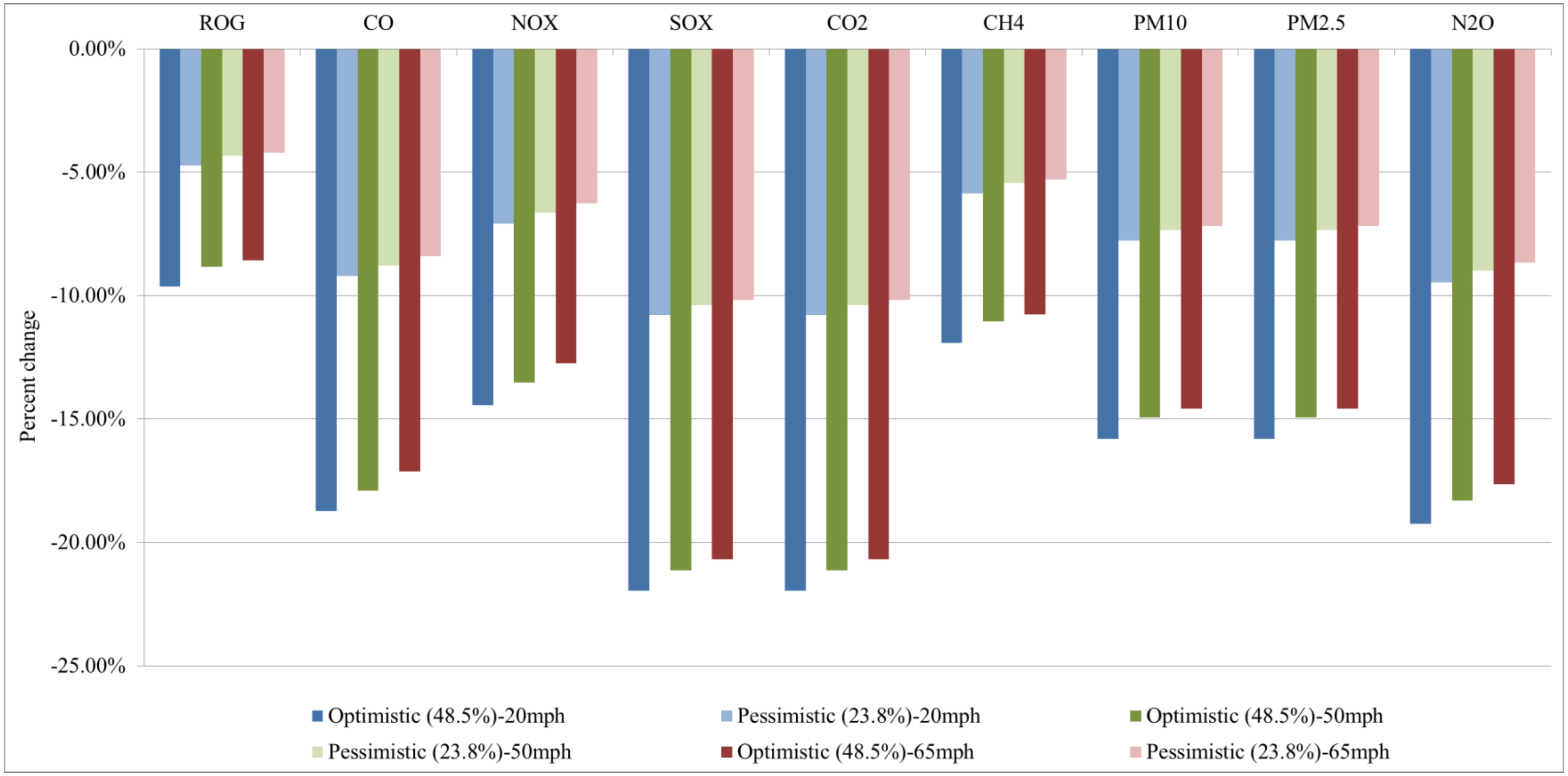

Figure 5.11: Total emissions reduction in with electrification scenario for gas LDVs (65mph, 50mph, 20mph)

For the speed of 20 mph, the results show certain differences. In particular, it is observed that all the emission estimates increased to a substantial degree except for diesel and gas N_2O that decreased compared to the level found using 65mph for both scenarios (with and without electrification). For diesel vehicles, the greatest reduction due to the new technology is associated with CO, followed by SO_x, CO_2 and N_2O. Considering that CO emitted by vehicles increases at lower speeds (European Environment Agency, 2011), the result that CO is greatly reduced with the ER technology sounds promising. The trend in gas vehicles is similar to that found for 65mph, meaning that SO_x and CO_2 are reduced the most after the implementation of the technology, followed by N_2O and CO. The level of emissions' change by pollutant from "with" to "without electrification" scenarios is higher using 20 mph. In general, the emissions reduction in this case varies from around 5% (lowest value at pessimistic scenario for gas vehicles) to 25% (highest value at optimistic scenario for diesel vehicles).

The following figures (Figures 5.12-5.15) show the total change of criteria pollutants and GHGs from 2018 to 2050 for all scenarios, speeds and fuel types.

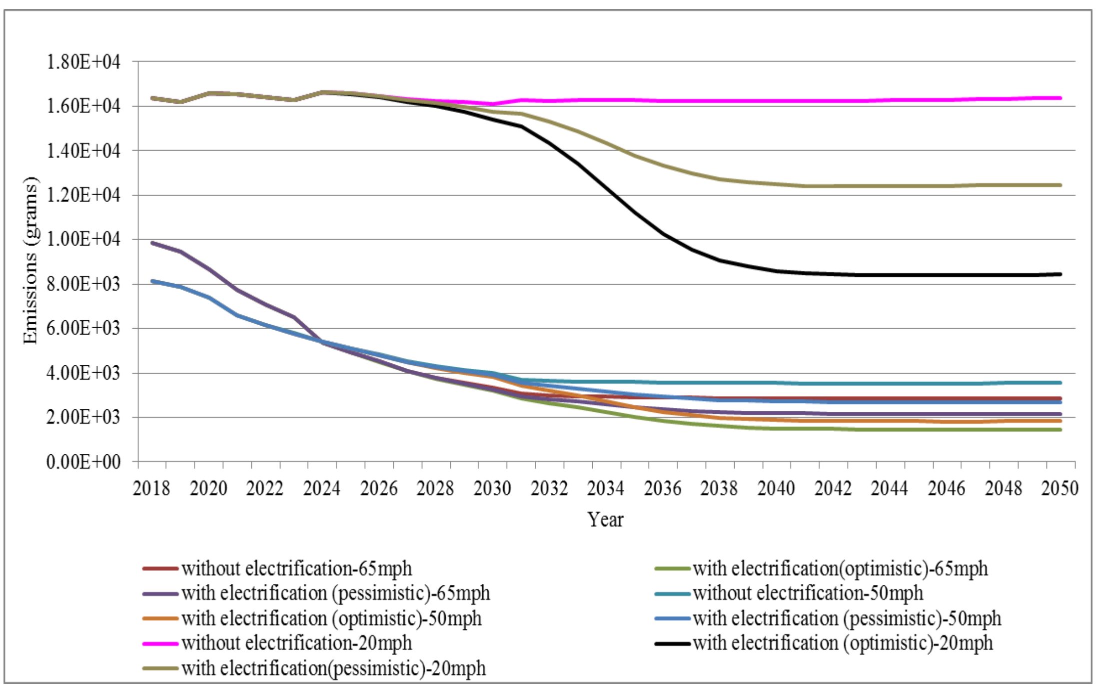

Figure 5.12: Total emissions change from 2018-2050 for diesel LDVs (criteria pollutants) (65mph, 50mph, 20mph)

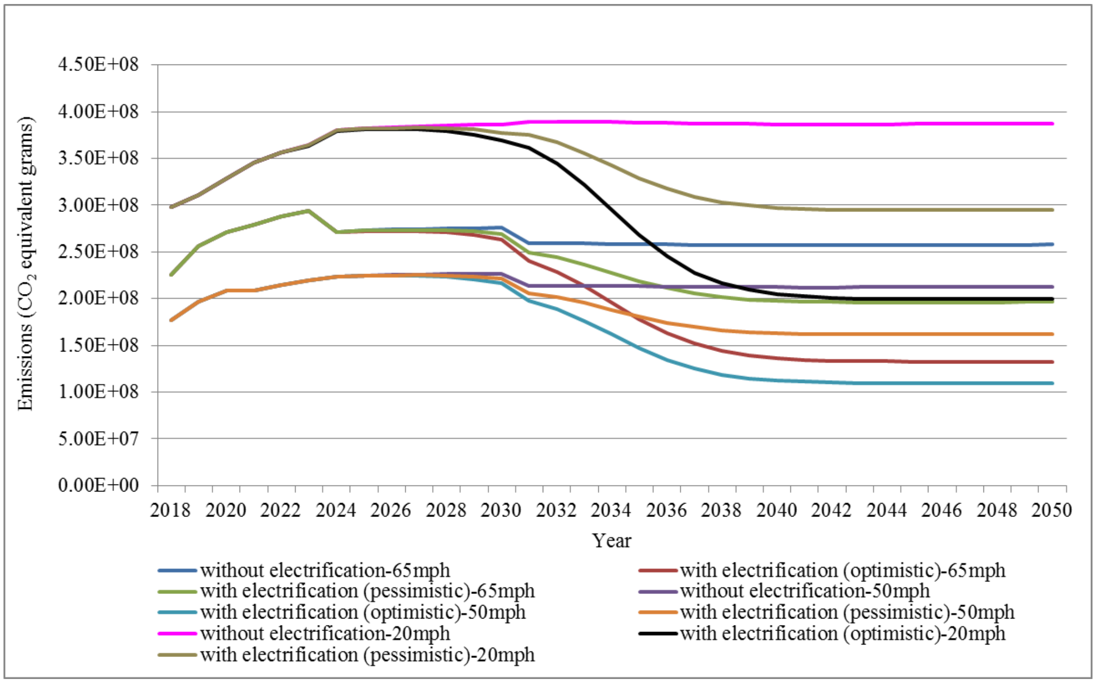

Figure 5.13: Total emissions change from 2018-2050 for diesel LDVs (GHGs) (65mph, 50mph, 20mph)

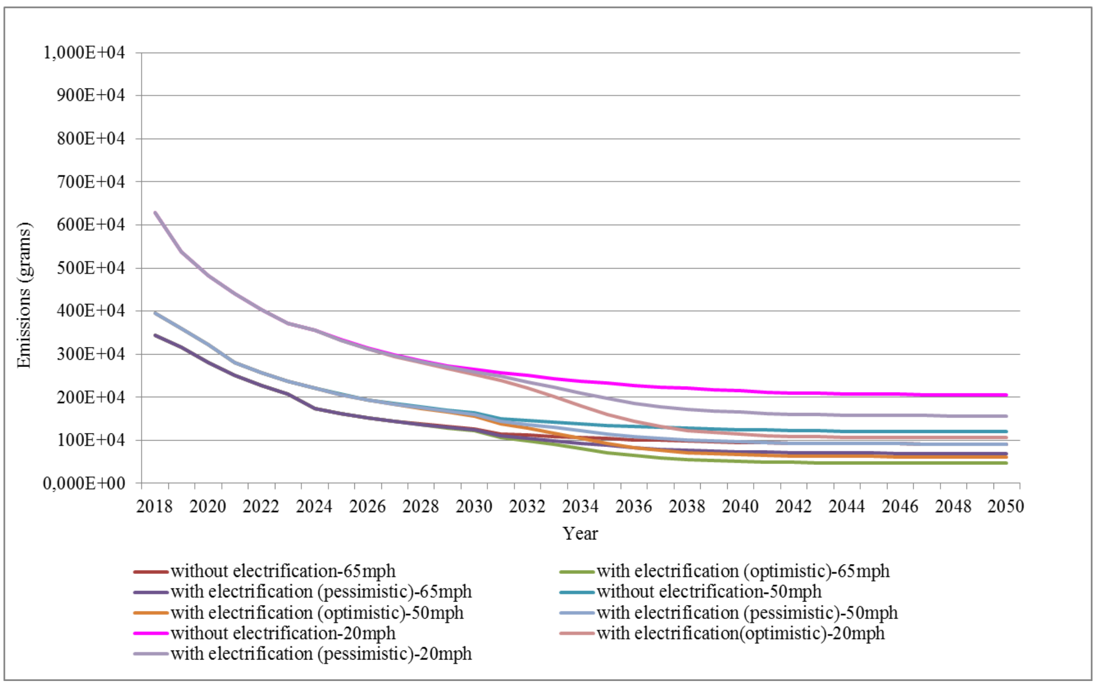

Figure 5.14: Total emissions change from 2018-2050 for gas LDVs (criteria pollutants) (65mph, 50mph, 20mph)

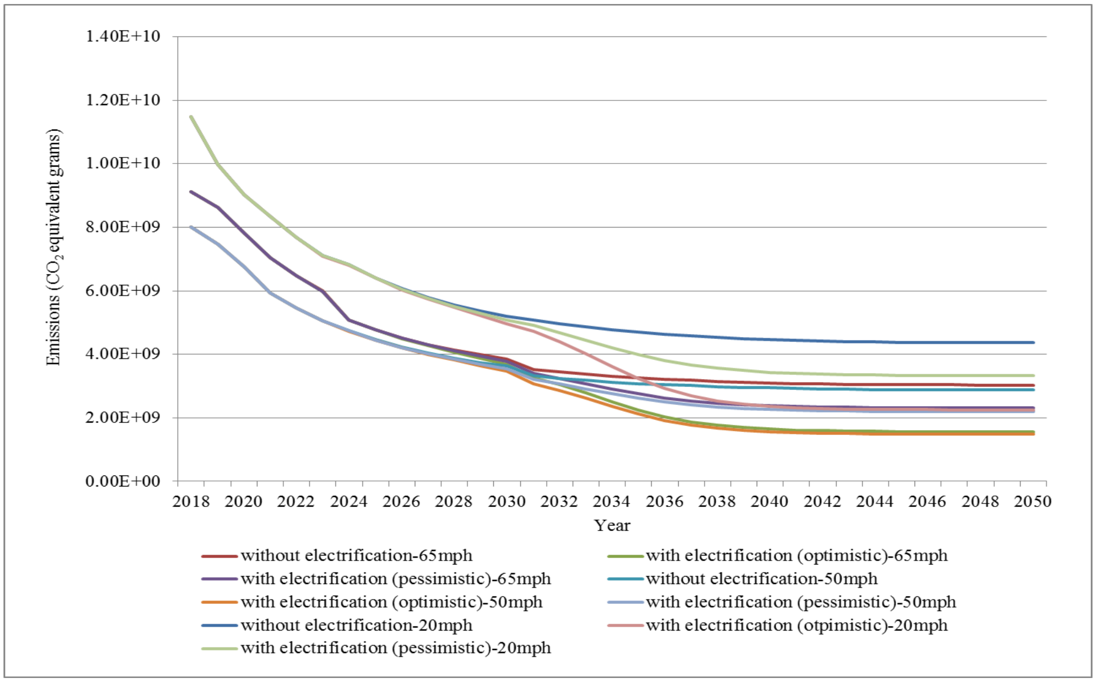

Figure 5.15: Total emissions change from 2018-2050 for gas LDVs (GHGs) (65mph, 50mph, 20mph)

These results may illustrate some ideas concerning the relationship of speed and emissions. In particular, for moderate speeds (40-60mph), emissions are expected to be lower compared to higher speeds (above 60mph). As found in literature, this is because vehicles traveling at higher speeds require higher engine loads and fuel and thus, produce more emissions (Barth & Boriboonsomsin, 2009). In addition, for speeds under congestion, the emissions levels increase dramatically. This may be because high peak speeds generally represent stop-and-go traffic conditions and therefore, the emission rates per mile are quite higher (Barth & Boriboonsomsin, 2009).

From the emissions reduction due to the ER technology at 20mph which represents traveling at congested periods, the results may indicate that regardless of the fuel type (gas or diesel in this analysis), the ER technology would significantly contribute to reducing the traffic emissions even during high peak periods. It is important to mention, though, that all the aforementioned conclusions can depend on different factors, both technological and non-technological (such as fleet mix, congestion, driving patterns, acceleration/deceleration frequency etc.) (European Environment Agency, 2011).

6. CONCLUSIONS

This thesis stemmed from the need for research on alternative fuel technologies and in particular, on technologies that address most of the limitations associated with electric vehicles (EVs). Electric roadways (ERs) are among these technologies that can offer a wide range of benefits in the field of electrification of transport. This thesis focuses on the wireless dynamic charging system associated with ERs. Since data on the market acceptance and the environmental implications of this technology are limited to non-existent, this thesis aimed to establish a general framework, provide initial insights toward understanding the market acceptance and impact of ERs on air pollution. In particular, the following questions are addressed:

1. What are the factors that affect the short- and long-term intention to use ERs and purchase an EV, knowing about the availability of ERs?
2. What is the level of adoption of the ER technology and what are the characteristics of the market segments?
3. What is the potential impact of ERs on criteria pollutants and greenhouse gas (GHGs) emissions?

To address these questions, a survey on the general population in Los Angeles, California was designed and used as the main data source, since this city is considered proactive in terms of electro-mobility. The survey data was analyzed through appropriate methods in order to answer the first two research questions. The market penetration of ERs found was used as an input in the analysis of emissions that followed to address the third research question.

The following sections present some of the main key findings, practical implications, potential limitations of this thesis and recommendations for future research.

6.1 Key Findings

6.1.1 Market Adoption

The short- or long-term intention to drive on ERs and the short- or long-term intention to purchase an EV knowing that ERs are or will be available are correlated, since the potential of using the ERs requires the purchase of an EV to use the system. Thus, the ER usage and EV purchase intentions were modeled simultaneously using econometric models, as a function of travel patterns, EV characteristics, respondents' preferences and opinions on ERs and socioeconomic characteristics.

Comparing the two models, it was observed that the variable of innovativeness and social and family influence had a stronger association with the long-term intention to drive on ERs or purchase an EV than with the short-term intention. The degree to which the ER technology is in line with respondents' lifestyle, needs, personal values or attitudes (compatibility) and respondents' tendency towards using sustainable forms of transportation were found to be important factors that positively affect the short-term intention to travel on ERs or purchase an EV. Respondents' innovativeness and the perceived environmental benefits of the ER technology were highly significant determinants of the long-term intention to travel on ERs or purchase an EV, knowing that ERs will be available in the foreseeable future. Among the individuals' socioeconomic characteristics, being young or having a higher educational level was associated with a higher long-term intention while a higher income level was associated with a higher short-term intention. Purchasing an EV may generally constitute the first step to become familiar with the new concept in the short run, as demonstrated in the model.

The level of adoption of the ER technology was estimated and the characteristics of the market segments of ERs were identified. A Principal Component Analysis (PCA) was conducted in order to identify which variables are the most salient and capture important information. The principal components found were related to: opinions on ERs, environmental consciousness, safety concerns and habits towards driving a car. Based on the aforementioned variables, a Cluster Analysis was performed by applying the k-means method. Three distinct market segments were identified: the early adopters, mid-adopters and late adopters based on the mean scores of each cluster across the four principal components. These scores were expressed in a 5-point Likert-type scale. Early adopters constitute 48.5% while mid- and late adopters represent 27.67% and 23.83% of the 600 total responses, respectively. The basic characteristics of each cluster were analytically presented in Section 4.2.3.4. Note that since this is the first study on ER market segments, the characteristics of these segments cannot be corroborated with findings of previous studies.

Early adopters have the fewest safety concerns about ERs, the most positive opinions towards ERs and the highest score in terms of the habits towards using a car. Early adopters are young (less than 34 years old) and of a higher income. Around half of them work full time and the majority consists of drivers traveling more than 15,000 miles per year and own or have used an EV. Early adopters charge their EVs usually at home and at a more frequent level than the other clusters. Ride-hailing services are popular among them. *Late adopters* seem to be the most suspicious about the ER technology, showing the lowest average values in opinions on ERs, habits towards driving a car and safety concerns. This category consists mainly of people aged 65 or above and of lower income. These respondents are unemployed or do not own a car by a higher percentage compared to other clusters. Only a small percentage has an experience with an EV or ride-hailing services before and individuals of this cluster show the lowest level of awareness with respect to electro-mobility. *Mid-adopters* appeared to have less optimistic responses on the four components compared to early adopters and less pessimistic responses than late adopters. With average scores close to 3 (on a scale from 1 to 5), respondents of this cluster seem more indecisive than early adopters. In general, this cluster consists of respondents that stand in between the other two clusters in terms of the percentage of individuals that exhibit the previously described characteristics or behaviors.

6.1.2 Impact on Criteria Pollutants and Greenhouse Gas Emissions

The potential impact of ERs on traffic emissions was analyzed using California Air Resources Board's (CARB) 2017 EMissions FACtor model (EMFAC). This analysis included only the tailpipe emissions of criteria pollutants and greenhouse gases (GHGs) while the vehicle is traveling and not the ER infrastructure or vehicle manufacturing emissions. The results from the emissions analysis assessment suggested that the ER technology has the potential to provide emissions savings for the period of 2018-2050, considering LDVs. Given a speed of 65mph, the analysis illustrated that the adoption of ERs can significantly decrease the emissions levels of GHGs (CO_2, N_2O and CH_4) and pollutants such as SO_x. The pollutants that contribute to the ozone, meaning NO_x, ROG and PM are also reduced with the implementation of the technology (over 5% reduction) but at a lower level. It has been demonstrated that variations in the level of adoption can significantly change the emissions levels and savings by fuel type and pollutant. Hence, if diesel and gas vehicles are reduced and vehicles equipped with ER technology are used instead, the emissions reductions would range from 4% for the pessimistic scenario (23.8% adoption) to 24% for the optimistic scenario (48.5% adoption), depending on the pollutant.

The sensitivity analysis showed that speed can cause variations in the emissions levels of pollutants and GHGs. The findings suggest that the general trend in emissions change before and after electrification at 50mph is similar to this at 65 mph. For the speed of 20 mph, the greatest reduction due to the new technology is associated with CO in diesel vehicles, while SO_x and CO_2 showed the greatest reduction for gas vehicles. In general, for higher or very low speeds, the emissions levels of the majority of the pollutants increase, while for moderate speeds such as 50mph, emissions levels appeared to decrease. Regardless of the fuel type (gas or diesel), the ER technology would significantly contribute in reducing traffic emissions either during peak periods or normal traffic conditions.

6.2 Practical Implications

This thesis provides a foundational framework on the upcoming technology of ERs in terms of market adoption and emissions reduction. By examining the market adoption of ERs, it was concluded that familiarity with the new technology is the key factor for achieving public acceptance. The probability of using the new technology or purchasing an EV, being aware of ERs, depends on the implementation time of this technology. At the earliest stages of the technology, people tend to be more skeptical while people are becoming more familiar and recognize its benefits, as the maturity of the technology grows. This indicates that increasing awareness related to electro-mobility may be a significant strategy for achieving a higher intention to drive on ERs or purchase an EV.

Although one could claim that the technology needs to be there to drive the adoption, the factors found to affect the adoption in this analysis can be used as a draft guide by state and local transportation agencies, transit operators and regulatory bodies-e.g., Los Angeles County Metropolitan Transportation Authority (LA Metro), California Department of Transportation (Caltrans), Southern California Association of Governments (SCAG)-and inform their strategic short- or long- range plans for mobility. For instance, the analysis showed that respondents who travel medium distances (10-50 miles) are more likely to adopt the technology in the short-run. Thus, if the technology were to be implemented soon, doing so on corridors that serve medium distance trips (10-50 miles) could make more sense. This may be because in shorter trips (up to 10 miles), drivers may not generally be really concerned about their driving range, while in longer trips (more than 50 miles) the technology may lose its competitiveness in terms of the cost of implementation and power requirements at least at its first stages of implementation. The electrification coverage of the road would also play an important role at this case in driving adoption. Similarly, the vehicle purchase cost and operational cost (cost to charge an EV) were found to be important factors in the long-term intention model; hence, by ensuring that the cost of the vehicle with WPT technology would be affordable in the future compared to a conventional EV would make the transition to the technology easier.

Furthermore, these factors can help improve the understanding of the roles of the various stakeholders involved. For instance, safety concerns in the short-term intention model, such as the possible user or animal physical contact with the charging zone, may yield that it is extremely important that certain stakeholders work to ensure that any concern will be addressed by the time of ERs implementation. Among these stakeholders may be construction companies or original equipment manufacturers (OEMs), utilities or in general policy makers that will establish safety policies concerning the innocuous use of the system. Likewise, charging time as a factor of the short-term intention model may also emphasize the importance of the role of utilities. The operational cost (cost per mile) and financial incentives were also significant factors in the short-term intention model, indicating the involvement of utilities, transportation operators, policy makers or regulatory agencies (e.g., California Air Resources Board [CARB]). It can be inferred that the implementation of such a system will be complex in terms of the adopted business model but will be mainly based on a joint partnership/collaboration of different organizations: OEMs, technology providers and public agencies (such as LA Metro, City of LA).

In addition, this analysis can provide policy makers and transport operators with a realistic description of the main challenges regarding the promotion of the ER technology to the users and with ideas for customizing the supply to meet demand expectations. Since information about the target demand is learned through the specific market segmentation analysis, the way that policies of accelerating adoption will be designed and implemented can become more effective.

The information obtained from the emissions analysis showed how the ER technology could reduce the on-road emissions by considering different levels of adoption and speeds. Thus, the results can stimulate state and local agencies to further investigate the technology with the view to implementing it. The findings from the analysis of the impact of ERs on criteria and GHG emissions can also inform the long range plans or existing regulations and policies and set new standards for certain emissions, based on the projection of ER adoption. In addition, the results may indicate that regardless of the fuel type (gas/diesel), the ER technology would significantly contribute to reducing the traffic emissions in congested periods or under higher speeds, depending on the pollutant. This can have implications for transportation decision making and specifically, regarding the set speed limit of a potential exclusive lane on I-710 with EVs equipped with wireless power transfer (WPT) technology.

6.3 Limitations and Recommendations

This thesis entails certain limitations due to its nature as well as to a number of assumptions and simplifications made in the process of developing the results. The following represent the main limitations of this thesis along with some recommendations which may help better elucidate the full scope of the study and guide future research in this area.

6.3.1 Survey Design and Sample

A stated preference survey was designed for the purposes of this thesis and thus, it is acknowledged that the corresponding inferences are subject to the limitations of stated preference surveys, such as their hypothetical nature. These limitations attempted to be addressed through appropriate data preparation and analysis such as removal of incomplete responses, cases of over-coverage, passive responses, inclusion of "cheap talks" to address hypothetical bias, etc. (Section 3.5) or proper modeling. A revealed preference survey could overcome the issue of hypothetical responses, since it is based on observations of actual choices. However, this type of survey is not suitable for concepts that are not currently implemented (such as ERs) and individuals are not familiar with. In addition, the survey conducted in this thesis is a cross-sectional study and not a longitudinal study, implying that the results will reflect only the current situation and public's perception and cannot assess changes in opinions and level of adoption over time. This would require several observations of the same objects over a period of time in order to detect for developments and changes in the characteristics of the target population.

The survey respondents constitute the general population and do not include medium and heavy-duty vehicle owners or operators or buses. Thus, the results of adoption rates refer only to this group of people. Future research can examine the perception of truckers, shippers, carriers, transit operators and other towards this technology and estimate market adoption for medium/heavy duty vehicles or buses in the study area. Likewise, the emissions analysis only considered LDVs. Further research could focus on assessing the environmental impact of the technology for all types of vehicles and fuels.

6.3.2 Research Methodology and Assumptions

The adoption curves used in the analysis assumed that there are two adoption scenarios: the optimistic (early adopters share in 2050) and the pessimistic (late adopters share in 2050). However, it is acknowledged that this does not exactly consider the time dimension of adoption. For example, the pessimistic scenario could include only early adopters by 2050, while the optimistic scenario could include all the adopters. Nevertheless, in this analysis it was assumed that the adoption of the technology cannot reach 100% by 2050, since it is still in its infancy.

Furthermore, the cluster solution indicated that the majority of late adopters is above 65 years old. It is believed though that the cluster results can be representative among the different age groups over the years. In other words, a potential respondent that is above 65 years old in any time would have similar behavior with a 65-year-old respondent in the sample.

The adoption rates found were not examined in terms of their sensitivity to factors such as energy prices, actual reduction of battery cost, etc. A Monte Carlo simulation could be used to show the distribution of demand and analyze the uncertainty of ER adoption. This way, the feasibility or viability of the ER technology could be explored in terms of its penetration rate.

The emissions analysis was conducted using a macro level model calibrated for Los Angeles, California, the EMFAC model. As such, aggregate values of speed and traffic volumes were used to estimate current and future traffic conditions and obtain the emissions estimates. Future research can consider integrating a traffic simulation model with an emissions model and use driving cycle data, hourly or peak hour corridor volumes and VMT for emissions modeling. Examples of such models include models that need traffic situations to find emissions (e.g., HBEFA) or models which include second-by-second engine or vehicle state data (e.g., PHEM, MOVES) for the complete driving profile (Smit et al., 2010). A further consideration for the simulation model could also be the respondent's preference for the lane configuration of this technology and the corresponding impacts on speed and thus, emissions. To illustrate this, if a dedicated lane is considered for ERs, the speed of the vehicles on the other lanes may become slower and emissions can potentially increase.

Furthermore, a number of assumptions were made for the emissions modeling. EMFAC2017 estimates tailpipe (tank-to-wheel) emissions and not well-to-tank emissions. Thus, one of the assumptions made is that infrastructure or vehicle manufacturing emissions are not included in the analysis. Future research can focus on conducting a life cycle assessment including all emissions related to fuel and vehicle production, processing, distribution, use, and recycling/disposal. This way, more concrete and complete conclusions could be made. Additional models could be used in that direction. An example of these models is the CARB's Vision model that also considers fuel blends and power mix information for well-to-tank emissions estimation. A life cycle assessment like this could show the difference in emissions between a traditional EV and an EV equipped with WPT capability, considering that the latter has a reduced battery size.

Another limitation or suggestion for this analysis is the fact that the emissions reduction did not account for the amount of energy that is used for the in-motion charging of the vehicle and can impact the results. Future research could investigate the relationship between the charging efficiency the technology supports and the energy consumption while driving. This could also have implications to the speed and the amount of power transferred while driving.

In conclusion, this thesis constitutes a preliminary study; it can be used to generate further discussion on the matter of dynamic charging, which can potentially be widely implemented to improve the efficiency and mitigate the adverse impact of transportation operations on the environment. The results of the thesis can be extended and used to show the broader impact on other regions across the US in major cities and along interstate highways. Lastly, there could be multiple future research directions based on this thesis that may include: investigating the load impact to the grid, estimating the optimal time for the ER technology implementation or the minimum level of adoption to compensate for the ER deployment, and exploring the synergies between the wireless power capability and autonomy of vehicles for greater charging efficiency, among others.

APPENDIX A. STREET GRID OF STUDY AREA

The following table summarizes important freeway routes, arterial streets, avenues, bus lines and metro rail lines that constitute the main street grid of the city (Los Angeles County GIS Data Portal, 2010).

Table A.1: Los Angeles major roads

Freeways	**Arterial streets**			**Bus lines**	**Metro Rail**
	Major east–west routes (boulevards)	**Major north–south routes (boulevards)**	**Major Avenues**		
Glendale Freeway (SR-2)	Victory	Topanga Canyon	Broadway	Metro Local	*Light Rail:*
Santa Ana Freeway (I-5/US-101)	Ventura	Crenshaw	Bundy Drive		Gold Line
Golden State Freeway (I-5)	Hollywood	Reseda	Barrington Avenue	*Metro Rapid:*	Expo Line
Santa Monica Freeway/San Bernardino Freeway (I-10)	Sunset	Lincoln	Centinela Avenue	Orange Line	Blue Line
Antelope Valley Freeway (SR-14)	Santa Monica	Sepulveda	Fountain Avenue	Silver Line	Green Line
Seaside Freeway (I-710/SR-47)	Beverly	Van Nuys Westwood Beverly Glen	Mulholland Drive	Metro Express	

Table A1 continued

Pomona Freeway (SR-60)	Wilshire	San Vicente Robertson	Slauson Avenue		*Underground:*
Marina Freeway (SR-90)	Olympic	La Cienega Laurel Canyon Glendale	Pacific Coast Highway		Red Line
Gardena Freeway (SR-91)	Pico	Avalon	Century Park		Purple Line
Hollywood Freeway (US-101/SR-170)	Venice		East Avenue of the Stars		
Ventura Freeway (US-101/SR-134)	Washington		Normandie Avenue		
Terminal Island Freeway (SR-103)	Adams		Highland Avenue		
Glenn M. Anderson Freeway/Century Freeway (I-105)	Jefferson		Melrose Avenue		
Harbor Freeway (I-110/SR-110)	Exposition		Florence Avenue		
Arroyo Seco Parkway (SR-110)	Martin Luther King Jr.		Vermont Avenue		
Ronald Reagan Freeway (SR118)			La Brea Avenue		
Foothill Freeway (I-210)			Fairfax Avenue		
San Diego Freeway (I-405)			Western Avenue		
Long Beach Freeway (I-710)			Figueroa Street		
Pacific Coast Highway/Lincoln Boulevard (SR-1)			Grand Avenue		
Santa Monica Boulevard (SR-2)			Huntington Drive		
Decker Canyon Road (SR-23)			Central Avenue		

Table A1 continued

Topanga Canyon Boulevard (SR-27) Alameda Street (SR-47) Slauson Avenue (SR-90) Highland Avenue (SR-170) Venice Boulevard (SR-187)	Alameda Street		

APPENDIX B. SURVEY MATERIAL

B1. SURVEY

A PUBLIC OPINION SURVEY ON ELECTRIC ROADWAYS IN LOWER LOS ANGELES COUNTY

IRB Research Project Number: 1709019705
Konstantina Gkritza, Ph.D.
Theodora Konstantinou
Christos Gkartzonikas, M.Sc.
Lyles School of Civil Engineering, Purdue University

What is the purpose of this study?
The purpose of this study is to identify the factors affecting the intention to use electric roadways. Electric roadways allow electric vehicles to be charged as they move along the roadway. Additionally, the study will examine how much people are willing to pay to use such a service on specific corridors in lower Los Angeles County, CA.

What will I do if I choose to be in this study?
If you choose to participate in this study, you will be asked to answer questions related to your travel patterns, mode choice decisions, your opinions about electric roadways, and questions about your willingness-to-pay to use the electric roadways.

How long the survey will take?
The survey will take approximately 25 minutes.

What are the possible risks or discomforts?
The risks of participating are minimal and no greater than those encountered in everyday activities. However, if you have distressing feelings after completing this questionnaire and feel that you may need to talk with someone, you can contact the national crisis hotline at 1-800-273-8255.

Will information about me and my participation be kept confidential?
The project's research records may be reviewed by departments at Purdue University responsible for regulatory and research oversight. Your responses and participation are completely anonymous and any information you provide will be confidential. Only Professor Konstantina Gkritza, Ph.D, Graduate Research Assistant Theodora Konstantinou, and Graduate Research Assistant Christos Gkartzonikas, M.Sc. will have access to the data. All data from the surveys will be coded and entered into a computerized data file that will be stored in password-protected computers accessible only to the research study personnel.

What are my rights if I take part in this study?
Your participation in this study is completely voluntary. You may choose not to participate or, if you agree to participate, you can withdraw your participation at any time without penalty or loss of benefits to which you are otherwise entitled.

Who can I contact if I have questions about the study?
If you have questions, comments or concerns about this project, you can talk to one of the researchers. Please contact Theodora Konstantinou at tkonstan@purdue.edu, or Christos Gkartzonikas at cgkartzo@purdue.edu.

If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu) or write to:
Human Research Protection Program - Purdue University
Ernest C. Young Hall, 10th floor - Room 1032
155 S. Grant Street, West Lafayette, IN 47907-2114

Please Print this Information Sheet for Your Records

SECTION 1

1. Level of awareness

1. Are you aware of California's goal of getting 1.5 million zero-emissions vehicles on the state's roads by 2025?

- ☐ I have never heard of it
- ☐ I think that I have heard of it
- ☐ I have heard of it but don't know much beyond the description provided
- ☐ I am following the news about it on a regular basis

2. Are you aware that California has given tax rebates to buyers of new Zero Emissions Vehicles? (A zero-emissions vehicle, or ZEV, is a vehicle that emits no exhaust gas from the onboard source of power)

- ☐ I have never heard of it
- ☐ I think that I have heard of it
- ☐ I have heard of it but don't know much beyond the description provided
- ☐ I am following the news about it on a regular basis

3. Have you ever heard about on-road charging of electric vehicles? (On-road charging refers to a technology that enables electric vehicles to charge from the road while in motion without user input or needing to plug into a socket. This can be achieved while moving or during short stops).

- ☐ I have never heard of it
- ☐ I think that I have heard of it
- ☐ I have heard of it but don't know much beyond the description provided
- ☐ I am following the news about it on a regular basis

4. Have you heard that there was a proposal to electrify a section of Interstate 710 with on-road charging?

- ☐ I have never heard of it
- ☐ I think that I have heard of it
- ☐ I have heard of it but don't know much beyond the description provided
  I am following the news about it on a regular basis
- ☐ I am following the news about it on a regular basis

SECTION 2

2.1 Travel characteristics

1. How many personal vehicles does your household own?

0_____ 1_____ 2_____ 3_____ > 4 ______

2a. How many of the personal vehicles that your household owns belong to the following fuel categories:

Fuel type/number of vehicles	0	1	2	3	>4
Diesel					
Gasoline					
Natural gas					
Biofuel					
Hydrogen					
Hybrid Electric					
Plug-in Hybrid					
Battery Electric					

2b. If you own an electric vehicle (EV), what is the vehicle's electric mode driving range?

□ I do not own an EV

□ 0-50 miles

□ 51-100 miles

□ 101-150 miles

□ 151-200 miles

□ 201-250 miles

□ 251-300 miles

□ > 300 miles

3. How many miles approximately did you drive your personal vehicle last year?

I do not own a personal vehicle_____ <5,000 miles_____ 5,000-9,999 miles_____ 10,000-14,999 miles_____ 15,000-19,999 miles______ 20,000-24,999 miles_____ >25,000 miles ______

I do not know______

4a. Are you a member of a car-sharing service (e.g. ZipCar, Turo, etc.) or do you have a ride-hailing service account (e.g. Uber, Lyft, etc.)?

□ Yes

□ No

4b. If you are a member of a car-sharing service or have a ride-hailing service account, how many times did you use it in the last month? _______

5. Which of the following is your primary mode of travel <u>for each</u> trip purpose? (*Please, select only one mode for each trip purpose).*

Trip Purpose	Walk	Bike (conventional)	Bike (electric)	Car (conventional vehicle)	Car (electric vehicle)	Public transportation	Ride hailing service (e.g. taxis, Uber, Lyft, carpool, etc.)	Car-sharing services (e.g. ZipCar, etc.)
Trips for work/school								
Trips for grocery and shopping								
Trips for personal business (e.g. errands, banks, medical/dental etc.)								
Trips for social/recreational activities (e.g. trips to gym, church, parks, theaters, etc.)								
Other types of trips								

6. How many single trips did you make for the following trip purposes during the last seven days? Please consider the primary mode you indicated for each trip purpose in the previous question (question 5). (A single trip is defined as a single journey made by an individual between two points using a specific mode of travel and a defined trip purpose).

Trip Purpose	0	1	2-3	4-5	6-7	>8
Trips for work/school						
Trips for grocery and shopping						
Trips for personal business (e.g. errands, banks, medical/dental etc.)						
Trips for social/recreational activities (e.g. trips to gym, church, parks, theaters, etc.)						
Other types of trips						

7a. How often on average do you travel on the following freeways and arterial streets?

	Never	Less often than every 6 months	Every 6 months	Every 3 months	Once a month	Once a fortnight	Once a week	A few times a week	Almost every day	Do not know
I-5										
I-105										
I-110										
I-210										
I-405										
I-605										
I-710										

7b. How often on average do you travel on the following transit corridors?

	Never	Less often than every 6 months	Every 6 months	Every 3 months	Once a month	Once a fortnight	Once a week	A few times a week	Almost every day	Do not know
Metro Orange Line										
Metro Silver Line										
Metro Line 720										
Metro Line 754										

7c. Thinking about how far you typically drive, how often on average do you travel to:

	Never	Less often than every 6 months	Every 6 months	Every 3 months	Once a month	Once a fortnig ht	Once a week	A few times a week	Almost every day
Distances near to where I live (up to 10 miles)									
Medium distances (10-50 miles									
Longer distances (up to 50 miles)									

8. Please indicate the level of importance of each factor below when planning your commute route?

Factor	Not at all Important	Slightly Important	Important	Fairly Important	Very Important	Do not know
Cost (cost per mile, tolls etc.)						
Travel time						
Convenience and comfort (number of traffic signals in the route, type of route preferred etc.)						
Ambience (beauty of route, scenery)						
Safety						
Reliability of travel						
Familiarity with the route						

2.2 Electric Vehicles

9a. Have you ever driven an electric vehicle?

- ☐ Yes
- ☐ No

9b. If you own an electric vehicle, where and how often do you charge your vehicle on average on a weekly basis?

	Never	Once per week	2-3 times per week	Every day	More than one time per day	N/A
At home						
At work						
At public/private stations						

9c. If you own an electric vehicle, what type of charger do you typically use to charge your vehicle?

	Level 1 AC	Level 2 AC	DC Fast Charge	N/A	Don't know
At home					
At work					
At public/private stations					

10. If you own an electric vehicle, what is your level of your battery when you leave your home on a typical day?

- ☐ Less than 50%
- ☐ 50%
- ☐ 50-90%
- ☐ Fully charged
- ☐ I do not pay attention on the level of my battery of my electric vehicle

11. Please, indicate how important each of the following factors would be to you when you think of electric vehicles.

Factors:	Not at all Important	Slightly Important	Important	Fairly Important	Very Important	Do not know
How far you could travel before it needs recharging (driving range)						
Charging time						
Availability of charging stations						
Battery warranty and lifetime						
Initial purchase cost						
Maintenance costs (such as servicing)						
Operational cost (cost to charge it/cost per mile)						
Financial incentives /rebates provided (such us subsidies)						
Social/Family Influence						
Environmental benefits						
Vehicle performance						
Safety performance						
How good the car looks						
Ability to buy one second-hand						
Maturity of vehicle's technology						

2.3 Electric Roadways

On electric roadways, electric vehicles can be charged from the road while in motion without user input or needing to plug into a socket. This can be achieved while moving or during short stops.

12. If a charging lane is deployed in an urban area, should access to it be:

	Yes	No	Do not know
Open for all vehicles (the charging is only activated when a registered electric vehicle is using it)			
Restricted to electric vehicles only, with traffic lights and camera enforcement			
Restricted to electric vehicles only, with physical barriers or bollards to control access			
Restricted to electric buses only, with traffic lights and camera enforcement			
Restricted to electric buses only, with physical barriers or bollards to control access			
Restricted to electric trucks only, with traffic lights and camera enforcement			
Restricted to electric trucks only, with physical barriers or bollards to control access			

13a. How likely do you think your commute trip will include an electric roadway in the next____

	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
5 years						
10 years						
15 years						
20 years						
25 years						
30 years						
35 years						

13b. How likely do you think your trips for grocery, shopping, personal business, social/recreational reasons etc. will include an electric roadway in the next _________

	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
5 years						
10 years						
15 years						
20 years						
25 years						
30 years						
35 years						

13c. How likely do you think your intercity trip (e.g. trip to San Diego, Las Vegas etc.) will include an electric roadway in the next _________

	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
5 years						
10 years						
15 years						
20 years						
25 years						
30 years						
35 years						

14a. Assuming that a percentage of your commute trip includes an electric roadway, how likely are you to purchase an EV and drive on this road to charge your vehicle? *(For example, if your trip is 10 miles, 10% represents 1 mile of electrified road).*

Percentage of electrification per mile of the route	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
1%-5%						
5%-10%						

10%-25%						
25%-50%						
50%-75%						
75%-100%						

14b. Assuming that a percentage of your trip for grocery and shopping, personal business trips, social/recreational trips includes an electric roadway, how likely are you to purchase an EV and drive on this road to charge your vehicle? *(For example, if your trip is 10 miles, 10% represents 1 mile of electrified road).*

Percentage of electrification per mile of the route	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
1%-5%						
5%-10%						
10%-25%						
25%-50%						
50%-75%						
75%-100%						

14c. Assuming that a percentage of your intercity trip (e.g. trip to San Diego, Las Vegas etc.) includes an electric roadway, how likely are you to purchase an EV and drive on this road to charge your vehicle? *(For example, if your trip is 10 miles, 10% represents 1 mile of electrified road).*

Percentage of electrification per mile of the route	Very unlikely	Quite unlikely	Neutral	Quite likely	Very likely	Do not know
1%-5%						
5%-10%						
10%-25%						
25%-50%						
50%-75%						
75%-100%						

15. If electric roadways become available, how much more are you willing to pay for on-road charging compared to what you pay for charging your EV at _____?

	Home (15 cents/kWh)	Public charging stations (60 cents/kWh)
I am not willing to pay more		
Less than 5%		
5%-10%		
10%-15%		
20%-25%		
25%-30%		
30%-35%		
35%-40%		
40%-45%		
45%-50%		
More than 50%		
Less than 5%		

16. If there were dedicated lanes with on-road charging for electric buses, how likely are you to take public transit to your destination (assuming it is well served by the bus route)?
Very likely __ Quite likely__ Neutral __ Quite unlikely__ Very unlikely__ Do not know__

SECTION 3

3.1 General Thoughts and Behaviors

1.1. I am adventurous and eager to be the first to test new innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.2. I am willing to be an early adopter of new technologies, but prefer to follow the lead of others and to ensure there is a clear benefit to me before doing so.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.3. I tend to be suspicious of new technologies and innovation.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.4. I am always looking for innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.5. I tend to adopt new technologies only after they are tested, proven and heavily adopted by others.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.6. I am resistant to changes.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.1. I think individuals have responsibility to protect the environment.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.2. I think we are not doing enough to save scarce natural resources from being used up.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.3. I think air pollution is becoming more and more serious in recent years.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.4. I think that cars are negatively impacting air quality.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.5. I think that trucks are negatively impacting air quality.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.6. I believe that transportation can have an important impact on the environment and our ability to be sustainable.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.1. If there were more sustainable choices available in transportation, I would be willing to change my travel behavior.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.2. No matter how convenient and sustainable the travel options are, I will always prefer to drive my personal vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.3. I already plan my travel around sustainable forms of transportation (i.e., I take public transit, walk, ride my bike, or carpool)
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.4. Not driving a car is something I would feel uncomfortable with.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.5. Driving a car is one of my habits
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.2 Opinions on electric roadways

On electric roadways, electric vehicles can be charged as they move along the roadway. Electric vehicles (EV) are charged from the road surface without any contact or need to plug into a socket. This can be achieved while moving or during short stops.

Please take a few minutes to tell us what you think about electric roadways.

There are no right or wrong responses; we are merely interested in your personal opinions. In your responses to the following questions, please share the thoughts that come immediately to mind.

3.1. Driving on electric roadways would offer more advantages to our society than driving on non-electric (conventional) roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.2 Driving on electric roadways would be more environmental-friendly than driving on non-electric (conventional) roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.3. Driving on electric roadways would enable me to travel for longer distances compared to driving on non-electric (conventional) roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.4. Driving on electric roadways would enable me to arrive at my destination faster compared than driving on non-electric (conventional) roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.1. It would be easy for me to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.2. I would find it easy to charge while driving on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.3. I think that I would not manage driving on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.1. The thought of driving on electric roadways would suit my lifestyle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.2. Driving on electric roadways would suit my daily needs.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.3. Driving on electric roadways would reflect my personal values and attitudes.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

In this subsection, please select your response based on a scale from 1 to 5.

6.1. I would ___ the thought of driving on electric roadways.
Not like 1__ 2__ 3__ 4 __ 5 __ Like

6.2. Driving on electric roadways would be a ___ idea for me.
Bad 1 __ 2 __ 3 __ 4__ 5__ Good

6.3. I would find driving on electric roadways ___ for my purposes.
Useless 1 __ 2 __ 3 __ 4 __ 5 __ Useful

6.4. Driving on electric roadways would sound ____ to me.
Stupid 1__ 2 __ 3 __ 4__ 5 __ Smart

6.5. Driving on electric roadways would sound ___ to me.

Scary 1 __ 2__ 3 __ 4 __ 5 __ Nice

6.6. Driving on electric roadways would be _____ for my needs.
Not suitable 1__ 2__ 3 __ 4 __ 5__ Suitable

6.7. For me, driving on electric roadways would be ___.
Undesirable 1__ 2 __ 3 __ 4 __ 5 __ Desirable

7.1. People who are important to me would support my decision on driving on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

7.2. The media would make it more appealing for me about driving on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

7.3. People who are important to me would try to convince me to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

7.4. People who are important to me would want me to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

7.5. People who are important to me would prefer I drove on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

7.6. Articles in the media would influence my intention to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.1. Because of my own principles, I would feel an obligation to drive on electric roadways due to its lower fuel consumption.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.2. Regardless of what other people do, I would feel morally obliged to drive on electric roadways due to its lower emissions.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.3. I would feel a moral obligation to drive on electric roadways as they are more environmentally friendly.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.1. I would have the necessary knowledge to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.2. I would be capable to drive on electric roadways.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.3. When electric roadways become widely available, I would know enough to drive on one.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.1. When electric roadways become widely available, I believe I would afford to drive on one.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.2. When electric roadways become widely available, I would have the ability to drive on electric roadways if I want to.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.3. When electric roadways become available, I would have the opportunity to charge on the go.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.4. I believe that the sales of conventional (internal-combustion) vehicles may be banned in the future.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

11.1. I would like driving on an electric roadway. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.2. I look forward toward to driving on an electric roadway. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.3. Driving on an electric roadway could make me frustrated. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.4. I would enjoy the scenery while driving on an electric roadway. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.5. I would feel less anxious when driving on an electric roadway. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.1. I would have safety concerns on driving on electric roadways. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.2. I would have safety concerns on driving on electric roadways if trucks are not banned from these corridors. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__ 12.3. On-road charging on electric roadways would cause me safety concerns. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.3 Intention to purchase an electric vehicle (EV)

13.1. I intend to purchase an EV, knowing that electric roadways are currently available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
13.2. I intend to purchase an EV, **shortly after** electric roadways become available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
13.3. I intend to purchase an EV, knowing that electric roadways will be available in the **foreseeable future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
13.4. I would recommend purchasing an EV, knowing that electric roadways will become available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.4 Intention to drive on electric roadways

14.1. I intend to drive my EV on electric roadways as soon as electric roadways become available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
14.2. I intend to drive my EV on electric roadways **shortly after** electric roadways become available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
14.3. I intend to drive my EV on electric roadways in the **foreseeable future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
14.4. I would recommend driving on electric roadways to other EV users. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.5 Intention to switch from personal vehicles in favor of traveling by electric buses (operating on electric roadways)

15.1. I expect that I will be taking an electric bus instead of my personal vehicle as soon as electric roadways become available.

Strongly Disagree__ Disagree__ Neutral__ Agree__ Strongly agree__

15.2 I expect that I will be taking an electric bus instead of my personal vehicle **shortly after** electric roadways become available.

Strongly Disagree__ Disagree__ Neutral__ Agree__ Strongly agree__

15.3. I expect that I will be taking an electric bus instead of my personal vehicle in the **foreseeable future**.
Strongly Disagree__ Disagree__ Neutral__ Agree__ Strongly agree__

15.4. I would recommend traveling on electric buses (operating on electric roadways) instead of personal vehicles to other people.

Strongly Disagree__ Disagree__ Neutral__ Agree__ Strongly agree__

SECTION 4

A) For this section of the survey, you will be provided with a number of scenarios about your daily commute. Please imagine that your house and your workplace are located in Los Angeles Metropolitan area and you are about to commute to your workplace by taking a freeway (such as I-710, I-210) on a typical weekday using a Nissan Leaf (an electric vehicle with a 151 mile battery-only range). The distance between your house and your work place is 9 miles. The state of charge (SOC) of the EV is 50% at the beginning of your trip. There are no right or wrong responses; we are merely interested in your personal opinions.

In this scenario, there the following options available to you throughout the I-710 corridor:

a) All lanes are non-electric (conventional): typical lanes where on-road-charging is not available with a mix of traffic (light-duty vehicles, trucks); in this case, you will need to stop to charge your electric vehicle.

b) On-road charging is available on one lane (electrified lane); the other lanes are conventional; a mix of traffic (light-duty vehicles conventional and electric, trucks) can drive on the electrified lane. Using on-road charging to charge your electric vehicle can result in average pollution reduction of 30.6% in the first 50 years of technology deployment.

c) On-road charging is available on one lane (electrified lane); the other lanes are conventional; only electric vehicles can drive on the electrified lane. Using on-road charging to charge your electric vehicle can result in average pollution reduction of 30.6% in the first 50 years of technology deployment.

As indicated in the table below, you can see:

-the travel time (in minutes): the total trip time from your origin to your final destination, including any activities during your trip (e.g. stop for charging your EV)

-the cost (in dollars): user cost for each alternative route to reach your final destination (including charging cost).

Which route will you choose for your commute to work?

Scenario 0

	Non-electric (conventional) lane	Electrified lane with mixed traffic (different types of vehicles)	Electrified lane exclusive for EVs
Travel time (minutes)	24	13.50	11
Cost (dollars)	2.60	4	6
Your choice			

B) For this section of the survey, you will be provided with a number of scenarios about your daily commute. Please imagine that your house and your workplace are located in Los Angeles Metropolitan area and you are about to commute to your workplace by taking an arterial road (such as Vermont Avenue) on a typical weekday using a Nissan Leaf (an electric vehicle with a 151 mile battery-only range). The distance between your house and your work place is 9 miles. The state of charge (SOC) of the EV is 50% at the beginning of your trip. There are no right or wrong responses; we are merely interested in your personal opinions.

In this scenario, there the following options available to you throughout the I-710 corridor:

a) All lanes are non-electric (conventional): typical lanes where on-road-charging is not available with a mix of traffic (light-duty vehicles, trucks); in this case, you will need to stop to charge your electric vehicle.

b) On-road charging is available on one lane (electrified lane); the other lanes are conventional; a mix of traffic (light-duty vehicles conventional and electric, trucks) can drive on the electrified lane. Using on-road charging to charge your electric vehicle can result in average pollution reduction of 30.6% in the first 50 years of technology deployment.

c) On-road charging is available on one lane (electrified lane); the other lanes are conventional; only electric vehicles can drive on the electrified lane. Using on-road charging to charge your electric vehicle can result in average pollution reduction of 30.6% in the first 50 years of technology deployment.

As indicated in the table below, you can see:

-the travel time (in minutes): the total trip time from your origin to your final destination, including any activities during your trip (eg. stop for charging your EV)

-the cost (in dollars): user cost for each alternative route to reach your final destination (including charging cost).

Which route will you choose for your commute to work?

Scenario 0

	Non-electric (conventional) lane	Electrified lane with mixed traffic (different types of vehicles)	Electrified lane exclusive for EVs
Travel time (minutes)	31	17	15
Cost (dollars)	2.60	3.50	5
Your choice			

SECTION 5

5.1 Demographic Questions

1. What is the gender you identify with?
Male__ Female__ Other__

2. What is your age range? 18-24 __ 25-34 __ 35-44 __ 45-54__ 55-64__ 65 and over__

3. What describes best your employment situation?
Work full time__ Work part time__ Currently unemployed __ Student__ Retired __ Homemaker___
Other, please specify________

4. Please indicate your approximate annual income before taxes.
Under $25,000____ $25,000-$49,999____ $50,000-$74,999____ $75,000-$99,999____ $100,000-$149,999____$150,000-$199,999____ $200,000 or more____ I do not want to disclose this information____

5. What is your highest level of education?
Grade school or less__ Some high school__ High school graduate__ Technical training beyond high school__
Some college__ College graduate__ Graduate school__

6. Are you Hispanic or Latino?
Yes__ No__ I do not want to disclose this information __

7. How would you describe yourself?
American Indian or Alaska Native__ Asian__ Black or African American__ Native Hawaiian or Other Pacific Islander__
White__ I do not want to disclose this information__

8. Including yourself, how many persons are in your household? One__ Two__ Three__ Four__ Five or more__

9. Please indicate the number of children in your household that are under the age of 18.
None__ One__ Two__ Three__ Four or more__

10. Do you have a driver's license? Yes__ No__

11. How many crashes have you experienced in the past 3 years while driving a car?
None__ One__ Two__ Three__ Four or more__

Thank you for completing this survey about electric roadways!

B2. VALUES FOR WILLINGNESS-TO-PAY SCENARIOS

Table B2.1: Fractional factorial design table*

	Cost ER-mixed	Cost ER-separate	Time ER-mixed	Time ER-separate
	-1	-1	-1	-1
	+1	-1	-1	+1
	-1	+1	-1	+1
	+1	+1	-1	-1
	-1	-1	+1	+1
	+1	-1	+1	-1
	-1	+1	+1	-1
	+1	+1	+1	+1
SUM	0	0	0	0

**high values are noted as +1 and low values are noted as -1*

2 levels of each attribute and vary cost and travel time of ERs (not conventional lanes)

- *2 levels for 4 attributes (cost of ERs and travel time of ERs)*
- *Fractional factorial design to achieve orthogonality and not having confounded main effects:* $2^{(4-1)} = 8$ *scenarios*
- *SUM needs to be 0 for orthogonality*

Table B2.2: Willingness-to-pay input values table

Use	Parameter	Hypotheses/ Assumptions	Formula/Value	References
Scenario narrative	**EV model**	Respondents are using an EV in their daily commute trip.	Nissan Leaf (Nissan Leaf drivers dominate survey population in LA. 97% or respondents were Leaf owners or lessees).	Center for Sustainable Energy, 2013
	State of charge	Respondents will choose a lane on ER given the fact that their EV needs charging. Fixed state of charge for all scenarios	50%	Assumptions
	Emissions	Emissions reduction will occur in the electrified lane options. Fixed reduction for the electrified lane options.	Total emissions from light duty vehicles and class 8 trucks will reduce by 30,6% .	Limb et al., 2017
Factors	**User cost**	The non-electric (conventional) lane option will have the lowest cost, including static charging time in Level 3 charging station. The user cost per mile in electrified lanes will be higher, because of the cost of the technology installed, the initial lower demand for the use of the system and the need to avoid congestion. This cost is assumed to be slightly higher than the cost of HOV/HOT/tolled lanes and includes an extra cost of the use of dynamic charging.	Formulae: User cost (non electric lane)=static recharging cost per mile User cost (electrified lane with mixed traffic)= HOV/HOT user cost per mile + extra cost of the use of dynamic charging per mile User cost (electrified lane exclusive for EVs)= HOV/HOT user cost per mile + extra cost of the use of dynamic charging per mile *(higher than cost in electrified lane with mixed traffic)*	LA Metro, 2013; Southern California Public Radio, 2011 McDonald, 2016; Chargepoint data, 2017 US DOE, (2017)

Table B2.2 continued

		The user cost in freeway route is more more expensive that the user cost in arterial route, as a base case. (For simplicity reasons, not all vehicle operating costs are not included)	Values: HOV/HOT user cost per mile: $0.25 -1.40 per mile Static recharging cost per mile:$0.295/mile (Charge speed: 50KW) extra cost of the use of dynamic charging per mile: $0.08/mile	Assumptions for the higher value of electrified lane exclusive for EVs
	Travel time	Highest speed for the electrified lane options and lowest for non-electric lane option. Lower travel time for the electrified lane options and highest travel time for non-electric options. Lowest travel time for the electrified lane exclusive for EVs. Static charging time is based on the fact that each vehicle will receive from the charging station the same energy power that it will receive from the ER	Fromulae: Travel time (non-electric lane) = travel time from origin to destination + stationary charging time + detour time Travel time (electrified lane with mixed traffic) = travel time from origin to the beginning of ER +travel time on ER+ travel time from the end of ER to destination Travel time (electrified lane exclusive for EVs) = travel time from origin to the beginning of ER +travel time on ER *(lower than in electrified lane with mixed traffic option)* + travel time from the end of ER to destination Values: Assumption for trip length: 9 miles from origin to destination; 7 miles of electrified lane Speed in non-electric lane, electrified lane with mixed traffic and electrified lane exclusive for EVs options (freeway):35mph;50mph;65mph	Goldstein, 2014; assumptions PeMS data; Google maps (taking average values using I-710 and Vermont Ave.);Federal-Aid Highway Program Guidance on High Occupancy Vehicle (HOV) Facility Lanes, 2016 (speed limits) Limb et al., 2017 McDonald, 2016; Chargepoint data, 2017

Table B2.2 continued

			Speed in non-electric lane, electrified lane with mixed traffic and electrified lane exclusive for EVs options (arterial):25mph;35mph;40mph Energy transfer from ER to vehicles: **20-**50kW for light duty vehicles or buses Energy efficiency at 87% Electric needs (non-electric lane) to get the same energy power that it will receive from ER (9miles trip): 3.132 kw (freeway) and 4.47kw (arterial) Charge speed (Nissan Leaf, Level 3 charging station): 50 kw in 1hour Detour time for charging (non-electric lane): 3-5 minutes	Google maps for detour time, considering Level 3 charging stations, I-710 and Vermont Ave.

B3. COMPARISONS OF SAMPLE DESCRIPTIVE CHARACTERISTICS

Table B3.1: Comparison of income

Source	**Description**	**Response Frequency**
Survey Sample	1: Under $25,000	1: 18.83%
	2: $25,000-$49,999	2: 23.17%
	3: $50,000-$74,999	3: 18.33%
	4: $75,000-$99.999	4: 15.83%
	5: $100,000-$149,999	5: 14.67%
	6: $150,000-$199,999	6: 4.67%
	7: $200,000 or more	7: 4.50%
Census (2010 data)	1: Under $25,000	1: 22.6%
	2: $25,000-$49,999	2: 22.9%
	3: $50,000-$74,999	3: 17.6%
	4: $75,000-$99.999	4: 12%
	5: $100,000-$149,999	5: 13.4%
	6: $150,000-$199,999	6: 5.5%
	7: $200,000 or more	7: 6%

Table B3.2: Comparison of education

Source	**Description**	**Response Frequency**
Survey Sample	1: Grade school	1: 15.5%
	2: Some high school	2: 2.5%
	3: High school graduate	3: 15.2%
	4: Technical training beyond high school	4: 5.7%

Table B3.2 continued

	5: Some college	5: 27%
	6: College graduate	6: 34.17%
	7: Graduate school	7: 15.5%
Census (2010 data)	1: Grade school	1: 13.4%
	2: Some high school	2: 9.2%
	3: High school graduate	3: 17.6%
	4: Technical training beyond high school	4: 13.8%
	5: Some college	5: 14.7%
	6: College graduate	6: 19.7%
	7: Graduate school	7: 11.6%

Table B3.3: Comparison of annual mileage

Source	**Description**	**Response Frequency**
Survey Sample	1: <5000 miles	1: 22.0%
	2: 5,000-9,999 miles	2: 24.67%
	3: 10,000-14,999 miles	3: 16.00%
	4: 15,000-19,999 miles	4: 9.67%
	5: 20,000-24,999 miles	5: 7.67%
	6: >25,000 miles	6: 4.83%
NHTS (2017data)	1: <5000 miles	1: 31.7%
	2: 5,000-9,999 miles	2: 18.2%
	3: 10,000-14,999 miles	3: 26.9%
	4: 15,000-19,999 miles	4: 10.89%
	5: 20,000-24,999 miles	5: 5.32%
	6: >25,000 miles	6: 6.95%

APPENDIX C. SHORT-TERM AND LONG-TERM BAHAVIORAL INTENTION MODELS

C1. DESCRIPTIVE STATISTICS

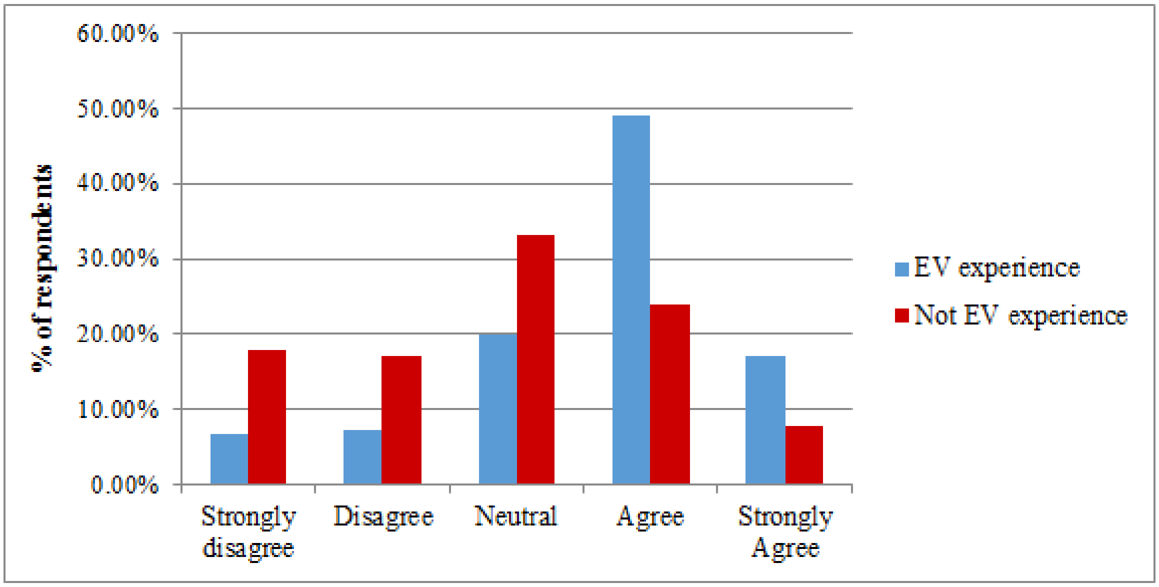

Figure C1.1: Intention to drive on ERs, as soon as they become available (respondents with EV experience or not)

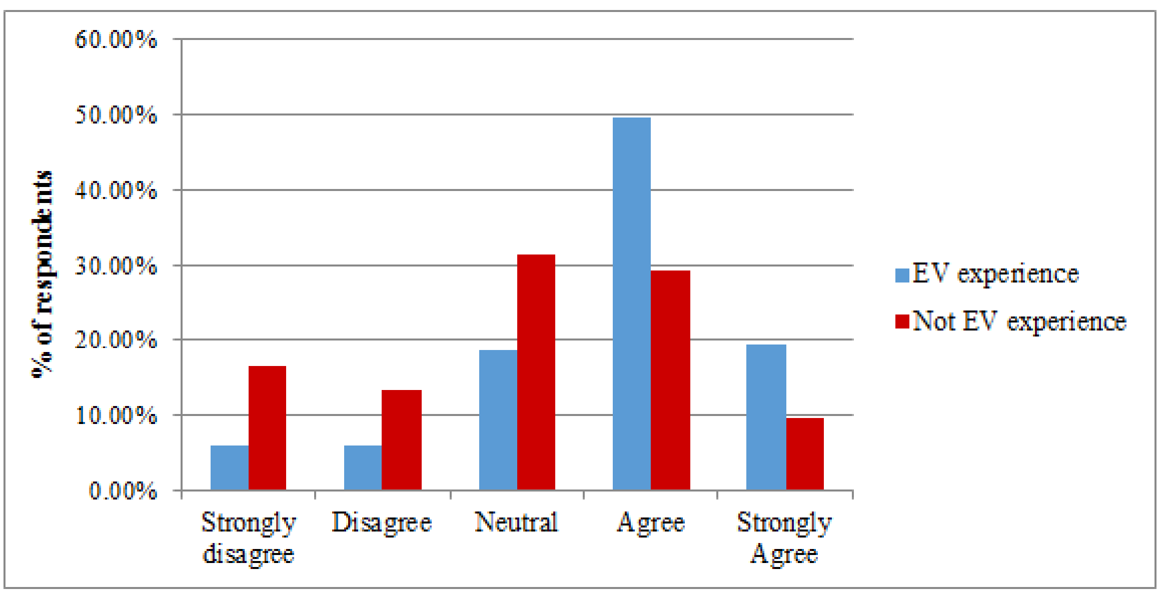

Figure C1.2: Intention to drive on ERs in the foreseeable future (respondents with EV experience or not)

Table C1.1: Descriptive statistics-analytical table

Variable	**Description**	**Response Frequency**
Gender	1: Male 2: Female	1: 47% 2: 53%
Age	1: 18-24 years old 2: 25-34 years old 3: 35-44 years old 4: 45-54 years old 5: 55-64 years old 6: 65 years or older	1: 18.2% 2: 19% 3: 17.3% 4: 17.2% 5: 13.7% 6: 14.7%
Education	1: Grade school 2: Some high school 3: High school graduate 4: Technical training beyond high school 5: Some college 6: College graduate 7: Graduate school	1: 0% 2: 2.5% 3: 15.17% 4: 5.67% 5: 27% 6: 34.17% 7: 15.5%
Income	1: Less than $25K 2: $25K to less than $50K 3: $50K to less than $75K 4: $75K to less than $100K 5: $100K to less than $150K 6: $150K to less than $200K 7. $200K or more	1: 18.8% 2: 23.2% 3: 18.3% 4: 15.8% 5: 14.7% 6: 4.7% 7: 4.5%
Employment Situation	1: Full time 2: Part time 3: Unemployed 4: Student 5: Retired 6: Homemaker	1: 45.5% 2: 13.7% 3: 9% 4: 9% 5: 14.8% 6: 6.5%
Household Size	1: One 2: Two 3: Three 4: Four 5: Five or more	1: 25.17% 2: 30.17% 3: 18.5% 4: 17.33% 5: 8.83%

Table C1.1 continued

Number of Children	1: None 2: One 3: Two 4: Three 5: Four	1: 65.83% 2: 16.33% 3: 13.67% 4: 2.83% 5: 1.33
Respondents who traveled medium distances (10-50 miles)	1: Never 2: Less often than 6 months 3: Every 6 months 4: Every 3 months 5: Once a month 6: Once a fortnight 7: Once a week 8: A few times a week 9: Almost every day 10: Don’t know	1: 9.33% 2: 5.67% 3: 5.67% 4: 6.83% 5: 10.33% 6: 8.67% 7: 18.67% 8: 17.83% 9: 14.17% 10: 2.83%
Respondents who agreed or strongly agreed on average that electric roadways are compatible with their lifestyle, daily needs or personal values and attitudes. (*)	1: Yes 2: No	1: 85.5% 2: 14.5%
1 if respondent rated driving range as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 3.67% 2: 4.33% 3: 7.83% 4: 17.67% 5: 51% 6: 15.5%
Respondents who agreed or strongly agreed on average that they would or have already changed their travel behavior/preferences because of the existence of sustainable forms of transportation.	1: Yes 2: No	1: 84.83% 2: 15.17%
Respondents who agreed or strongly agreed on average that they have safety concerns about ERs.	1: Yes 2: No	1: 77.67% 2: 22.33%

Table C1.1 continued

Respondents who agreed or strongly agreed on average that they are positive towards trying new innovations.	1: Yes 2: No	1: 71.17% 2: 28.83%
1 if respondent rated charging time as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 3.33% 2: 3.5% 3: 10% 4: 28% 5: 39.67% 6: 15.5%
1 if respondent rated financial incentives/rebates provided (such as subsidies) as very or extremely important factor when they think of purchasing an EV, 0-otherwise	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 4.67% 2: 5.67% 3: 17.5% 4: 27.5% 5: 29.83% 6: 14.83%
1 if respondent rated operational cost (cost to charge the EV/cost per mile) as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 2.83% 2: 4.33% 3: 12.17% 4: 25.67% 5: 40.5% 6: 14.5%
1 if respondent rated social/family influence as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 16.83% 2: 15% 3: 19.5% 4: 16.17% 5: 16% 6: 16.5%
1 if respondent rated safety as very or extremely important factor when planning their commute route, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don’t know	1: 4% 2: 5.67% 3: 12.5% 4: 31.33% 5: 42.5% 6: 4%

Table C1.1 continued

Respondents who agreed or strongly agreed on average that ERs would offer more advantages compared to driving on non-electric (conventional) roadways.	1: Yes 2: No	1: 86.5% 2: 13.5%
1 if respondent rated EV's purchase cost as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don't know	1: 3.83% 2: 2.17% 3: 12.83% 4: 22.5% 5: 43.5% 6: 15.17%
1 if respondent rated environmental benefits as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don't know	1: 5.17% 2: 8.5% 3: 16.33% 4: 24.5% 5: 30.83% 6: 14.67%
1 if respondent owns an EV and their vehicle's driving range is 150 miles or below.	1: I do not own an EV 2: 0-50 miles 3: 51-100 miles 4: 101-150 miles 5: 151-200 miles 6: 201-250 miles 7: 251-300 miles 8: Over 300 miles	1: 83.33% 2: 2.5% 3: 4% 4: 1.5% 5: 0% 6: 2.67% 7: 2.33% 8: 1.67%
1 if respondent rated vehicle performance as very or extremely important factor when they think of purchasing an EV, 0-otherwise.	1: Not at all important 2: Slightly important 3: Moderately important 4: Very important 5: Extremely important 6: Don't know	1: 2.67% 2: 3.33% 3: 11% 4: 26.83% 5: 41.67% 6: 14.5%
If you own an electric vehicle, what type of charger do you typically use to charge your vehicle? - At home	1: Level 1 AC 2: Level 2 AC 3: DC Fast Charge 4: N/A 5: Don't know	1: 7.5% 2: 7% 3: 7.33% 4: 66.33% 5: 11.83%
If you own an electric vehicle, what type of charger do you typically use to charge your vehicle? - At work	1: Level 1 AC 2: Level 2 AC 3: DC Fast Charge 4: N/A 5: Don't know	1: 6% 2: 8.17% 3: 5.33% 4: 69.33% 5: 11.17%

Table C1.1 continued

If you own an electric vehicle, what type of charger do you typically use to charge your vehicle? - At public/private stations	1: Level 1 AC 2: Level 2 AC 3: DC Fast Charge 4: N/A 5: Don't know	1: 5.5% 2: 7.17% 3: 7.5% 4: 67.67% 5: 12.17%
Which of the following is your primary mode of travel for each trip purpose? (Please select only one mode for each trip purpose listed on the left side below.) - Trips for work/school	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 12.84% 2: 3.21% 3: 0.51% 4: 68.07% 5: 5.07% 6: 7.77% 7: 1.86% 8: 0.68%
Which of the following is your primary mode of travel for each trip purpose? (Please select only one mode for each trip purpose listed on the left side below.) - Trips for grocery and shopping	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 10.4% 2: 3.02% 3: 1.51% 4: 72.99% 5: 6.38% 6: 3.52% 7: 1.68% 8: 0.5%
Which of the following is your primary mode of travel for each trip purpose? (Please select only one mode for each trip purpose listed on the left side below.) - Trips for personal business (e.g. errands, trips to medical/dental facilities, banks, etc.)	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 5.21% 2: 2.02% 3: 1.51% 4: 73.28% 5: 5.88% 6: 7.73% 7: 3.53% 8: 0.84%
Which of the following is your primary mode of travel for each trip purpose? (Please select only one mode for each trip purpose listed on the left side below.) - Trips for social/recreational activities (e.g. trips to gym, church, parks, theaters, etc.)	1: Walk 2: Bike (conventional) 3: Bike (electric) 4: Car (conventional) 5: Car (electric) 6: Public transportation 7: Ride-hailing service 8: Car-sharing service	1: 7.54% 2: 3.35% 3: 1.51% 4: 69.35% 5: 7.04% 6: 6.2% 7: 4.36% 8: 0.67%

C2. SHORT-TERM INTENTION MODEL OUTPUT

Correlation matrix

Cor.Mat.	EVNOW	ERNOW	EVFUT	ERFUT	MEDDIST	COMPAT	IMPRANGE	SUST
EVNOW	1.00000	.74238	.81633	.72941	.07215	.49986	.10119	.32951
ERNOW	.74238	1.00000	.78323	.82175	.11146	.54830	.16128	.29641
EVFUT	.81633	.78323	1.00000	.77321	.05758	.49882	.10762	.35590
ERFUT	.72941	.82175	.77321	1.00000	.09172	.57732	.19093	.28792
MEDDIST	.07215	.11146	.05758	.09172	1.00000	.06140	.10907	-.04483
COMPAT	.49986	.54830	.49882	.57732	.06140	1.00000	.19004	.29094
IMPRANGE	.10119	.16128	.10762	.19093	.10907	.19004	1.00000	.13024
SUST	.32951	.29641	.35590	.28792	-.04483	.29094	.13024	1.00000

Cor.Mat.	EVNOW	ERNOW	EVFUT	ERFUT	MEDDIST	COMPAT	IMPRANGE	SUST
SAFE	.12644	.03825	.10838	.07730	.02275	.05824	.04050	.18890
INNOV	.44773	.43315	.45199	.38295	.08241	.38091	.11069	.33838
RICH1	.09332	.03984	.03139	.04603	.06910	.06474	.12487	-.00986
IMTIME	.09037	.11396	.10026	.10745	.08463	.14813	.70836	.14859
INCENT	.22992	.18229	.21000	.22417	.04277	.22866	.49972	.17383
COSTMILE	.19667	.17309	.13495	.19337	.02990	.19678	.61052	.16488
INFLU	.35164	.27982	.34227	.27121	.01713	.25157	.17287	.25801

Cor.Mat.	SAFE	INNOV	RICH1	IMTIME	INCENT	COSTMILE	INFLU
SAFE	1.00000	.11861	-.08135	.02846	.09363	.03563	.20565
INNOV	.11861	1.00000	.02478	.13217	.20223	.19915	.37145
RICH1	-.08135	.02478	1.00000	.15251	.12665	.11890	.00001
IMTIME	.02846	.13217	.15251	1.00000	.52754	.59014	.24717
INCENT	.09363	.20223	.12665	.52754	1.00000	.55116	.36320
COSTMILE	.03563	.19915	.11890	.59014	.55116	1.00000	.28881
INFLU	.20565	.37145	.00001	.24717	.36320	.28881	1.00000

Model output

Bivariate Ordered Probit Model
Dependent variable BivOrdPr
Log likelihood function -1497.04712
Restricted log likelihood -1670.54335
Chi squared [23](P= .000) 346.99247
Significance level .00000
McFadden Pseudo R-squared .1038562
Estimation based on N = 600, K = 23
Inf.Cr.AIC = 3040.1 AIC/N = 5.067

Y827 Y823	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
	Index function for Probability Model for Y827......................					
Constant	-1.23650***	.33678	-3.67	.0002	-1.89658	-.57643
MEDDIST	.15647*	.08122	1.93	.0540	-.00271	.31566
PCOMP	1.66879***	.37018	4.51	.0000	.94325	2.39433
IMPRANGE	.18714**	.08335	2.25	.0247	.02379	.35050
PSUST	2.09623***	.35582	5.89	.0000	1.39883	2.79364
PSAFE	-.67040	.44019	-1.52	.1278	-1.53316	.19236
PINNOV2	.76447*	.42900	1.78	.0748	-.07635	1.60530
	Index function for Probability Model for Y823......................					
Constant	-1.69141***	.26245	-6.44	.0000	-2.20581	-1.17701
RICH1	.18636**	.08311	2.24	.0249	.02347	.34926

```
  IMTIME|    -.23516***      .09048    -2.60  .0093     -.41249   -.05783
  INCENT|     .15429*        .08326     1.85  .0639     -.00889    .31746
COSTMILE|     .13377         .08828     1.52  .1297     -.03926    .30680
   INFLU|     .22545***      .08644     2.61  .0091      .05604    .39486
   PCOMP|    1.95153***      .38127     5.12  .0000     1.20425   2.69881
   PSUST|    1.68398***      .36008     4.68  .0000      .97823   2.38973
 PINNOV2|    1.06698**       .44078     2.42  .0155      .20308   1.93089
        |Threshold Parameters for Probability Model for Y827................
  MU(01)|     .58601***      .06262     9.36  .0000      .46328    .70873
  MU(02)|    1.43243***      .07797    18.37  .0000     1.27962   1.58525
  MU(03)|    2.58980***      .10067    25.73  .0000     2.39249   2.78711
        |Threshold Parameters for Probability Model for Y823................
LMDA(01)|     .69372***      .06251    11.10  .0000      .57120    .81625
LMDA(02)|    1.60642***      .07992    20.10  .0000     1.44978   1.76306
LMDA(03)|    2.62425***      .10519    24.95  .0000     2.41809   2.83041
        |Disturbance Correlation = RHO(1,2)................................
RHO(1,2)|     .74155***      .01996    37.16  .0000      .70244    .78067
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

Cross tabulation of predictions

```
===================================================================

+---------+-----------------------------------------------+--------+
|
+---------+-----------------------------------------------+--------+
|        0|       77        8        1        1        2  |    89  |
|        1|        8       52       19        5        2  |    86  |
|        2|       13       29      103       31        2  |   178  |
|        3|        4       16       54       94       17  |   185  |
|        4|        0        2        7       15       38  |    62  |
+---------+-----------------------------------------------+--------+
|   Total|      102      107      184      146       61  |   600  |
+---------+-----------------------------------------------+--------+
Frequencies for Predicted Joint Outcomes
---------+-------------------------------------------
         |      Y823
---------+-------------------------------------------
Y827     |       0      1      2      3      4  Total
---------+-------------------------------------------
    0    |     156      0      0      0      0    156
    1    |       0      0      0      0      0      0
    2    |       0      0    163      2      0    165
    3    |       0      0     59    181      0    240
    4    |       0      0      0      0     39     39
---------+-------------------------------------------
Total    |     156      0    222    183     39    600
---------+-------------------------------------------
```

Marginal effects output

```
Marginal effects for ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.
--------+-------------------------------------------------------------
        |     Partial                            Prob.      95% Confidence
    Y823|      Effect    Elasticity      z     |z|>Z*         Interval
--------+-------------------------------------------------------------
        |--------------[Partial effects on Prob[Y=00] at means]--------------
  *RICH1|    -.03493*       -.27765    -1.81  .0707     -.07282    .00295
 *IMTIME|     .07984***      .63455     3.65  .0003      .03699    .12268
 *INCENT|    -.03622        -.28784    -1.50  .1348     -.08368    .01125
*COSTMIL|    -.03745        -.29765    -1.39  .1659     -.09043    .01553
  *INFLU|    -.07241***     -.57549    -3.60  .0003     -.11188   -.03294
   PCOMP|    -.39849***    -1.78908    -5.01  .0000     -.55449   -.24249
   PSUST|    -.33406***    -1.62076    -4.21  .0000     -.48970   -.17841
 PINNOV2|    -.23592**      -.98312    -2.57  .0102     -.41583   -.05600
        |--------------[Partial effects on Prob[Y=01] at means]--------------
  *RICH1|    -.02642*       -.14336    -1.70  .0890     -.05686    .00403
 *IMTIME|     .06191***      .33601     3.45  .0006      .02675    .09707
 *INCENT|    -.02499        -.13562    -1.54  .1240     -.05683    .00685
*COSTMIL|    -.02520        -.13675    -1.46  .1437     -.05897    .00857
  *INFLU|    -.05580***     -.30281    -3.40  .0007     -.08798   -.02362
   PCOMP|    -.28142***     -.86274    -5.11  .0000     -.38929   -.17355
   PSUST|    -.23592***     -.78157    -4.28  .0000     -.34388   -.12796
 PINNOV2|    -.16661***     -.47408    -2.59  .0097     -.29279   -.04042
        |--------------[Partial effects on Prob[Y=02] at means]--------------
  *RICH1|    -.00380        -.01032     -.78  .4341     -.01332    .00572
 *IMTIME|     .01264         .03431     1.32  .1863     -.00611    .03139
 *INCENT|    -.00021        -.00056     -.07  .9435     -.00594    .00553
*COSTMIL|     .00072         .00197      .21  .8318     -.00596    .00740
  *INFLU|    -.01057        -.02870    -1.26  .2076     -.02701    .00587
   PCOMP|    -.01064        -.01631     -.33  .7447     -.07467    .05340
   PSUST|    -.00892        -.01478     -.33  .7447     -.06260    .04476
 PINNOV2|    -.00630        -.00896     -.32  .7458     -.04437    .03177
        |--------------[Partial effects on Prob[Y=03] at means]--------------
  *RICH1|     .04226*        .16163     1.73  .0836     -.00561    .09013
 *IMTIME|    -.09781***     -.37411    -3.49  .0005     -.15281   -.04281
 *INCENT|     .04119         .15753     1.52  .1287     -.01195    .09433
*COSTMIL|     .04187         .16015     1.43  .1516     -.01537    .09911
  *INFLU|     .08843***      .33822     3.45  .0006      .03815    .13872
   PCOMP|     .46061***      .99513     4.89  .0000      .27588    .64534
   PSUST|     .38613***      .90150     4.14  .0000      .20328    .56898
 PINNOV2|     .27269**       .54683     2.55  .0107      .06341    .48198
        |--------------[Partial effects on Prob[Y=04] at means]--------------
  *RICH1|     .02289         .38066     1.58  .1148     -.00556    .05133
 *IMTIME|    -.05657***     -.94087    -2.91  .0037     -.09472   -.01842
 *INCENT|     .02022         .33635     1.53  .1266     -.00573    .04617
*COSTMIL|     .02005         .33343     1.48  .1396     -.00655    .04665
  *INFLU|     .05034***      .83721     2.88  .0040      .01606    .08462
   PCOMP|     .22994***     2.16011     4.50  .0000      .12982    .33006
   PSUST|     .19276***     1.95688     3.92  .0001      .09649    .28903
 PINNOV2|     .13613**      1.18700     2.51  .0121      .02979    .24247
--------+-------------------------------------------------------------
z, prob values and confidence intervals are given for the partial effect
***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
```

C3. LONG-TERM INTENTION MODEL OUTPUT

Correlation matrix

Cor.Mat.	EVNOW	ERNOW	EVFUT	ERFUT	COLLEGE	SROUTE	INNOV	RELADV
EVNOW	1.00000	.74238	.81633	.72941	.01918	.16932	.44773	.45612
ERNOW	.74238	1.00000	.78323	.82175	.06048	.17547	.43315	.43105
EVFUT	.81633	.78323	1.00000	.77321	.00688	.16029	.45199	.44759
ERFUT	.72941	.82175	.77321	1.00000	.09844	.18434	.38295	.49543
COLLEGE	.01918	.06048	.00688	.09844	1.00000	.04811	.03366	.08163
SROUTE	.16932	.17547	.16029	.18434	.04811	1.00000	.16826	.16582
INNOV	.44773	.43315	.45199	.38295	.03366	.16826	1.00000	.33473
RELADV	.45612	.43105	.44759	.49543	.08163	.16582	.33473	1.00000

Cor.Mat.	EVNOW	ERNOW	EVFUT	ERFUT	COLLEGE	SROUTE	INNOV	RELADV
PCOST	.05403	-.00997	-.00034	.02680	.09459	.17817	.04988	.09176
ENVBEN	.30021	.29233	.29402	.29103	.06711	.24310	.27690	.26869
SRANGE	.20792	.19920	.19324	.19486	-.02967	.03188	.12336	.06827
YOUNG	.26718	.21253	.28707	.20432	-.17097	-.07571	.18159	.05934
VEHPERF	.12717	.13448	.10445	.16750	.08398	.22485	.12148	.21423
DCCHARGE	.33132	.23246	.28193	.19378	-.03574	.04703	.17663	.14819
INFLU	.35164	.27982	.34227	.27121	-.00815	.19078	.37145	.22649
WBIKE	.09983	.09651	.12339	.01700	-.10168	-.05881	.04325	-.02066

Cor.Mat.	PCOST	ENVBEN	SRANGE	YOUNG	VEHPERF	DCCHARGE	INFLU	WBIKE
PCOST	1.00000	.22708	-.05045	-.13221	.42856	-.14570	.12987	-.04579
ENVBEN	.22708	1.00000	.04544	.03890	.50938	.13425	.46798	.02204
SRANGE	-.05045	.04544	1.00000	.14896	-.02489	.22255	.14835	.11215
YOUNG	-.13221	.03890	.14896	1.00000	-.07243	.19986	.12750	.20363
VEHPERF	.42856	.50938	-.02489	-.07243	1.00000	.06710	.29031	-.05899
DCCHARGE	-.14570	.13425	.22255	.19986	.06710	1.00000	.29050	.16125
INFLU	.12987	.46798	.14835	.12750	.29031	.29050	1.00000	.05002
WBIKE	-.04579	.02204	.11215	.20363	-.05899	.16125	.05002	1.00000

Model output

```
Bivariate Ordered Probit Model
Dependent variable                BivOrdPr
Log likelihood function        -1460.39999
Restricted log likelihood      -1674.73885
Chi squared [ 25](P= .000)       428.67771
Significance level                  .00000
McFadden Pseudo R-squared         .1279834
Estimation based on N =    600, K =  25
Inf.Cr.AIC  =   2970.8 AIC/N =    4.951
```

Y829 / Y825	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
	Index function for Probability Model for Y829......................					
Constant	-1.12776***	.30846	-3.66	.0003	-1.73234	-.52318
COLLEGE	.20001***	.07389	2.71	.0068	.05519	.34484
SROUTE	.28191***	.10378	2.72	.0066	.07850	.48532
PINNOV2	1.83970***	.41114	4.47	.0000	1.03389	2.64551
PRELA	1.19849***	.44549	2.69	.0071	.32533	2.07164
PCOST	-.13425*	.07155	-1.88	.0606	-.27449	.00599
ENVBEN	.35591***	.10495	3.39	.0007	.15020	.56161
SRANGE	.35569***	.11417	3.12	.0018	.13192	.57946

	Index function for Probability Model for Y825					
Constant	-.88027***	.31886	-2.76	.0058	-1.50522	-.25533
YOUNG	.16073*	.08227	1.95	.0507	-.00051	.32197
SROUTE	.24373**	.10373	2.35	.0188	.04042	.44704
VEHPERF	-.27340***	.08737	-3.13	.0018	-.44465	-.10215
DCCHARGE	.34102***	.11585	2.94	.0032	.11396	.56808
INFLU	.24615***	.08204	3.00	.0027	.08535	.40695
PINNOV2	1.86953***	.46344	4.03	.0001	.96120	2.77786
ENVBEN	.39772***	.11457	3.47	.0005	.17318	.62227
PRELA	.73405	.48520	1.51	.1303	-.21692	1.68502
WBIKE	.19773***	.07271	2.72	.0065	.05522	.34025
	Threshold Parameters for Probability Model for Y829					
MU(01)	.52122***	.06946	7.50	.0000	.38508	.65737
MU(02)	1.32697***	.08242	16.10	.0000	1.16543	1.48852
MU(03)	2.51023***	.10153	24.72	.0000	2.31122	2.70923
	Threshold Parameters for Probability Model for Y825					
LMDA(01)	.61453***	.06044	10.17	.0000	.49607	.73299
LMDA(02)	1.50309***	.07930	18.95	.0000	1.34765	1.65852
LMDA(03)	2.48099***	.10502	23.62	.0000	2.27516	2.68682
	Disturbance Correlation = RHO(1,2)					
RHO(1,2)	.80139***	.01682	47.66	.0000	.76843	.83435

***, **, * ==> Significance at 1%, 5%, 10% level.

Cross tabulation of predictions

0	77	3	1	1	0	82
1	6	43	14	4	1	68
2	14	33	102	14	4	167
3	5	20	61	107	16	209
4	1	0	7	20	46	74
Total	103	99	185	146	67	600

Frequencies for Predicted Joint Outcomes

	Y825					
Y829	0	1	2	3	4	Total
0	147	0	0	0	0	147
1	0	0	0	0	0	0
2	0	0	55	0	0	55
3	0	0	141	229	2	372
4	0	0	0	0	26	26
Total	147	0	196	229	28	600

Marginal effects output

Marginal effects for ordered probability model
M.E.s for dummy variables are Pr[y|x=1]-Pr[y|x=0]
Names for dummy variables are marked by *.

Y829	Partial Effect	Elasticity	z	Prob. |z|>Z*	95% Confidence Interval	
	[Partial effects on Prob[Y=00] at means]					
*COLLEGE	-.04464**	-.58324	-2.01	.0440	-.08809	-.00120
*SROUTE	-.06012***	-.78539	-2.65	.0080	-.10457	-.01566
PINNOV2	-.33661***	-2.30572	-4.31	.0000	-.48955	-.18367
PRELA	-.21466***	-2.02929	-2.74	.0061	-.36807	-.06126
*PCOST	.03993**	.52167	2.19	.0283	.00423	.07563
*ENVBEN	-.06924***	-.90462	-3.51	.0004	-.10787	-.03062
*SRANGE	-.08105***	-1.05882	-5.18	.0000	-.11171	-.05038
	[Partial effects on Prob[Y=01] at means]					
*COLLEGE	-.02481**	-.28523	-2.21	.0274	-.04686	-.00276
*SROUTE	-.03279***	-.37698	-2.98	.0029	-.05439	-.01119
PINNOV2	-.20299***	-1.22354	-4.43	.0000	-.29279	-.11319
PRELA	-.12945***	-1.07685	-2.77	.0056	-.22097	-.03793
*PCOST	.02356**	.27081	2.27	.0235	.00317	.04394
*ENVBEN	-.04019***	-.46200	-3.77	.0002	-.06110	-.01927
*SRANGE	-.06262***	-.71989	-4.32	.0000	-.09106	-.03418
	[Partial effects on Prob[Y=02] at means]					
*COLLEGE	-.01919**	-.07117	-2.48	.0131	-.03434	-.00403
*SROUTE	-.02446***	-.09072	-3.23	.0012	-.03929	-.00963
PINNOV2	-.18581***	-.36130	-3.81	.0001	-.28141	-.09020
PRELA	-.11849***	-.31798	-2.60	.0094	-.20791	-.02907
*PCOST	.02078**	.07705	2.24	.0254	.00256	.03899
*ENVBEN	-.03482***	-.12914	-3.49	.0005	-.05436	-.01528
*SRANGE	-.09204***	-.34135	-2.99	.0028	-.15240	-.03168
	[Partial effects on Prob[Y=03] at means]					
*COLLEGE	.05368**	.13046	2.09	.0364	.00341	.10396
*SROUTE	.07158***	.17395	2.79	.0053	.02130	.12186
PINNOV2	.41851***	.53324	4.32	.0000	.22881	.60820
PRELA	.26689***	.46931	2.73	.0064	.07517	.45861
*PCOST	-.04910**	-.11932	-2.22	.0264	-.09244	-.00576
*ENVBEN	.08409***	.20435	3.64	.0003	.03877	.12941
*SRANGE	.09708***	.23591	6.52	.0000	.06791	.12624
	[Partial effects on Prob[Y=04] at means]					
*COLLEGE	.03496**	.22505	2.30	.0213	.00520	.06472
*SROUTE	.04579***	.29478	3.06	.0022	.01643	.07515
PINNOV2	.30690***	1.03585	4.11	.0000	.16048	.45333
PRELA	.19572***	.91167	2.71	.0068	.05411	.33733
*PCOST	-.03516**	-.22635	-2.24	.0249	-.06588	-.00444
*ENVBEN	.06016***	.38728	3.57	.0004	.02710	.09322
*SRANGE	.13863***	.89243	2.84	.0045	.04288	.23438

z, prob values and confidence intervals are given for the partial effect
***, **, * ==> Significance at 1%, 5%, 10% level.

APPENDIX D. MARKET SEGMENTATION

D1. CLUSTERING PROCEDURE AND NUMBER OF CLUSTERS

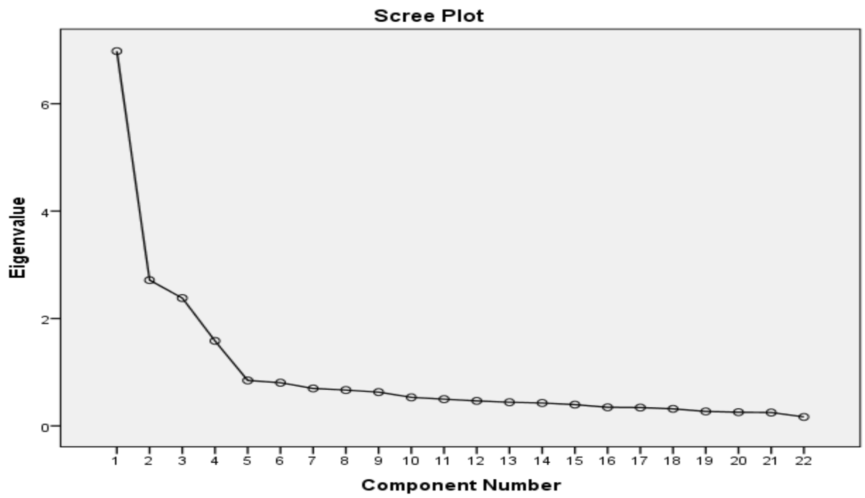

Figure D1.1: Scree Plot test (SPSS output)

Table D1.1: Iteration history of clustering algorithm (IBM SPSS)

Iteration History[a]			
Iteration	Change in Cluster Centers		
	1	2	3
1	3.308	3.089	3.099
2	0.194	0.169	0.075
3	0.188	0.09	0.051
4	0.167	0.119	0.048
5	0.071	0.015	0.036
6	0.021	0.006	0.012
7	0.035	0	0.02
8	0.007	0	0.004
9	0.00	0.00	0.00

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 9. The minimum distance between initial centers is 7.117.

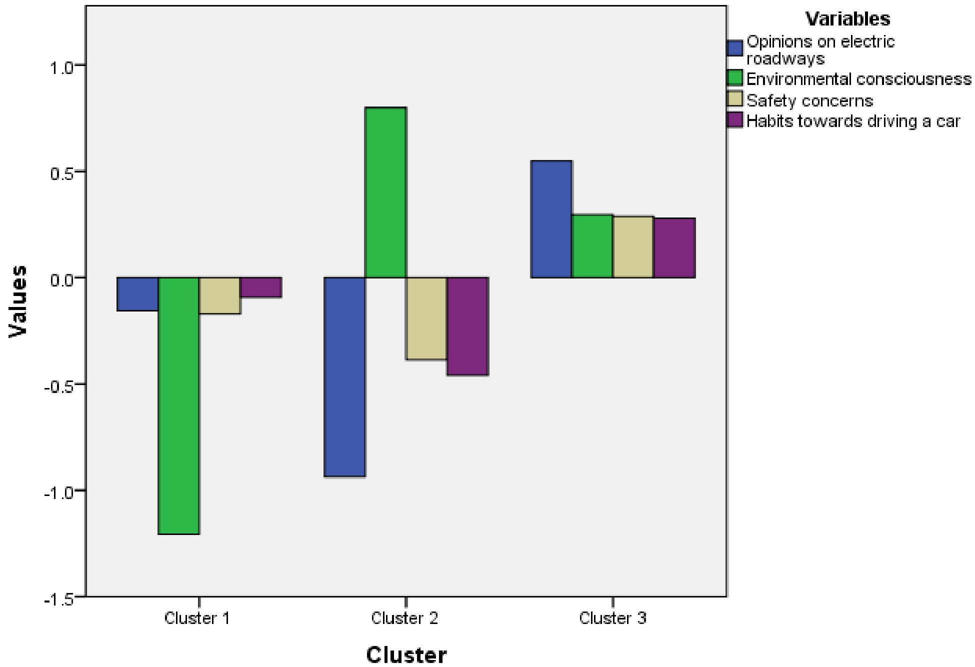

Figure D1.2: Final cluster centers (SPSS output)

Table D1.2: Post Hoc test

Dependent Variable	(I) Cluster Number of Case	(J) Cluster Number of Case	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Opinions on ERs	1	2	.78106355*	0.091252	0	0.601849	0.960278
		3	-.70433257*	0.077794	0	-0.85712	-0.55155
	2	1	-.78106355*	0.091252	0	-0.96028	-0.60185
		3	-1.48539612*	0.08168	0	-1.64581	-1.32498
	3	1	.70433257*	0.077794	0	0.55155	0.857115
		2	1.48539612*	0.08168	0	1.32498	1.645812

Table D1.2 continued

Environmental consciousness	1	2	-2.00538153*	0.072439	0	-2.14765	-1.86311
		3	-1.50215742*	0.061755	0	-1.62344	-1.38087
	2	1	2.00538153*	0.072439	0	1.863115	2.147648
		3	.50322411*	0.064841	0	0.375881	0.630568
	3	1	1.50215742*	0.061755	0	1.380873	1.623441
		2	-.50322411*	0.064841	0	-0.63057	-0.37588
Safety concerns	1	2	0.214633	0.109402	0.03	-0.00023	0.429492
		3	-.45794501*	0.093266	0	-0.64112	-0.27478
	2	1	-0.21463	0.109402	0.03	-0.42949	0.000226
		3	-.67257787*	0.097926	0	-0.8649	-0.48026
	3	1	.45794501*	0.093266	0	0.274775	0.641115
		2	.67257787*	0.097926	0	0.480257	0.864899
Habits towards driving a car	1	2	.36815117*	0.108992	0.001	0.154096	0.582206
		3	-.37004865*	0.092917	0	-0.55253	-0.18756
	2	1	-.36815117*	0.108992	0.001	-0.58221	-0.1541
		3	-.73819981*	0.097559	0	-0.9298	-0.5466
	3	1	.37004865*	0.092917	0	0.187564	0.552533
		2	.73819981*	0.097559	0	0.546598	0.929801

*The mean difference is significant at the 0.05 level.

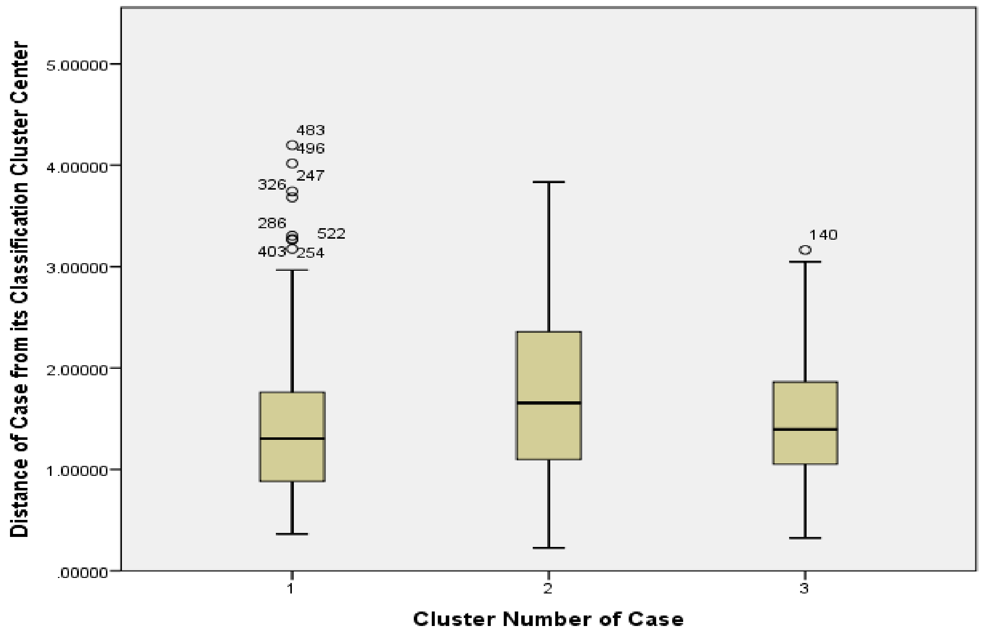

Figure D1.3: Outliers detection (SPSS output)

D2. CLUSTERS' LABELING AND CHARACTERISTICS

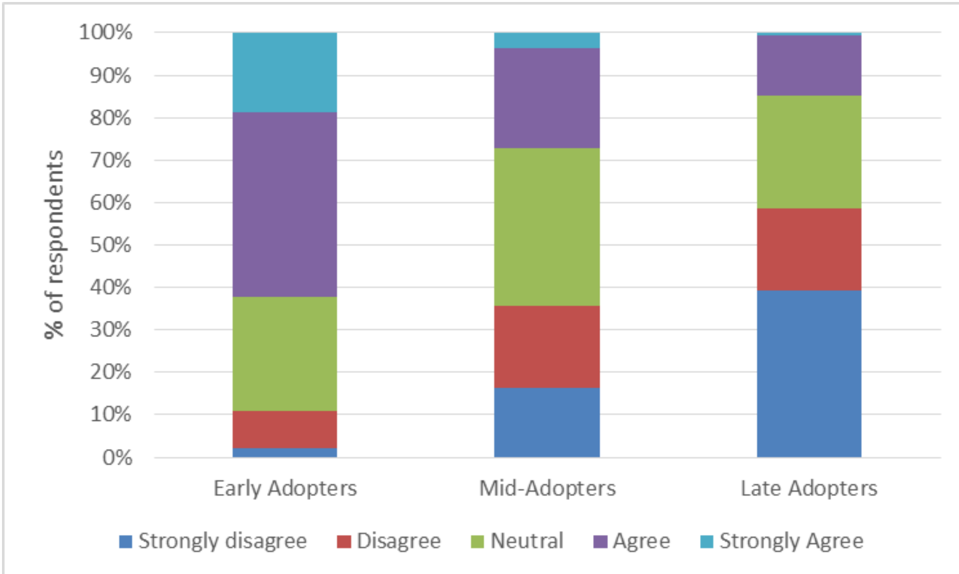

Figure D2.1: Intention to drive on ERs as soon as ERs become available by cluster

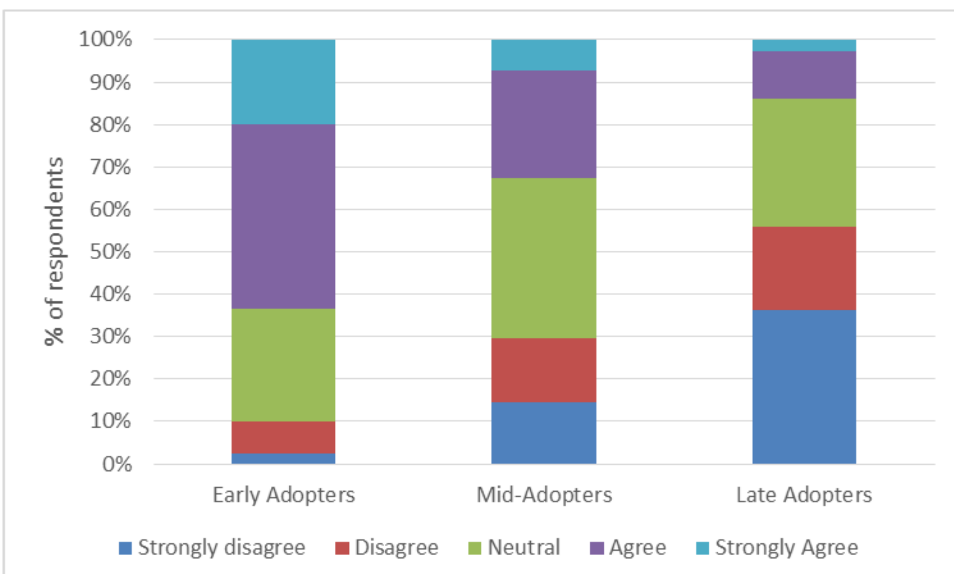

Figure D2.2: Intention to drive on ERs shortly after ERs become available by cluster

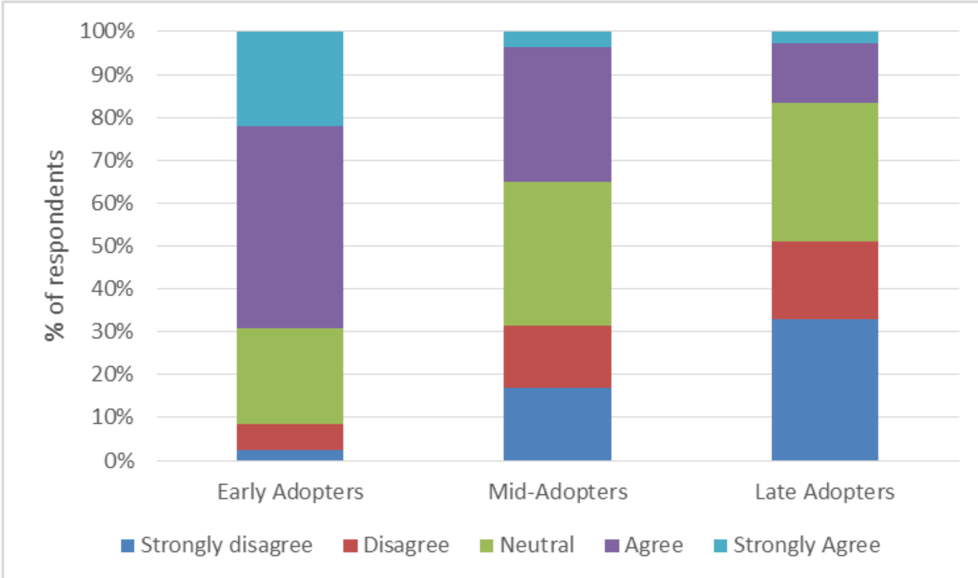

Figure D2.3: Intention to drive on ERs in the foreseeable future by cluster

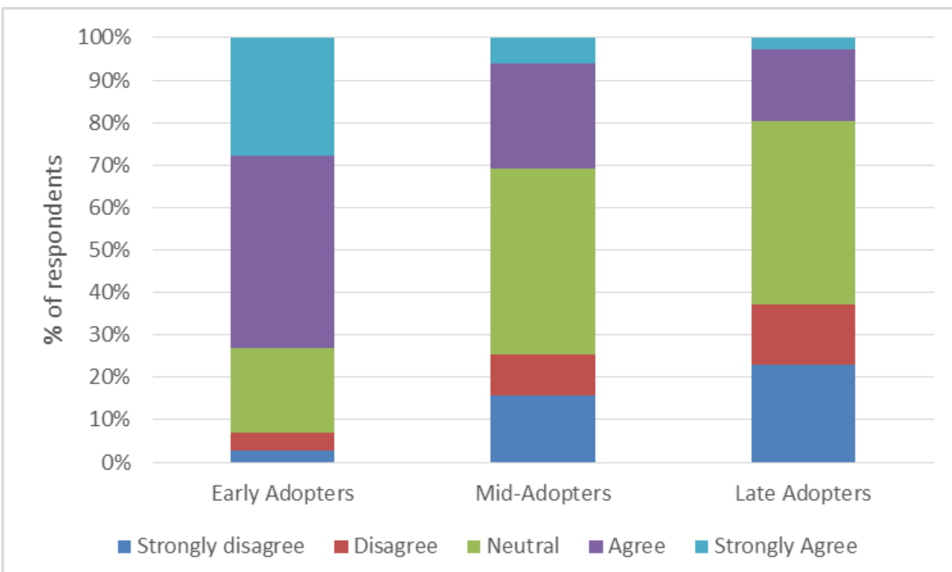

Figure D2.4: Recommendation of driving on ERs to other EV owners/users by cluster

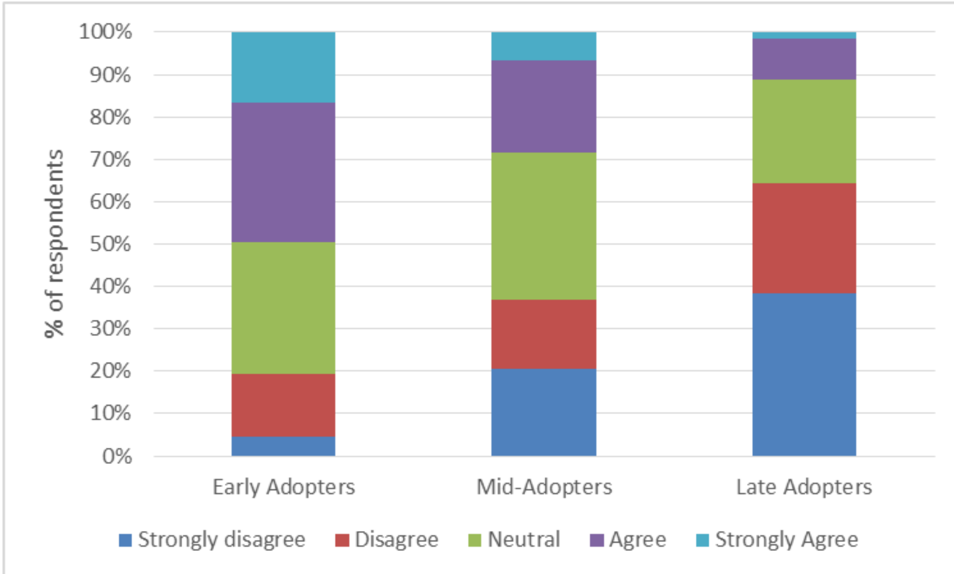

Figure D2.5: Intention to purchase an EV, knowing that ERs are currently available by cluster

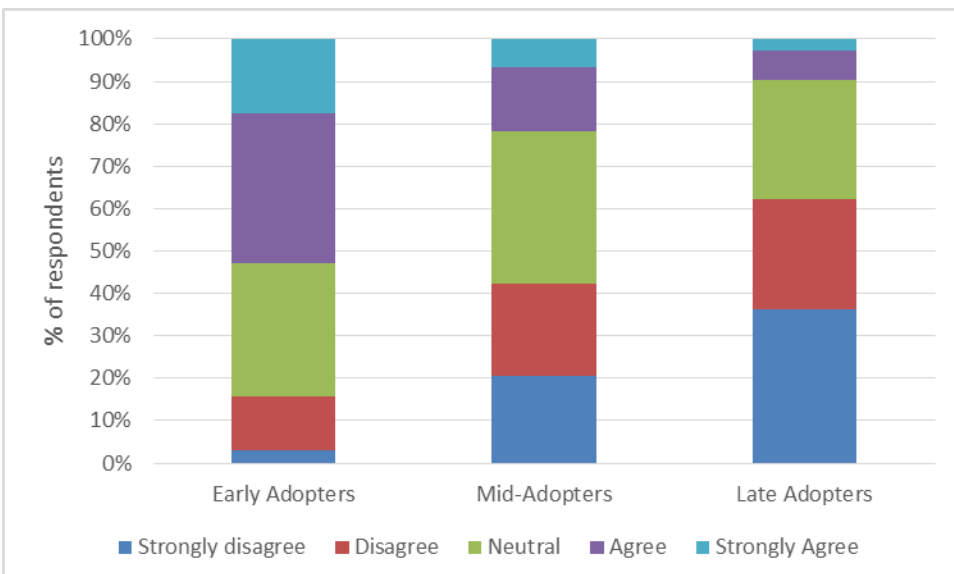

Figure D2.6: Intention to purchase an EV, shortly after ERs become available by cluster

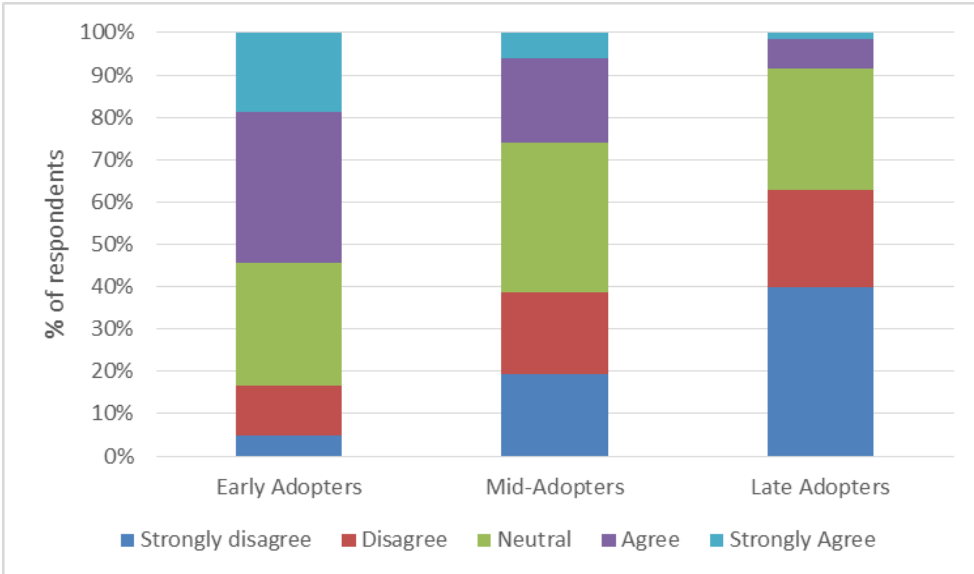

Figure D2.7: Intention to purchase an EV, knowing that ERs will be available in the foreseeable future by cluster

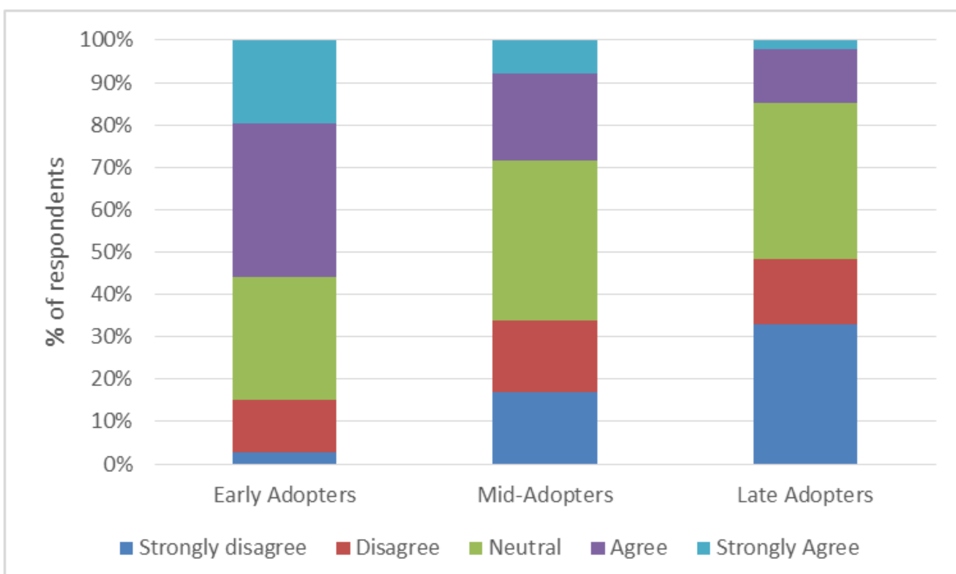

Figure D2.8: Recommendation of purchasing an EV knowing that ERs will become available by cluster

Table D2.1: Clusters' profile and level of relationship with sociodemographic variables

Variable categories	**Early Adopters (cluster 3)**	**Mid-Adopters (Cluster 1)**	**Late Adopters (cluster 2)**
Sample size (%)	291 (48.5%)	166 (27.67%)	143 (23.83%)
Gender (χ^2 = 31.549, df=2, p=0.000)			
Male	53.95%	52.41%	26.57%
Female	46.05%	47.59%	73.43%
Age (χ^2 = 25.470, df=10, p=0.005)			
18-24 years old	16.84%	19.28%	18.18%
25-34 years old	23.02%	18.07%	11.89%
35-44 years old	18.90%	20.48%	10.49%
45-54 years old	15.12%	18.07%	20.28%
55-64 years old	13.40%	12.65%	15.38%
65 or above	12.71%	10.24%	23.78%
Employment situation (χ^2 = 18.854, df=10, p=0.042)			
Work full time	52.92%	43.98%	32.17%
Work part time	13.40%	13.25%	14.69%
Currently unemployed	7.56%	9.04%	11.89%
Student	7.22%	10.24%	11.19%
Retired	12.71%	13.86%	20.28%
Homemaker	5.15%	7.83%	7.69%
Other	1.03%	1.81%	2.10%
Income level (χ^2 = 22.982, df=12, p=0.028)			
<$25,000	16.49%	20.48%	21.68%
$25,000-$50,000	17.53%	28.31%	28.67%
$50,000-$75,000	18.21%	15.66%	21.68%
$75,000-$100,000	19.93%	14.46%	9.09%
$100,000-$150,000	17.87%	12.65%	10.49%
$150,000-$200,000	5.15%	4.22%	4.20%
>$200,000	4.81%	4.22 %	4.20%
Educational level (χ^2 = 25.527, df=10, p=0.004)			
Grade school or less	0.00%	0.00%	0.00%
Some high school	2.75%	1.81%	2.80%
High school graduate	9.97%	23.49%	16.08%
Technical training beyond high school	4.81%	5.42%	7.69%
Some college	25.09%	30.12%	27.27%
College graduate	37.46%	28.31%	34.27%
Graduate school	19.93%	10.84%	11.89%

Table D2.1 continued

Household size (χ^2 = 12.501, df=8, p=0.130)			
1 person	22.68%	24.10%	31.47%
2 people	29.21%	28.31%	34.27%
3 people	17.87%	21.69%	16.08%
4 people	21.31%	15.66%	11.19%
5 or more people	8.93%	10.24%	6.99%
Number of children (χ^2 = 32.100, df=8, p=0.000)			
0 children	59.79%	65.66%	78.32%
1 child	19.24%	17.47%	9.09%
2 children	18.56%	10.24%	7.69%
3 children	2.06%	3.01%	4.20%
4 or more children	0.34%	3.61%	0.70%
Number of personal vehicles (χ^2 = 16.606, df=8, p=0.034)			
0 vehicles	3.78%	10.84%	11.89%
1 vehicle	44.67%	40.96%	42.66%
2 vehicles	33.68%	27.71%	33.57%
3 vehicles	13.06%	15.66%	8.39%
4 or more vehicles	4.81%	4.82%	3.50%
Number of miles driven (χ^2 = 37.214, df=12, p=0.000)			
<5,000 miles	6.53%	13.25%	17.48%
5,000-9,999 miles	17.87%	20.48%	32.17%
10,000-14,999 miles	27.84%	21.69%	21.68%
15,000-19,000 miles	18.56%	17.47%	9.09%
20,000-24,999 miles	10.65%	10.84%	6.29%
>25,000 miles	9.97%	7.23%	3.50%
Driver's license (χ^2 = 13.812, df=2, p=0.001)			
No	5.84%	15.06%	15.38%
Yes	94.16%	84.94%	84.62%

Table D2.2: Clusters' profile and level of relationship with travel and EV charging related variables

Variable categories	Early Adopters (cluster 3)	Mid-Adopters (Cluster 1)	Late Adopters (cluster 2)
Sample size (%)	291 (48.5%)	166 (27.67%)	143 (23.83%)
Car sharing or ride-hailing membership (χ^2 =15.168, df=2, p=0.001)			
No	65.64%	82.53%	58.74%
Yes	34.36%	17.47%	3.50%
Car ownership by fuel type-diesel (χ^2 =12.886, df=8, p=0.116)			
0 vehicles	90.03%	89.16%	97.20%
1 vehicle	6.19%	9.04%	1.40%
2 vehicles	1.03%	0.60%	0.70%
3 vehicles	2.06%	0.60%	0.00%
4 or more vehicles	0.69%	0.60%	0.70%
Car ownership by fuel type-gasoline (χ^2=15.064, df=8, p=0.058)			
0 vehicles	11.68%	16.27%	15.38%
1 vehicle	48.80%	42.77%	44.76%
2 vehicles	26.46%	21.69%	30.77%
3 vehicles	9.28%	16.87%	6.29%
4 or more vehicles	3.78%	2.41%	2.80%
Car ownership by fuel type-HEV (χ^2=6.846, df=8, p=0.553)			
0 vehicles	95.53%	89.16%	90.91%
1 vehicle	0.69%	7.83%	5.59%
2 vehicles	2.41%	1.81%	2.80%
3 vehicles	1.03%	0.00%	0.70%
4 or more vehicles	0.69%	1.20%	0.00%
Car ownership by fuel type-PHEV (χ^2=8.147, df=8, p=0.419)			
0 vehicles	85.22%	92.77%	96.50%
1 vehicle	10.31%	3.61%	2.10%
2 vehicles	2.75%	1.20%	1.40%
3 vehicles	1.03%	1.20%	0.00%
4 or more vehicles	0.69%	1.20%	0.00%

Table D2.2 continued

Car ownership by fuel type-BEV (χ^2 =9.857, df=8, p=0.275)			
0 vehicles	91.41%	90.96%	97.20%
1 vehicle	5.50%	4.82%	1.40%
2 vehicles	1.03%	1.81%	1.40%
3 vehicles	1.72%	1.20%	0.00%
4 or more vehicles	0.34%	1.20%	0.00%
Previous EV experience (χ^2 =27.409, df=2, p=0.000)			
No	63.23%	77.11%	86.01%
Yes	36.77%	22.89%	13.99%
EV charging frequency at home (χ^2=24.175, df=8, p=0.002)			
never	11.34%	25.30%	15.38%
once per week	6.53%	4.22%	4.90%
a few times per week	7.56%	8.43%	2.80%
every day	9.28%	4.82%	3.50%
more than one time per day	4.47%	2.41%	0.00%
N/A	60.82%	54.82%	73.43%
EV charging frequency at work (χ^2=26.355, df=8 , p=0.001)			
never	14.78%	24.70%	18.88%
once per week	4.12%	3.61%	4.20%
a few times per week	6.19%	6.02%	2.80%
every day	9.97%	6.02%	0.00%
more than one time per day	2.41%	5.42%	0.00%
N/A	62.54%	54.22%	74.13%
EV charging frequency at public/private stations (χ^2=16.838, df=8, p=0.032)			
never	14.09%	24.10%	17.48%
once per week	7.56%	6.02%	5.59%
a few times per week	7.90%	8.43%	2.80%
every day	5.84%	3.01%	0.70%
more than one time per day	2.41%	2.41%	0.00%
N/A	62.20%	56.02%	73.43%

Table D2.2 continued

Type of charger at home (χ^2=4.925, df=4, p=0.295)			
Level 1AC	7.90%	11.45%	2.10%
Level 2AC	8.93%	6.63%	3.50%
DC Fast charge	10.31%	7.23%	1.40%
n/a	63.23%	57.83%	82.52%
don’t know	9.62%	16.87%	10.49%
Type of charger at work (χ^2=6.242, df=4, p=0.182)			
Level 1AC	6.19%	10.24%	0.70%
Level 2AC	9.97%	10.24%	2.10%
DC Fast charge	7.22%	4.22%	2.80%
n/a	67.01%	60.24%	84.62%
don’t know	9.62%	15.06%	9.79%
Type of charger at public/private stations (χ^2=3.551, df=4, p=0.470)			
Level 1AC	5.84%	9.04%	0.70%
Level 2AC	8.93%	7.83%	2.80%
DC Fast charge	9.97%	8.43%	1.40%
n/a	64.95%	58.43%	83.92%
don’t know	10.31%	16.27%	11.19%
Battery level when they leave home (χ^2=21.884, df=8, p=0.005)			
less than 50%	4.12%	7.23%	4.90%
50%	3.78%	6.02%	4.90%
50%-90%	8.59%	6.63%	2.10%
Fully charged	25.77%	16.27%	13.99%
I do not pay attention to the battery level	57.73%	63.86%	74.13%
Level of awareness 1 (χ^2=23.117, df=6, p=0.001)			
I have never heard of this	24.05%	32.53%	41.26%
I think I have heard of this	33.33%	35.54%	30.07%
I have read of it, but don't know much beyond the description provided	25.43%	22.89%	23.08%
I am following the news about this on a regular basis	17.18%	9.04%	5.59%

Table D2.2 continued

Level of awareness 2(χ^2=20.157, df=6, p=0.003)			
I have never heard of this	19.59%	28.31%	33.57%
I think I have heard of this	28.18%	30.72%	32.87%
I have read of it, but don't know much beyond the description provided	34.02%	30.12%	25.87%
I am following the news about this on a regular basis	18.21%	10.84%	7.69%
Level of awareness 3(χ^2=43.078, df=6, p=0.000)			
I have never heard of this	36.43%	40.36%	65.73%
I think I have heard of this	19.59%	26.51%	13.99%
I have read of it, but don't know much beyond the description provided	29.21%	22.89%	16.78%
I am following the news about this on a regular basis	14.78%	10.24%	3.50%
Level of awareness 4(χ^2=42.510, df=6, p=0.000)			
I have never heard of this	58.42%	57.23%	84.62%
I think I have heard of this	15.46%	15.66%	6.99%
I have read of it, but don't know much beyond the description provided	12.71%	19.28%	6.99%
I am following the news about this on a regular basis	13.40%	7.83%	1.40%

APPENDIX E. IMPACT ON CRITERIA POLLUTANTS AND GREENHOUSE GAS EMISSIONS

Table E.1: EMFAC2011, EMFAC2007 vehicle classifications available to select for EMFAC2017 (or EMFAC 2014)

EMFAC2011 Vehicle	Description	Source	EMFAC2007 Vehicle	EMFAC2007 Vehicle Code	Truck / Non-Truck Category	Truck 1 / Truck 2 / Non-Truck Category
LDA	Passenger Cars	EMFAC2011-LDV	LDA	PC	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
LDT1	Light-Duty Trucks (GVWR <6000 lbs. and ETW <= 3750 lbs)	EMFAC2011-LDV	LDT1	T1	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
LDT2	Light-Duty Trucks (GVWR <6000 lbs. and ETW 3751-5750 lbs)	EMFAC2011-LDV	LDT2	T2	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
LHD1	Light-Heavy-Duty Trucks (GVWR 8501-10000 lbs)	EMFAC2011-LDV	LHDT1	T4	Trucks	Truck 1
		EMFAC2011-LDV			Trucks	Truck 1
LHD2	Light-Heavy-Duty Trucks (GVWR 10001-14000 lbs)	EMFAC2011-LDV	LHDT2	T5	Trucks	Truck 1
		EMFAC2011-LDV			Trucks	Truck 1
MCY	Motorcycles	EMFAC2011-LDV	MCY	MC	Non-Trucks	Non-Trucks
MDV	Medium-Duty Trucks (GVWR 6000-8500 lbs)	EMFAC2011-LDV	MDV	T3	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
MH	Motor Homes	EMFAC2011-LDV	MH	MH	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks

Table E.1 continued

T6 Ag	Medium-Heavy Duty Diesel Agriculture Truck	EMFAC2011-HD	MHDT	T6	Trucks	Truck 2
T6 CAIRP heavy	Medium-Heavy Duty Diesel CA International Registration Plan Truck with GVWR>26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 CAIRP small	Medium-Heavy Duty Diesel CA International Registration Plan Truck with GVWR<=26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 instate constructio n heavy	Medium-Heavy Duty Diesel instate construction Truck with GVWR>26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 instate constructio n small	Medium-Heavy Duty Diesel instate construction Truck with GVWR<=26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 instate heavy	Medium-Heavy Duty Diesel instate Truck with GVWR>26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 instate small	Medium-Heavy Duty Diesel instate Truck with GVWR<=26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 OOS heavy	Medium-Heavy Duty Diesel Out-of-state Truck with GVWR>26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 OOS small	Medium-Heavy Duty Diesel Out-of-state Truck with GVWR<=26000 lbs	EMFAC2011-HD			Trucks	Truck 2
T6 Public	Medium-Heavy Duty Diesel Public Fleet Truck	EMFAC2011-HD			Trucks	Truck 2
T6 utility	Medium-Heavy Duty Diesel Utility Fleet Truck	EMFAC2011-HD			Trucks	Truck 2
T6TS	Medium-Heavy Duty Gasoline Truck	EMFAC2011-LDV			Trucks	Truck 2

Table E.1 continued

T7 Ag	Heavy-Heavy Duty Diesel Agriculture Truck	EMFAC2011-HD	HHDT	T7	Trucks	Truck 2
T7 CAIRP	Heavy-Heavy Duty Diesel CA International Registration Plan Truck	EMFAC2011-HD			Trucks	Truck 2
T7 CAIRP constructio n	Heavy-Heavy Duty Diesel CA International Registration Plan Construction Truck	EMFAC2011-HD			Trucks	Truck 2
T7 NNOOS	Heavy-Heavy Duty Diesel Non-Neighboring Out-of-state Truck	EMFAC2011-HD			Trucks	Truck 2
T7 NOOS	Heavy-Heavy Duty Diesel Neighboring Out-of-state Truck	EMFAC2011-HD			Trucks	Truck 2
T7 other port	Heavy-Heavy Duty Diesel Drayage Truck at Other Facilities	EMFAC2011-HD			Trucks	Truck 2
T7 POAK	Heavy-Heavy Duty Diesel Drayage Truck in Bay Area	EMFAC2011-HD			Trucks	Truck 2
T7 POLA	Heavy-Heavy Duty Diesel Drayage Truck near South Coast	EMFAC2011-HD			Trucks	Truck 2
T7 Public	Heavy-Heavy Duty Diesel Public Fleet Truck	EMFAC2011-HD			Trucks	Truck 2
T7 Single	Heavy-Heavy Duty Diesel Single Unit Truck	EMFAC2011-HD			Trucks	Truck 2
T7 single constructio n	Heavy-Heavy Duty Diesel Single Unit Construction Truck	EMFAC2011-HD			Trucks	Truck 2
T7 SWCV	Heavy-Heavy Duty Diesel Solid Waste Collection Truck	EMFAC2011-HD			Trucks	Truck 2
T7 tractor	Heavy-Heavy Duty Diesel Tractor Truck	EMFAC2011-HD			Trucks	Truck 2

Table E.1 continued

T7 tractor construction	Heavy-Heavy Duty Diesel Tractor Construction Truck	EMFAC2011-HD			Trucks	Truck 2
T7 utility	Heavy-Heavy Duty Diesel Utility Fleet Truck	EMFAC2011-HD			Trucks	Truck 2
T7IS	Heavy-Heavy Duty Gasoline Truck	EMFAC2011-LDV			Trucks	Truck 2
PTO	Power Take Off	EMFAC2011-HD			Trucks	Truck 2
SBUS	School Buses	EMFAC2011-HD	SBUS	SB	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
UBUS	Urban Buses	EMFAC2011-LDV	UBUS	UB	Non-Trucks	Non-Trucks
		EMFAC2011-LDV			Non-Trucks	Non-Trucks
Motor Coach	Motor Coach	EMFAC2011-HD	OBUS	OB	Non-Trucks	Non-Trucks
OBUS	Other Buses	EMFAC2011-LDV			Non-Trucks	Non-Trucks
All Other Buses	All Other Buses	EMFAC2011-HD			Non-Trucks	Non-Trucks

Table E.2: I-710 geometric characteristics

Segments	Limits	Post miles	Facility Type	Mixed Flow Lanes	HOV Lanes	Lane Miles
1	Begin Fwy. to I-405	4.96-9.41	Interstate	3	7.83	23.49
2	I-405 to SR-91	9.41-12.97	Interstate	4	3.56	14.24
3	SR-91 to I-105	12.97-R15.69	Interstate	4	2.72	10.88
4	I-105 to I-5	R15.69-23.28	Interstate	4	7.59	30.36
5	I-5 to SR-60	23.28-24.63	Interstate	4	1.35	5.4
6	SR-60 to I-10	24.63-26.5	Interstate	3	1.85	5.61
7	I-10 to Valley Blvd.	26.5-T27.48	State Route	3	2.94	0.98

(California Department of Transportation, [Caltrans], 2013a)

REFERENCES

Aarts, H., Paulussen, T., & Schaalma, H., (1997). Physical exercise habit: On the conceptualization and formation of habitual health behaviours. Health Education Research: Theory and Practice, 12, 363-374. https://doi.org/10.1093/her/12.3.363

Aarts, H., Verplanken, B. & van Knippenberg, A., (1997b). Habit and information use in travel mode choices. Acta Psychologica, 96(1-2), 1–14. https://doi.org/10.1016/s0001-6918(97)00008-5

Abe, H., Sakamoto, H. & Harada, K., (1998). A noncontact charger using resonant converter with parallel capacitor of the secondary coil, Published In: APEC '98 Thirteenth Annual Applied Power Electronics Conference and Exposition, 1, 136–141. https://doi.org/10.1109/apec.1998.647681

Achtnicht, M., Bühler, G., & Hermeling, C., (2012). The impact of fuel availability on demand for alternative-fuel vehicles. Transportation Research Part D: Transport and Environment, 17(3), 262–269. https://doi.org/10.1016/j.trd.2011.12.005

Ajzen, I., (1991). The theory of planned behavior. Organizational behavior and human decision processes, 50, 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Alawi, B. M., & Bradley, T. H. (2013). Review of hybrid, plug-in hybrid, and electricvehicle market modeling Studies. Renewable and Sustainable Energy Reviews, 21(0), 190–203. https://doi.org/10.1016/j.rser.2012.12.048

Alternative Fuels Data Center, (2017). Electric Vehicle Charging Stations. US Department of Energy. Retrieved April 10, 2017, from: https://www.afdc.energy.gov/fuels/electricity_stations.html

Amemiya, T., (1985). Advanced Econometrics. Cambridge, MA: Harvard University Press.

American Lung Association (2018). State of the air 2018. Retrieved from: https://www.lung.org/assets/documents/healthy-air/state-of-the-air/sota-2018-full.pdf

Anastasopoulos, P.C., Karlaftis, M.G., Haddock, J.E. & Mannering, F.L., (2012). Household Automobile and Motorcycle Ownership Analyzed with Random Parameters Bivariate Ordered Probit Model. Transportation Research Record: Journal of the Transportation Research Board, 2279(1), 12–20. https://doi.org/10.3141/2279-02.

Andersson, S. & Edfeldt, E., (2013). Electric road systems for trucks. Master's thesis, KTH – Royal Institute of Technology.

Axsen, J. & Kurani, K.S., (2009). Early U.S. market for plug-in hybrid electric vehicles: Anticipating consumer recharge potential and design priorities, Transportation Research Record: Journal of the Transportation Research Board, 2139(1), 64-72. https://doi.org/10.3141/2139-08

Axsen, J. & Kurani, K.S., (2011). Interpersonal influence in the early plug-in hybrid market: Observing social interactions with an exploratory multi-method approach. Transportation Research Part D: Transport and Environment, 16(2), 150–159. https://doi.org/10.1016/j.trd.2010.10.006

Axsen, J., Mountain, D. & Jaccard, M., (2009). Combining Stated and Revealed Choice Research to Simulate the Neighborhood Effect: The Case of Hybrid-Electric Vehicles. Resource and Energy Economics, 31(3), 221-238. https://doi.org/10.1016/j.reseneeco.2009.02.001

Bagozzi, R.P., Gopinath, M. & Nyer, P.U., (1999). The role of emotions in marketing, Journal of the Academy of Marketing Science, 27(2), 184–206. https://doi.org/10.1177/0092070399272005

Balducci, P., (2008). Plug-in hybrid electric vehicle market penetration scenarios. PNNL-17441 Report. Richland, WA: Pacific Northwest National Laboratory. https://doi.org/10.2172/961683

Bamberg, S. & Moser, G., (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analyses of psycho-social determinants of pro-environmental behaviour. Journal of Environmental Psychology 27, 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002

Bamberg, S., (2003). How does environmental concern influence specific environmentally related behaviors? A new answer to an old question, Journal of Environmental Psychology, 23, 21–32. https://doi.org/10.1093/her/12.3.363

Barth, M. & Boriboonsomsin, K. (2009). Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transportation Research Part D: Transport and Environment, 14 (6), pp. 400-410. https://doi.org/10.1016/j.trd.2009.01.004

Bennett, D.A., (2001). How can I deal with missing data in my study? Australian and New Zealand Journal of Public Health, 25(5), 464 – 469. https://doi.org/10.1111/j.1467-842x.2001.tb00294.x

Beresteanu, A., Li, S., (2011). Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States. International Economic Review, 52(1), 161-182. https://doi.org/10.1111/j.1468-2354.2010.00623.x

Bi, Z., Kan, T., Mi, C.C., Zhang, Y., Zhao, Z. & Keoleian, G.A., (2016). A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility, 179, 413–425. https://doi.org/10.1016/j.apenergy.2016.07.003

Bian, H., (2012). SPSS Discriminant Function Analysis. Presentation (pp.1-58), Office for Faculty Excellence. Retrieved from: http://kharazmi-statistics.ir/Uploads/Public/MY%20article/SPSS%20Discriminant%20Function%20Analysis.pdf

Bockarjova, M., Knockaert, J., Rietveld, P. & Steg, L., (2014). Dynamic Consumer Heterogeneity in Electric Vehicle Adoption. Transportation Research Board 93rd Annual Meeting, Washington, DC. Retrieved from: http://docs.trb.org/prp/14-1579.pdf

Bolger, J.G., Kirsten, F.A. & Ng, L.S., (1978). Inductive power coupling for an electric highway system (pp. 137–144), in Proc. of 28th IEEE Vehicular Technology Conference. https://doi.org/10.1109/vtc.1978.1622522

Borage, M., Tiwari, S. & Kotaiah, S., (2005). Analysis and design of an LCL-T resonant converter as a constant-current power supply, IEEE Transactions on Industrial Electronics, 52(6), 1547-1554. https://doi.org/10.1109/tie.2005.858729

Boston Consulting Group, (2009). The comeback of the electric car? How Real, How Soon, and What Must Happen Next. Retrieved May 16, 2018, from: www.bcg.com/documents/file15404.pdf

Boys, J. & Covic, G., (2010). Inductive power transfer (IPT) – Powering our future. Auckland, New Zealand: The University of Auckland.

Brady, J. & O'Mahony, M., (2011). Travel to work in Dublin. The potential impacts of electric vehicles on climate change and urban air quality. Transportation Research Part D: Transport and Environment, 16(2), 188–193. https://doi.org/10.1016/j.trd.2010.09.006

Brandewinder, M., (2008). S-shaped Market Adoption Curve. Clear Lines Consulting LLC. Retrieved from: http://www.clear-lines.com/blog/post/S-shaped-market-adoption-curve.aspx#comment

Brecher, A. & Arthur, D., (2014). Review and Evaluation of Wireless Power Transfer (WPT) for Electric Transit Applications. Retrieved from: https://www.transit.dot.gov/sites/fta.dot.gov/files/FTA_Report_No._0060.pdf

Brown, B., Drew, M., Erenguc, C., Hasegawa, M., Hill, R., Schmith, R. & Ganula, B., (2014). Global automotive consumer study: The changing nature of mobility - Exploring consumer preferences in key markets around the world, Technical Report, Deloitte. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Manufacturing/gx-mfg-geny-automotive-consumer.pdf

Budhia, M., Covic, G.A. & Boys, J.T., (2011). Design and optimization of circular magnetic structures for lumped inductive power transfer systems, IEEE Transactions on Power Electronics, 26(11), 3096–3108. https://doi.org/10.1109/tpel.2011.2143730

Burgess, M., King, N., Harris, M. & Lewis, E., (2013). Electric Vehicle Drivers' Reported Interactions with the Public: Driving Stereotype Change? Transportation Research Part F: Traffic Psychology and Behaviour, 17, 33-44. https://doi.org/10.1016/j.trf.2012.09.003

California Air Resources Board, (2015). EMFAC 2014 Training (pp. 1-59). California Environmental Protection Agency. Retrieved from: https://www.arb.ca.gov/msei/downloads/emfac2014/06042015_webinar/emfac2014_online_training_webinar_06042015.pdf

California Air Resources Board, (2017a). EMFAC2017 - An update to California on-road mobile source emission inventory. Mobile Source Analysis Branch. Air Quality Planning and Science Division (pp. 1-207). California Air Resources Board. California Environmental Protection Agency. Retrieved from: https://www.arb.ca.gov/msei/downloads/emfac2017_workshop_june_1_2017_final.pdf

California Air Resource Board, (2017b). EMFAC2017 User's Guide - Version 1.0.1. - Mobile Source Analysis Branch - Air Quality Planning & Science Division (pp. 1-82). Retrieved from: https://www.arb.ca.gov/msei/downloads/emfac2017_users_guide_final.pdf

California Air Resource Board, (2018). EMFAC2017 Volume III - Technical Documentation - Version 1.0.2. - Mobile Source Analysis Branch - Air Quality Planning & Science Division (pp. 1-253). Retrieved from: https://www.arb.ca.gov/msei/downloads/emfac2017-volume-iii-technical-documentation.pdf

California Air Resources Board, (2015). California Diesel Fuel Program. Retrieved from: https://www.arb.ca.gov/fuels/diesel/diesel.htm

California Air Resources Board, (2017c). Zero Emission Vehicle (ZEV) Program. Retrieved from: https://www.arb.ca.gov/msprog/zevprog/zevprog.htm

California Air Resources Board, (2018). History. Retrieved from: https://ww2.arb.ca.gov/about/history

California Department of Transportation and Los Angeles Metro, (2012). I-710 Corridor Project. Environmental Impact Report/Environmental Impact Statement and Section 4(f) Evaluation. Executive Summary. Los Angeles County, California District 07-LA-710-PM 4.9/24.9EA 249900. Retrieved from: http://www.dot.ca.gov/d7/envdocs-/docs/710corridor/docs/710%20DEIR%20EIS%20Executive%20Summary%20final%20.pdf

California Department of Transportation, (2013). 2010-2012 California Household Travel Survey: Final Report. Retrieved from: http://www.dot.ca.gov/hq/tpp/offices/omsp/statewide_travel_analysis/files/CHTS_Final_Report_June_2013.pdf

Calinski, T. & Harabasz, J., (1974). A dendrite method for cluster analysis. Communication in Statistics – Theory and Methods, 3(1), 1–27. https://doi.org/10.1080/03610927408827101

Carley, S., Krause, R.M., Lane, B.W. & Graham, J.D., (2013). Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transportation Research Part D: Transport and Environment, 8, 39-45. http://dx.doi.org/10.1016/j.trd.2012.09.007

Carvalho, N.B., Rodrigues-Minim, V.P., Nascimento, M., Teixeiria-Ribeiro-Vidigal, M.C., Marques-Ferreira, M.A, Arruda-Gonçalves, A.C. & Minim, L.A., (2015). A discriminant function for validation of the cluster analysis and behavioral prediction of the coffee market, Food Research International, 77, 400–407. https://doi.org/10.1016/j.foodres.2015.10.013

Cattell, R.B., (1966). The scree test for the number of factors. Multivariate Behavioral Research, 1(2), 245-276. https://doi.org/10.1207/s15327906mbr0102_10

Center for Sustainable Energy, (2013). California plug-in electric vehicle driver survey results, California Environmental Protection Agency, Air Resources Board, San Diego. Retrieved from: https://energycenter.org/sites/default/files/docs/nav/transportation/cvrp/survey-results/California_Plug-in_Electric_Vehicle_Driver_Survey_Results-May_2013.pdf

Chambers, N., (2011). Ford Focus Electric Likely Won't Support DC Fast Charging at Launch. Plug-In America. Retrieved May 15, 2018, from: http://www.plugincars.com/ford-focus-electric-likely-wont-support-dc-fastcharging-launch-106739.html

Chargepoint data, (2017). Charging the Chevy Bolt EV: Everything you need to know, EV Life. Retrieved from: https://www.chargepoint.com/blog/charging-chevy-bolt-ev-everything-you-need-know/

Chawla, D. & Joshi, H. (2017). Consumer perspectives about mobile banking adoption in India – a cluster analysis, International Journal of Bank Marketing, 35(4), 616-636. https://doi.org/10.1108/IJBM-03-2016-0037.

Chawla, D. & Sondhi, N., (2016). Research Methodology: Concept and Cases (2nd ed.), New Delhi: Vikas Publishing House.

Chen, C.J., Chu, T.H., Lin, C.L. & Jou, Z.C., (2010). A study of loosely coupled coils for wireless power transfer, IEEE Transactions on Circuits and Systems II: Express Briefs, 57(7), 536–540. https://doi.org/10.1109/tcsii.2010.2048403

Chen, Z., He, F., & Yin, Y., (2016). Optimal deployment of charging lanes for electric vehicles in transportation networks. Transportation Research Part B: Methodological, 91, 344–365. https://doi.org/10.1016/j.trb.2016.05.018

Choi, D.G., Kreikebaum, F., Thomas, V.M., & Divan, D., (2013). Coordinated EV Adoption: Double-Digit Reductions in Emissions and Fuel Use for $40/Vehicle-Year. Environmental Science & Technology, 47(18), 10703–10707. https://doi.org/10.1021/es4016926

Chorus, C.G., Koetse, M.J. & Hoen, A., (2013). Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model. Energy Policy, 61, 901–908. https://doi.org/10.1016/j.enpol.2013.06.064

City of Los Angeles, Department of Transportation, (2012). LADOT Moving Los Angeles forward. Live traffic information. Retrieved from: http://trafficinfo.lacity.org/?x=34.02042314692197&y=-118.4109007317578&z=10

Comrey, A.L., (1973). A First Course in Factor Analysis. New York, NY: Academic Press.

Covic, G.A., Boys, J.T., Tam, A.M.W. & Peng, J.C.H., (2008). Self tuning pick-ups for inductive power transfer (pp. 3489-3494). Published in: 2008 IEEE Power Electronics Specialists Conference. https://doi.org/10.1109/pesc.2008.4592495

Dahlberg, T., (2006). Catenary, pantograph, and their interaction, Vehicle System Dynamics, 44(8), 591-593. https://doi.org/10.1080/00423110600735894

Deloitte Consulting, (2010). Gaining traction: A customer view of electric vehicle mass adoption in the U.S. automotive market. Retrieved May 16, 2018, from: http://www.deloitte.com/assets/Dcom-UnitedStates/Local%20Assets/Documents/us_automotive_Gaining%20Traction%20FINAL_0 61710.pdf

Diamond, D., (2009). The Impact of Government Incentives for Hybrid-Electric Vehicles: Evidence from US States, Energy Policy, 37(3), 972-983. https://doi.org/10.1016/j.enpol.2008.09.094

Dibb, S., (1999). Criteria guiding segmentation implementation: reviewing the evidence. Journal of Strategic Marketing, 7(2) 107–129. https://doi.org/10.1080/096525499346477

Dickerson, M.D. & James W.G., (1983). Characteristics of Adopters and Non-Adopters of Home Computers, Journal of Consumer Research, 10(2), 225-235. https://doi.org/10.1086/208961

Discover Magazine, (2013). California's Air Pollution Causes Asthma, Allergies and Premature Births DiscoverMagazine.com. Retrieved February 22, 2017, from: http://discovermagazine.com/2013/julyaug/19-californias-air-pollution-causes-asthma-allergies-and-premature-births

Draper M., Rodriquez, E., Kaminsky, P., Sidhu, I. & Tenderich, B., (2008). Economic impact of electric vehicle adoption in the United States. U.C. Berkeley. Center for Entrepreneurship and Technology. Management of Technology Program. Global Venture lab technical brief. Retrieved from: https://ikhlaqsidhu.files.wordpress.com/2010/03/nr_electric_vehicle_economics_3gvlv1-1_2008.pdf

Dubal, P., (2015). Rezence-Wireless Charging Standard based on Magnetic Resonance, International Journal of Advanced Research in Computer and Communication Engineering, Somaiya College of Engineering, India.

Dubin, J., Barney, R., Um, J. & Wu, N., (2011). Realizing the Potential of the Los Angeles Electric Vehicle Market. UCLA Luskin School of Public Affairs, Luskin School for innovation. UCLA Anderson, School of Management.

Edison, S.W. & Geissler, G.L., (2003). Measuring attitudes towards general technology: Antecedents, hypothesis and scale development. Journal of Targeting, Measurement and Analysis for Marketing, 12 (2), 137–156. https://doi.org/10.1057/palgrave.jt.5740104

Egbue, O. & Long, S., (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions, Energy policy, 8, 717-729. https://doi.org/10.1016/j.enpol.2012.06.009

Eghtesadi, M. (1990). Inductive power transfer to an electric vehicle –an analytical model, Published in: 40th IEEE Vehicular Technology Conference (pp 100-104). https://doi.org/10.1109/vetec.1990.110303

ElectRoad, (2017). Drive the future with wireless energy. Retrieved from: https://www.electroad.me/

Elliott, G.A.J., Raabe, S., Covic, G.A & Boys, J.T., (2010). Multi-phase pickups for large lateral tolerance contactless power transfer systems, IEEE Transactions on Industrial Electronics, 57(5), 1590-1598. https://doi.org/10.1109/tie.2009.2031184

Elonroad, (2017). Elonroad. Charging infrastructure with electric roads and automatic park charging. Retrieved from: http://elonroad.com/info/

Elways, (2011). Elways solution. Retrieved from: http://elways.se/elways-solution/?lang=en

Endesa, (2013). Endesa develops wireless en-route charging for electric buses in Malaga. Retrieved from: http://www.endesa.com/en/ saladeprensa/noticias/wireless-en-route-charging-electric-buses.

eRoadArlanda, (2017a). Electrified Roads – a sustainable transport solution of the future. Retrieved from: https://eroadarlanda.com/

eRoadArlanda, (2017b). The technology. Retrieved from https://eroadarlanda.com/the-technology/

eRoadArlanda, (2018). Film from the opening of eRoadArlanda. Retrieved from: https://eroadarlanda.com/film-from-the-opening-of-eroadarlanda/

European Commission, (2017). Electrification of the transportation System. Studies and reports. Directorate-General for Research and Innovation. Smart, Green and Integrated Transport. Retrieved from: http://ec.europa.eu/newsroom/horizon2020/document.cfm?doc_id=46368

European Environment Agency, (2011). Do lower speed limits on motorways reduce fuel consumption and pollutant emissions? Environmental Topics. Transport. Retrieved from: https://www.eea.europa.eu/themes/transport

FABRIC, (2014a). Assessment of the technical feasibility of ICT and charging solutions, D4.2.1, Workpackage No. WP4.2 Workpackage Title: Technical feasibility of ICT and charging solutions.

FABRIC, (2014b). Technical and User Requirements, D3.2.1, Workpackage No. WP3.2 5

FABRIC, (2017). FABRIC first results and overview. Madrid IV European Electric Vehicle Congress, CEVE 2017. Retrieved from: https://www.fabric-project.eu/index.php?option=com_k2&view=item&id=138:fabric-initial-findings-presented-at-the-iv-european-electric-vehicle-congress-in-madrid&Itemid=220

Fagnant, D.J. & Kockelman, K.M., (2015). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Proceedings of Transportation Research Board Annual Meeting, Washington, DC. https://doi.org/10.1007/s11116-016-9729-z

Field, A., (2005). Discovering Statistics Using SPSS (2nd ed., pp.1-780). London, UK: Sage.

Fujii, S. & Gärling, T., (2003). Application of attitude theory for improved predictive accuracy of stated preference methods in travel demand analysis, Transportation Research Part A: Policy and Practice, 37(4), 389–402. https://doi.org/10.1016/s0965-8564(02)00032-0

Fuller, M., (2016). Wireless charging in California: Range, recharge, and vehicle electrification. Transportation Research Part C, 67, 343–356. http://dx.doi.org/10.1016/j.trc.2016.02.013

Gallagher, K.S. & Muehlegger, E., (2011). Giving Green to Get Green? Incentives and Consumer Adoption of Hybrid Vehicle Technology. Journal of Environmental Economics and Management, 61(1), 1-15. https://doi.org/10.1016/j.jeem.2010.05.004

Gärling, T., Karlsson, N., Romanus, J. & Selart, M., (1997). Influences of the past on choices of the future. In R. Crozier, R. Ranyard & O. Svenson (Eds.), Decision Making: Cognitive Models and Explanations (pp.167–188). London, UK: Routledge. https://doi.org/10.4324/9780203444399

Gatignon, H. & Robertson, T.S., (1991). Innovative Decision Processes. In T. Robertson, H. Kassarjian (Eds.), Handbook of Consumer Behavior, Englewood Cliffs, NJ.: Prentice Hall.

German, J., (2015). Hybrid Vehicles: Technology Development and Cost Reduction. Web: International Council on Clean Transportation.

Giler, E., (2009). Eric Giler demos wireless electricity. (TEDGlobal, Interviewer)

Gill, J. S., Bhavsar, P., Chowdhury, M., Johnson, J., Taiber, J. & Fries, R., (2014). Infrastructure cost issues related to inductively coupled power transfer for electric vehicle, Procedia Computer Science, 32, 545–552. https://doi.org/10.1016/j.procs.2014.05.459

Glerum, A., Stankovikj, L., Thémans, M. & Bierlaire, M., (2014). Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions. Transportation Science, 48(4), 483–499. https://doi.org/10.1287/trsc.2013.0487

Goldstein, (2015a). Federal-Aid Highway Program Guidance on High Occupancy Vehicle (HOV) Facility Lanes. Retrieved from: https://ops.fhwa.dot.gov/freewaymgmt/hovguidance/chapter4.htm

Goldstein, S., (2015b). Here are the typical commutes for every big metro area. Retrieved from: https://www.marketwatch.com/story/here-are-the-typical-commutes-for-every-big-metro-area-2015-03-25

Gorsuch, R.L., (1983). Factor Analysis (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R. & Stannard, J., (2012). Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations. Transportation Research Part A: Policy and Practice, 46(1), 140–153. https://doi.org/10.1016/j.tra.2011.09.008

Greene, D.L., (2004). Future Potential of Hybrid and Diesel Powertrains in the U.S. Light-duty Vehicle Market. United States. https://doi.org/10.2172/885725

Greene, W.H., (2007). LIMDEP, Version 9.0. Econometric Software, Inc, Plainview, NY. In W. Greene & D. Hensher (Eds.). Modeling Ordered Choices: a Primer, (1st ed.). Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/cbo9780511845062

Hackbarth, A. & Madlener, R., (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. Transportation Research Part D: Transport and Environment, 25, 5–17. https://doi.org/10.1016/j.trd.2013.07.002

Hair, J., Anderson R.E., Tatham R.L. & Black, W.C., (1995). Multivariate data analysis (4th ed.). New Jersey, NJ: Prentice-Hall Inc.

Han, L., Wang, S., Zhao, D. & Li, J., (2017). The intention to adopt electric vehicles: Driven by functional and non-functional values. Transportation Research Part A: Policy and Practice, 103, 185–197. https://doi.org/10.1016/j.tra.2017.05.033

Hassan, M.A. & Elzawawi, A., (2015). Wireless Power Transfer through inductive coupling (pp. 115-118), Proc. of 19th International Conference on Circuits (part of CSCC '15).

He, F., Yin, Y. & Zhou, J., (2013). Integrated pricing of roads and electricity enabled by wireless power transfer. Transportation Research Part C: Emerging Technologies, 34, 1–15. https://doi.org/10.1016/j.trc.2013.05.005

He, J., Huang, H.J., Yang, H. & Tang, T.Q., (2017). An electric vehicle driving behavior model in the traffic system with a wireless charging lane. Physica A: Statistical Mechanics and its Applications, 481, 119–126. https://doi.org/10.1016/j.physa.2017.04.013

Heath, Y. & Gifford, R., (2002). Extending the theory of planned behavior: Predicting the use of public transportation, Journal of Applied Social Psychology, 32, 2154-2189. https://doi.org/10.1111/j.1559-1816.2002.tb02068.x

Heffner, R.R., Kurani, K.S. & Turrentine, T.S., (2007a). Symbolism in California's early market for hybrid electric vehicles. Transportation Research Part D: Transport and Environment, 12(6), 396–413. https://doi.org/10.1016/j.trd.2007.04.003

Heffner, R.R., Kurani, K.S. & Turrentine, T.S., (2007b). Symbolism and the Adoption of Fuel-Cell Vehicles. World Electric Vehicle Journal, 1(1), 24–31. https://doi.org/10.3390/wevj1010024

Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampfl, E. & Michalek, J.J., (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transportation Research Part A: Policy and Practice, 73, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Henson, R.K., Roberts, J.K., (2006). Use of Exploratory Factor Analysis in Published Research: Common Errors and Some Comment on Improved Practice. Educational and Psychological Measurement, 66(3), 393-416. https://doi.org/10.1177/0013164405282485

Hess, S., Fowler, M., Adler, T. & Bahreinian, A., (2012). A Joint Model for Vehicle Type and Fuel Type Choice: Evidence from a Cross-Nested Logit Study. Transportation, 39(3), 593–625. https://doi.org/10.1007/s11116-011-9366-5

Hidrue, M.K., Parsons, G.R., Kempton, W. & Gardner, M.P., (2011). Willingness to pay for electric vehicles and their attributes. Resource and Energy Economics, 33 (3), 686-705. https://doi.org/10.1016/j.reseneeco.2011.02.002

Hoen, A. & Koetse, M.J., (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transportation Research Part A: Policy and Practice, 61, 199–215. https://doi.org/10.1016/j.tra.2014.01.008

Hogarty, K.Y., Hines, C.V., Kromrey, J.D., Ferron, J.M. & Mumford, K.R., (2005). The Quality of Factor Solutions in Exploratory Factor Analysis: The Influence of Sample Size, Communality, and Overdetermination. Educational and Psychological Measurement. 65(2), 202-226. https://doi.org/10.1177/0013164404267287

Horn, J.L., (1965) A rationale and test for the number of factors in factor analysis, Psychometrika, 30(2), 179-185. https://doi.org/10.1007/bf02289447

Horne, M., Jaccard, M. & Tiedemann, K., (2005). Improving behavioral realism in hybrid energy economy models using discrete choice studies of personal transportation decisions. Energy Economics, 27(1), 59–77. https://doi.org/10.1016/j.eneco.2004.11.003

Howell, D.C., (2014). Fundamental Statistics for the Behavioral Sciences (8th ed.), Wadsworth, Cengage Learning.

Hoy, K. & Weken, H., (2017). I-CVUE Final Results, I-CVUE. Retrieved from: http://frevue.eu/wp-content/uploads/2016/03/I-CVUE-.pdf

Humphrys, M., (1987). Continuous output, the sigmoid function. Properties of the sigmoid, including how it can shift along axes and how its domain may be transformed. Retrieved from: https://www.computing.dcu.ie/~humphrys/Notes/Neural/sigmoid.html

I-710 Energy Technical Report, (2017). Interstate 710 corridor project between Ocean Boulevard and State Route 60 Interchange - County of Los Angeles, California 07-LA-710-PM 5.4/24.5 EA 249900 - WBS ID:165.10.40. Prepared for LA Metro and Caltrans. Retrieved from: http://www.dot.ca.gov/d7/env-docs/docs/710corr-eir/Technical%20Studies/Energy%%202017.pdf 20Report%20June

Im, S., Bayus, B.L. & Manson, C.H., (2003). An Empirical Study of Innate Consumer Innovativeness, Personal Characteristics, and New-Product Adoption Behavior, Journal of the Academy of Marketing Science, 31(1), 61-73. https://doi.org/10.1177/0092070302238602

Imura T. & Hory, Y., (2011). Maximizing air gap and efficiency of magnetic resonant coupling for wireless power transfer using equivalent circuit and Neumann formula, IEEE Transactions on Industrial Electronics, 58(10), 4746–4752. https://doi.org/10.1109/tie.2011.2112317

INRIX, (2016). Traffic Scorecard. Table 1. 10 most congested urban areas in the US. Retrieved from: http://inrix.com/press-releases/los-angeles-tops-inrix-global-congestion-ranking/

International Council on Clean Transportation, (2016). Evolution of incentives to sustain the transition to a global electric vehicle fleet. Retrieved from: https://www.theicct.org/publications/evolution-incentives-sustain-transition-global-electric-vehicle-fleet

International Council on Clean Transportation, (2017). Update: California's electric vehicle market. Briefing. Retrieved from: https://www.theicct.org/publications/update-californias-electric-vehicle-market

International Council on Clean Transportation, (2018). California's continued electric vehicle market development. Briefing. Retrieved from: https://www.theicct.org/publications/california-electric-vehicle-2018

International Energy Agency, (2017a). Energy Technology Perspectives 2017, IEA Publications. Retrieved from: https://www.iea.org/etp/

International Energy Agency, (2017b). Global EV Outlook 2017: two million and counting, online bookshop, IEA Publications. Retrieved from: https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf

INTIS, (2016). Wireless power road-the future is wireless! Retrieved from: http://www.intis.de/wireless-power-transfer.html

Jabeen, F., Olaru, D., Smith, B., Braunl, T. & Speidel, S., (2012). Acceptability of electric vehicles: findings from a driver survey (pp. 1-15). Proceeding of the ATRF (Australasian Transport Research Forum). Perth, Australia. Retrieved from: http://atrf.info/papers/2012/2012_Jabeen_Olaru_Smith_Braunl_Speidel.pdf

James, J., Boys, J.T. & Covic, G.A., (2005). A variable inductor based tuning method for ICPT pickups, Published in: 2005 International Power Engineering Conference, 2, 1142–1146. https://doi.org/10.1109/ipec.2005.207079

Jang, Y.J., Jeong, S. & Ko, Y.D., (2015). System optimization of the On-Line Electric Vehicle operating in a closed environment. Computers & Industrial Engineering, 80, 222-235. https://doi.org/10.1016/j.cie.2014.12.004

Jansson, J., Marell, A. & Nordlund, A., (2011). Exploring consumer adoption of a high involvement eco-innovation using value-belief-norm theory, Journal of Consumer Behaviour, 10, 51–60. https://doi.org/10.1002/cb.346

Jelica, D., (2017). The effect of electric roads on future energy demand for transportation. A case study of a Swedish highway, Master's thesis in Industrial Ecology. Department of Energy and Environment Division of Energy Technology, Gothenburg, Sweden, EU: Chalmers University of Technology

Jeong, S., Jang, J. & Kum, D., (2015). Economic analysis of the dynamic charging electric vehicle, IEEE Transactions on Power Electronics, 30(11), 6368 – 6377. https://doi.org/10.1109/tpel.2015.2424712

Jones, P. (2003). Acceptability of road user charging: Meeting the challenge. Acceptability of Transport Pricing Strategies. 27-62.

Kahn, M.E., (2007). Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice. Journal of Environmental Economics and Management, 54(2), 129–145. https://doi.org/10.1016/j.jeem.2007.05.001

Kaiser, H.F., (1960). The application of electronic computers to factor analysis. Educational and Psychological Measurement, 20(1), 141-151. https://doi.org/10.1177/001316446002000116

Kaufmann, H.R. & Panni, M.F.A.K., (2017). Socio-Economic Perspectives on Consumer Engagement and Buying Behavior, Business Science Reference, IGI, Global Publications. https://doi.org/10.4018/978-1-5225-2139-6

Kaufmann, H.R., Panni, M.F.A.K. & Orphanidou, Y., (2012), Factors affecting consumers' green purchasing behaviour: an integrated conceptual framework, Amfiteatru Economic, 15(31), 50-69.

Kennickell, A.B. & Kwast, M.L., (1997). Who Uses Electronic Banking? Results from the 1995 Survey of Consumer Finances. Board of Governors of the Federal Reserve System, Finance and Economics Discussion, Paper Series: 1997/35. https://doi.org/10.2139/ssrn.38560

Kim, J., Rasouli, S. & Timmermans, H., (2014). Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. Transportation Research Part A: Policy and Practice, 69, 71–85. https://doi.org/10.1016/j.tra.2014.08.016

Kissin, M.L.G., Covic, G.A. &. Boys, J.T., (2011). Steady-state flat-pickup loading effects in polyphase inductive power transfer systems, IEEE Transactions on Industrial Electronics, 58(6), 2274-2282. https://doi.org/10.1109/tie.2010.2060455

Klöckner, C.A. & Matthies, E., (2004). How habits interfere with norm directed behaviour: A normative decision-making model for travel mode choice. Journal of Environmental Psychology, 24(3), 319–327. https://doi.org/10.1016/j.jenvp.2004.08.004

Ko, Y.D. & Jang, Y.J., (2013). The optimal system design of the online electric vehicle utilizing wireless power transmission technology, IEEE Transactions on Intelligent Transportation Systems, 14(3), 1255–1265. https://doi.org/10.1109/tits.2013.2259159

Kotler, P. & Keller, K.L., (2009). Marketing management (13th ed.). Upper Saddle River, NJ: Pearson/Prentice Hall.

Kurs, A., Karalis, A., Moffatt, R., Joannopoulos, J.D., Fisher, P., Soljacic, M., (2007). Power Transfer Through Strongly Coupled Resonances, MIT, 317(5834), 83-86. https://doi.org/10.1126/science.1143254

Lane, B. & Potter, S., (2007). The adoption of cleaner vehicles in the UK: exploring the consumer attitude–action gap. Journal of Cleaner Production, 15(11–12), 1085–1092. https://doi.org/10.1016/j.jclepro.2006.05.026

Lattin, J., Carroll, D. & Green, P., (2005). Analyzing Multivariate Data (Duxbury Applied Series) (2nd ed., pp.1-580), Brooks/Cole.

Li, S. & Mi, C.C., (2015). Wireless power transfer for electric vehicle applications, IEEE journal of emerging and selected topics in power electronics, 3(1), 4–17. Retrieved from: https://ieeexplore.ieee.org/document/6804648

Li, Y., Wang, W., Xing, L., Fan, Q. & Wang, H., (2018). Longitudinal safety evaluation of electric vehicles with the partial wireless charging lane on freeways. Accident Analysis and Prevention, 111, 133–141. https://doi.org/10.1016/j.aap.2017.11.036

Li, Z., Chowdhury, M., Bhavsar, P. & He, Y., (2015). Optimizing the performance of vehicle-togrid (V2G) enabled battery electric vehicles through a smart charge scheduling model. International Journal of Automotive Technology, 16(5), 827–837. https://doi.org/10.1007/s12239-015-0085-3

Li, Z., Dey, K., Chowdhury, M. & Bhavsar, P., (2016). Connectivity supported dynamic routing of electric vehicles in an inductively coupled power transfer environment, IET Intelligent Transport Systems, 10(5), 370-377. https://doi.org/10.1049/iet-its.2015.0154

Liao, F., Molin, E. & Van Wee, B., (2017). Consumer preferences for electric vehicles: a literature review, Transport Reviews, 37(3), 252-275. https://doi.org/10.1080/01441647.2016.1230794

Lieven, T., Mühlmeier, S., Henkel, S. & Waller, J.F., (2011). Who will buy electric cars? An empirical study in Germany. Transportation Research Part D: Transport and Environment, 16(3), 236-243. https://doi.org/10.1016/j.trd.2010.12.001

Limb, B.J., Crabb, B., Zane, R., Bradley, T.H. & Quinn, J. C., (2016). Economic feasibility and infrastructure optimization of in-motion charging of electric vehicles using wireless power transfer (pp. 42-46), IEEE. https://doi.org/10.1109/wow.2016.7772064

Limb, J.B., Bradley, T.H., Crab, B., Zane, R. & Quinn, J.C., (2017). Systems Optimization of Dynamic Charging of Electric Vehicles Integrating Wireless Power Transfer: Economic Viability and Environmental Impact.

Liu, Z. & Song, Z., (2017). Robust planning of dynamic wireless charging infrastructure for battery electric buses, Transportation Research Part C: Emerging Technologies, 83, 77-103. https://doi.org/10.1016/j.trc.2017.07.013

Lleras-Muney, A. & Lichtenberg, F., (2002). The Effect of Education on Medical Technology Adoption: Are the More Educated More Likely to Use New Drugs? Working Paper 9185, National Bureau of Economic Research. https://doi.org/10.3386/w9185

Lohr, S.L., (2009). Sampling design and analysis (2nd ed., pp. 1-19). USA: Cengage Learning.

Los Angeles County GIS Data Portal, (2010). Tiger Roads. Retrieved from: https://egis3.lacounty.gov/dataportal/2011/04/25/2010-tiger-roads/

Los Angeles Department of City Planning, (2014). Mobility Plan 2035. Draft for public review. Retrieved from: https://planning.lacity.org/documents/policy/mobilityplnmemo.pdf

Los Angeles Metro, (2013). Express lanes performance update-preliminary report. Retrieved from: https://wfww.scribd.com/document/155363140/ExpressLanes-Performance-Update-Prelim-Report-July-2013

Los Angeles Metro, (2018). I-710 Corridor Project Overview. Los Angeles County Metropolitan Transportation Authority. Retrieved May 13, 2018, from: https://www.metro.net/projects/i-710-corridor-project/

Lyons, J.M., Heirigs, P.L. & Williams, L.L., (2005). The contribution of diesel engines to emissions of ROG, NO_X, and $PM_{2.5}$ in California: past, present and future. Report No. SR2005-02-01. Prepared for Diesel Technology Forum. Sierra Research, Inc. Sacramento, California. Retrieved from: http://www.dieselforum.org/files/dmfile/TheContributionofDieselEnginestoEmissionsofROG.pdf

Mabit, S.L. & Fosgerau, M., (2011). Demand for alternative-fuel vehicles when registration taxes are high. Transportation Research Part D: Transport and Environment, 16(3), 225–231. https://doi.org/10.1016/j.trd.2010.11.001

MacCallum, R.C., Widaman, K.F., Zhang, S. & Hong, S., (1999). Sample size in factor analysis. Psychological Methods, 4(1), 84-99. https://doi.org/10.1037//1082-989x.4.1.84

Mau, P., Eyzaguirre, J., Jaccard, M., Collins-Dodd, C. & Tiedemann, K., (2008). The “neighbor effect”: Simulating dynamics in consumer preferences for new vehicle technologies. Ecological Economics, 68(1–2), 504–516. https://doi.org/10.1016/j.ecolecon.2008.05.007

McDonald Z., (2016). A simple guide to DC fast charging, EV Charging. Retrieved from: https://www.fleetcarma.com/dc-fast-charging-guide/

Meins, J., Buhler, G., Czainski, R. & Turki, F., (2006). Contactless inductive power supply (p.p. 1-9), in Proc. of 19th International Conference on Magnetically Levitated Systems and Linear Drives.

Milligan, G.W. & Cooper, M.C., (1985). An examination of procedures for determining the number of clusters in a data set, Psychometrika, 50(2), 159–179. https://doi.org/10.1007/bf02294245

Molin, E., van Stralen, W. & van Wee, B., (2012). Car drivers’ preferences for electric cars, paper submitted for presentation at the 91st Transportation Research Board Annual Meeting, Washington, DC.

Moller, C.M., (2017). Carbon neutral road transportation: an assessment of the potential of electrified road systems. Master of Science, Industrial Ecology, Stockholm, Sweden: Royal Institute of Technology.

Mooi, E. & Sarstedt, M.A., (2011). A Concise Guide to Market Research. The process, data and methods using IBM SPSS Statistics. Berlin-Heidelberg: Springer-Verlag. DOI: 10.1007/978-3-642-12541-6

Moons, I. & De Pelsmacker, P., (2015). An Extended Decomposed Theory of Planned Behaviour to Predict the Usage Intention of the Electric Car: A Multi-Group Comparison, Sustainability, 7(5), 6212- 6245. https://doi.org/10.3390/su7056212

Moovit Insights, (2018). Facts and usage statistics about public transit in Los Angeles, US. Retrieved from: https://moovitapp.com/insights/en/Moovit_Insights_Public_Transit_Index_USA_Los_Angeles_CA-302

Morris, C., (2015). Utah State University builds a dynamic wireless charging test track. Retrieved August 17, 2017, from: http://chargedevs.com/features/utah-state-university-builds-a-dynamic-wireless-charging-test-track/

Morris, M.G., Venkatesh, V. & Ackerman, P.L., (2005) Gender and Age Differences in Employee Decisions about New Technology: An Extension to the Theory of Planned Behavior. IEEE Transactions on Engineering Management, 52(1), 69-84. https://doi.org/10.1109/tem.2004.839967

Musselwhite, C.B.A. & Haddad, H., (2007). Prolonging the Safe Driving of Older People through Technology. Final report of project supported by Strategic Promotion of Ageing Research Capacity (SPARC) BBSRC/EPSRC research initiative. Centre for Transport & Society, UWE, Bristol, UK.

Musselwhite, C.B.A., (2004). Driver Attitudes, Behaviour and Speed Management Strategies. University of Southampton, PhD thesis.

Musti, S. & Kockelman, K.M., (2011). Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. Transportation Research Part A: Policy and Practice, 45(8), 707–720. https://doi.org/10.1016/j.tra.2011.04.011

Myhre, G., Shindell, D., Bréon, F.M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J.F., Lee, D., Mendoza, B., Nakajima, T., Robock, A., Stephens, G., Takemura, T., Zhang, H., (2013). Anthropogenic and Natural Radiative Forcing. In: T. Stocker, D. Qin, G. Plattner, M. Tignor, J. Allen, A. Boschung, …P. Midgley (Eds.). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Appendix 8.A.1., Cambridge, UK & New York, NY, USA: Cambridge University Press. Available at: https://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter08_FINAL.pdf

Newman, P. & Kenworthy J., (1992). Winning Back the Cities. Sydney: Australian Consumers' Association & Pluto Press.

Nesbitt, K., Sperling, D., & DeLuchi, M. A. (1990). An initial assessment of roadway-powered electric vehicles. In Transportation Research Record 1267, Institute of Transportation Studies, University of California, Davis. 41-55.

Norman, P. & Smith, L., (1995). The theory of planned behaviour and exercise: An investigation into the role of prior behaviour, behavioural intentions and attitude variability. European Journal of Social Psychology, 25(4), 403–415. https://doi.org/10.1002/ejsp.2420250405

Nuzzo R.L., (2016). The Box Plots Alternative for Visualizing Quantitative Data. Published in PM&R, 8(3), 268–272.

Nysveen, H., Pedersen, P.E. & Thorbjornsen, H., (2005). Explaining intention to use mobile chat services: moderating effects of gender, Journal of Consumer Marketing, 22(5), 247–256. https://doi.org/10.1108/07363760510611671

O'Rourke, N., & Hatcher, L. (2013). A Step-by-Step Approach to Using SAS for Factor Analysis and Structural Equation Modeling (2nd ed.). Cary, NC.: SAS Institute.

Olsson, O., (2014). Slide-in electric road system, conductive project report, phase 1, technical report, Viktoria Swedish ICT. Found at: https://www.viktoria.se/publications/Slide-in-ERS-Conductive-project-report

Osborne, J.W. & Overbay, A., (2004). The power of outliers (and why researchers should always check for them). Practical Assessment, Research & Evaluation, 9(6), 1-8. Retrieved March 11, 2016 from: http://PAREonline.net/getvn.asp?v=9&n=6

Ozaki, R. & Sevastyanova, K., (2011). Going hybrid: An analysis of consumer purchase motivations, Energy Policy, 39, 2217-2227. https://doi.org/10.1016/j.enpol.2010.04.024

Payre, W., Cestac, J. & Delhomme, P., (2014). Intention to use a fully automated car: Attitudes and a priori acceptability, Transportation Research Part F: Traffic Psychology and Behavior, 27, 252–263. https://doi.org/10.1016/j.trf.2014.04.009

Perlusz, S., (2004). Emotions and Technology Acceptance: Development and validation of a technology affect scale. Published in: 2004 IEEE International Engineering Management Conference https://doi.org/10.1109/iemc.2004.1407500

Petschnig, M., Heidenreich, S. & Spieth, P., (2014). Innovative alternatives take action – Investigating determinants of alternative fuel vehicle adoption. Transportation Research Part A: Policy and Practice, 61, 68–83. https://doi.org/10.1016/j.tra.2014.01.001

Pett, M.A., Lackey N.R. & Sullivan J.J., (2003). Making Sense of Factor Analysis: The use of factor analysis for instrument development in health care research. California, USA: Sage Publications Inc. https://doi.org/10.4135/9781412984898

Philip, R. & Wiederer, A., (2010). Policy options for electric vehicle charging infrastructure in C40 cities, Harvard Kennedy School.

PLANYC, (2010). plaNYC – Exploring electric vehicle adoption in New York City. January 2010. A Greener, Greater New York. Retrieved from: http://www.nyc.gov/html/om/pdf/2010/pr10_nyc_electric_vehicle_adoption_study.pdf

Plug-in America, (2011). In the driver's seat: understanding electric vehicle charging. Retrieved May 15, 2018 from: https://pluginamerica.org/understanding-electric-vehicle-charging/

Polatoglu, N.V. & Ekin, S., (2001). An empirical investigation of the Turkish consumers' acceptance of Internet banking services. The International Journal of Bank Marketing, 19(4), 156-165. https://doi.org/10.1108/02652320110392527

Potoglou, D. & Kanaroglou, P.S., (2007). Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment, 12(4), 264–274. https://doi.org/10.1016/j.trd.2007.03.001

Primove, (2016). Successful dynamic charging tests with PRIMOVE in Mannheim. Retrieved 30 June, 2016, from: http://primove.bombardier.com/media/news/news-detail-page/article/2016/06/30/298.html

Punj, G. & Stewart, D.W., (1983). Cluster analysis in marketing research: review and suggestions for application. Journal of Marketing Research, 20(2), 134–148. https://doi.org/10.2307/3151680

Raabe, S., Elliott, G.A.J., Covic G.A. & Boys J.T., (2007). A quadrature pickup for inductive power transfer systems (pp. 68-73). Published In: 2007 2nd IEEE Conference on Industrial Electronics and Applications. https://doi.org/10.1109/iciea.2007.4318371

Raaijmakers, Q.A.W., (1999). Effectiveness of Different Missing Data Treatments in Surveys With Likert-Type Data: Introducing the Relative Mean Substitution Approach. Educational & Psychological Measurement, 59(5), 725-743. https://doi.org/10.1177%2F0013164499595001

RAND Corporation, (2008). Reducing Traffic Congestion in Los Angeles. Transportation, Space, and Technology. A RAND infrastructure, safety, and environmental program. RB-9385-JAT/METRO/MCLA(2008) Retrieved from: https://www.rand.org/content/dam/rand/pubs/research_briefs/2008/RAND_RB9385.pdf

Rasouli, S. & Timmermans, H., (2013). Influence of Social Networks on Latent Choice of Electric Cars: A Mixed Logit Specification Using Experimental Design Data. Networks and Spatial Economics, 16(1), 99–130. https://doi.org/10.1007/s11067-013-9194-6

Rezvani, Z., Jansson, J. & Bodin, J., (2015). Advances in consumer electric vehicles adoption research: A review and research agenda, Transportation Research Part D: Transport and Environment, 34, 122-136. https://doi.org/10.1016/j.trd.2014.10.010

Ricci, M., Bellaby, P., & Flynn, R. (2008). What do we know about public perceptions and acceptance of hydrogen? A critical review and new case study evidence. International Journal of Hydrogen Energy, 33(21), 5868–5880. https://doi.org/10.1016/j.ijhydene.2008.07.106

Riemann, R., Wang, D.Z. & Busch, F., (2015). Optimal location of wireless charging facilities for electric vehicles: flow-capturing location model with stochastic user equilibrium. Transportation Research Part C: Emerging Technologies, 58, 1–12. https://doi.org/10.1016/j.trc.2015.06.022

Rogers, E.M., (1995). Diffusion of Innovations (4th ed.). New York, NY: The Free Press.

Rogers, E.M., (2003). Diffusion of Innovations (5th ed.). New York, NY: The Free Press of Glencoe.

Roy, R., Potter, S., Yarrow, K. & Smith, M., (2005). Towards Sustainable Higher Education: Environmental Impacts of Campus-based and Distance Higher Education Systems, Design Innovation Group/Factor 10 Visions Project, The Open University. Retrieved from: http://oro.open.ac.uk/6816/

Sallan, J., Villa, J.L., Llombart A. & Sanz, J.F., (2009). Optimal design of ICPT systems applied to electric vehicle battery charge, IEEE Transactions on Industrial Electronics, 56(6), 2140-2149. https://doi.org/10.1109/tie.2009.2015359

Samuels, P., (2017). Advice on Exploratory Factor Analysis. Centre for Academic Success, Birmingham City University.

Sarker, A., Qiu, C., Shen, H., Gil, A., Taiber, J., Chowdhury, M., Martin, J., Devine, M., Rindos, A., (2016). An efficient wireless power transfer system to balance the state of charge of electric vehicles (pp. 324-333), published in 2016 45th International Conference on Parallel Processing, IEEE. https://doi.org/10.1109/icpp.2016.44

Shin, J. Bhat, C.R, You, D. & Garikapati, V.M., (2015). Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types. Transportation Research Part C: Emerging Technologies, 60, 511–524. https://doi.org/10.1016/j.trc.2015.10.003

Shin, J., Shin, S., Kim, Y., Ahn, S., Lee, S., Jung, G. & Jeon, S., (2014). Design and implementation of shaped magnetic-resonance-based wireless power transfer system for roadway-powered moving electric vehicles, IEEE Transactions on Industrial Electronics, 61(3), 1179-1192. Retrieved from: https://ieeexplore.ieee.org/document/6502703

Siemens, (2012a). Intelligent pantograph enables full vehicle flexibility. Retrieved July 4, 2012, from:https://www.siemens.com/press/en/presspicture/?press=/en/presspicture/2012/infrastructure-cities/mobility-logistics/soicmol201203-16.htm

Siemens, (2012b). Siemens tests electric-powered system for heavy good vehicles. Retrieved from:https://www.siemens.com/press/en/presspicture/?press=/en/presspicture/2012/infrastructure-cities/mobility-logistics/soicmol201203-04.htm

Siemens, (2015). Siemens builds first eHighway in Sweden. Munich, EU: Press. Retrieved October 29, 2018, from: https://www.siemens.com/press/en/pressrelease/?press=/en/pressrelease/2015/mobility/pr2015060246moen.htm

Siemens, (2017a). “Siemens demonstrates first eHighway system in the U.S”. Munich: Press. Retrieved October 29, 2018, from: https://www.siemens.com/press/en/pressrelease/?press=/en/pressrelease/2017/mobility/pr2017110069moen.htm&content[]=MO

Siemens, (2017b). Siemens builds eHighway in Germany. Munich, EU: Press Publishing. Retrieved August 11, 2017, from: https://www.siemens.com/press/en/feature/2015/mobility/2015-06-eHighway.php?content[]=MO#event-toc-3

Sieminski, A., (2017). Annual Energy Outlook 2017. United States Energy Information Administration. Retrieved from: https://www.eia.gov/pressroom/presentations/sieminski_01052017.pdf

Sierzchula, W., Bakker, S., Maat, K. & Wee, B., (2014). The Influence of Financial Incentives and other Socio-Economic Factors on Electric Vehicle Adoption. Energy Policy, 68, 83-194. https://doi.org/10.1016/j.enpol.2014.01.043

Singh, A., (2016). Electric road systems: A feasibility study investigating a possible future of road transportation. Master's thesis, KTH - Royal Institute of Technology.

Skippon, S. & Garwood, M., (2011). Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance. Transportation Research Part D: Transport and Environment, 16(7), 525-531. https://doi.org/10.1016/j.trd.2011.05.005

Slowik, P. & Lutsey, N., (2018). The continued transition to electric vehicles in U.S. cities. White paper. The International Council of Clean Transportation (ICCT).

Smit, R., Ntziachristos, L. & Boulter, P., (2010). Validation of road vehicle and traffic emission models - A review and meta-analysis. Atmospheric Environment, 44(25), 2943-2953. https://doi.org/10.1016/j.atmosenv.2010.05.022

Smith, W. J., (2010). Plug-in hybrid electric vehicles - A low-carbon solution for Ireland? Energy Policy, 38(3), 1485–1499. https://doi.org/10.1016/j.enpol.2009.11.031

Söderholm, P. & Ek, K., (2010) The devil is in the details: Household electricity saving behavior and the role of information. Energy Policy, 38(3), 1578–1587. https://doi.org/10.1016/j.enpol.2009.11.041

Song, Z. & Singleton, P., (2017). Optimal Deployment of Dynamic Charging Lanes for Plug-in Hybrid Trucks. Utah State University. Retrieved from: https://www.mountain-plains.org/research/projects/downloads/2017-mpc-558.pdf

Southern California Association of Governments, (2012). Southern California Plug-in Electric Vehicle Readiness Plan. UCLA Luskin School of Public Affairs. Retrieved from: http://www.scag.ca.gov/programs/Pages/PEVReadinessPlan.aspx and found at http://www.blinknetwork.com/blinkMap.html#.

Southern California Public Radio, (2011). Los Angeles toll lanes on I-10, 110 to cost between 25 cents and $1.40 per mile. Retrieved from: https://www.scpr.org/news/2011/07/06/27604/los-angeles-toll-lanes-i-10-110-cost-between-25-ce/

Stamati, T.E. & Bauer, P., (2013). On-road charging of Electric Vehicles. Netherlands: Delft University of Technology, IEEE. Retrieved from: http://ieeexplore.ieee.org/document/6573511/?reload=true

State Zero-Emission Vehicle Programs - Memorandum of Understanding, (2013). Retrieved from: http://www.nescaum.org/documents/zev-mou-8-governors-signed-20131024.pdf/

Steinley, D., (2006). K-means clustering: A half-century synthesis, British Journal of Mathematical and Statistical Psychology, 59(1), 1–34. https://doi.org/10.1348/000711005x48266

Stielau, O.H. & Covic, G.A., (2000). Design of loosely coupled inductive power transfer systems, in Proc. 2000 International Conference on Power System Technology, 1, 85–90. https://doi.org/10.1109/icpst.2000.900036

Streiner, D.L., (1994). Figuring out factors: the use and misuse of factor analysis. The Canadian Journal of Psychiatry, 39(3), 135-140. https://doi.org/10.1177/070674379403900303

Suh, N.P. & Cho, D.H. (eds.), (2017). The On-line Electric Vehicle, chapter 2: Wireless Power Transfer for Electric Vehicles, Springer International Publishing. https://doi.org/10.1007/978-3-319-51183-2_2

Suh, N.P., Cho, D.H. & Rim, C.T., (2011). Design of on-line electric vehicle (OLEV). In Global Product Development (pp. 3-8), Berlin-Heidelberg: Springer- Verlag. https://doi.org/10.1007/978-3-642-15973-2_1

Sullivan, S.R., (1999). Optimal choice of number of strands in a Litz-wire transformer winding (pp. 283-291), IEEE Transactions on Power Electronics.

Sundelin, H., (2016). Electric Roads around the world. Presented at Conference of European Directors of Roads (CEDR), Belgium, EU: Victoria Swedish ICT AB. Retrieved from: http://www.cedr.eu/home/publications/search-publications/

Sundelin, H., Gustavsson, M. & Tongur, S., (2016). The maturity of Electric Road Systems. Published in: Proceedings for the 2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles and the International Transportation Electrification Conference 2016. Retrieved from: https://doi.org/10.1109/ESARS-ITEC.2016.7841380

Tabachnick, B.G. & Fidell, L.S., (2007). Using Multivariate Statistics. Boston, MA: Pearson Education Inc.

Tabachnick, B.G. & Fidell, L.S., (2014). Using Multivariate Statistics. (6th ed.). Harlow, UK: Pearson.

Thackeray, M.M., Wolverton, C. & Isaacs, E.D., (2012). Electrical energy storage for transportation—approaching the limits of, and going beyond, lithium-ion batteries, Energy & Environmental Science, 5, 7854-7863. https://doi.org/10.1039/c2ee21892e

Thøgersen, J. & Olander, F., (2006). The dynamic interaction of personal norms and environment friendly buying behavior: A panel study, Journal of Applied Social Psychology, 36, 1758–1780. https://doi.org/10.1111/j.0021-9029.2006.00080.x

Thompson B., (2004). Exploratory and confirmatory factor analysis: Understanding concepts and applications. Washington, DC: American Psychological Association. http://psycnet.apa.org/doi/10.1037/10694-000

Tonks, D.G., (2009). Validity and the design of market segments, Journal of Marketing Management, 25(3–4), 341–356. https://doi.org/10.1362/026725709x429782

Tran, M., Banister, D., Bishop, J.D.K. & McCulloch, M.D., (2013). Simulating Early Adoption of Alternative Fuel Vehicles for Sustainability. Technological Forecasting and Social Change, 80(5), 865-875. https://doi.org/10.1016/j.techfore.2012.09.009

Transport Research Laboratory, (2015). Feasibility study: powering electric vehicles on England’s major roads, technical report. Highways England. Retrieved from: https://highwaysengland.co.uk/knowledge-compendium/knowledge/publications/1902/index.html

Transportation Electrification Accord, (2018). Retrieved from: https://www.theevaccord.com/

Uhl, K., Andrus R., & Poulsen, L., (1970). How Are Laggards Different? An Empirical Inquiry, Journal of Marketing Research, 7(1), 51-54. https://doi.org/10.2307/3149506

United States Census Bureau, (2016). Means of Transportation to Work by Age American Community Survey 1-year estimates. Retrieved from: https://censusreporter.org/data/table/?table=B08101&geo_ids=16000US0644000&primary_geo_id=16000US0644000

United States Department of Energy, (2016). Workplace Charging Challenge: Progress Update 2016: A New Sustainable Commute. Retrieved from: https://energy.gov/sites/prod/files/2017/01/f34/WPCC_2016%20Annual%20Progress%20Report.pdf.

United States Department of Transportation, (2017). National transportation statistics. Bureau of Transportation Statistics, Washington, DC. Retrieved from: https://www.bts.gov/topics/national-transportation-statistics

United States Environmental Protection Agency, (2002). User's guide to MOBILE6.0. Mobile Source Emission Factor Model. Washington, DC.

United States Environmental Protection Agency, (2018). California plans to reduce greenhouse gas emissions 40% by 2030. Today in Energy. Retrieved from: https://www.eia.gov/todayinenergy/detail.php?id=34792

United States National Research Council, (1995). Expanding Metropolitan Highways. Implications for air quality and energy use. Special Report 254. 1995 Executive Committee. Transportation Research Board. Washington, DC. Retrieved from: https://www.nap.edu/read/9676/chapter/1

University of Auckland, (2010). Inductive power transfer (IPT): Powering our future. Presentation, Faculty of Engineering Grant Covic, New Zealand. Retrieved from: http://cemeold.ece.illinois.edu/seminars/CEME910Covic.pdf

URS Corporation, (2009). Attachment 7: I-710 Alternatives Screening Analysis Final Report. I-710 Corridor Project EIR/EIS. Final – Technical Memorandum-Alternatives Screening Analysis (pp. 1-94). Prepared for Los Angeles Metro, Los Angeles County Metropolitan Transportation Authority, Los Angeles, CA. Retrieved from: http://www.polb.com/civica/filebank/blobdload.asp?BlobID=6417

US DOE ARPA-E IDEAS program, (2017). Feasibility Analysis of Electric Roadways Through Localized Traffic, Cost, Adoption and Environmental Impact Modeling. Logan, UT: Utah State University. Retrieved from: https://arpa-e.energy.gov/?q=slick-sheet-project/feasibility-analysis-electric-roadways

Utah House of Representatives, (2017). Press Release: Utah research facility leading the way in groundbreaking technology. Retrieved from: https://house.utah.gov/tag/aggie-bus/

Utah State University today, (2012). Utah State University Unveils Wirelessly Charged Electric Bus. Retrieved from: http://www.usu.edu/today/index.cfm?id=51862

Utah State University, (n.d). Electric vehicle and roadway. Retrieved from: http://evr.usu.edu/

Valeri, E. & Danielis, R., (2015). Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy. Transport Policy, 37, 44–56. https://doi.org/10.1016/j.tranpol.2014.10.003

Viktoria Swedish ICT, (2013). "Slide-in Electric Road System - Inductive project report," Viktoria Swedish ICT, Gothenburg.

Viktoria Swedish ICT, (2014). "Slide-in Electric Road System - Inductive project report," Viktoria Swedish ICT, Gothenburg.

Vilathgamuwa, D.M. & Sampath, J.P.K., (2015). Wireless power transfer (WPT) for electric vehicles (EVs) - present and future trends. In: Plug in Electric Vehicles in Smart Grids (pp. 33–60). Singapore: Springer.

Virginia Clean Cities, (2010). Virginia Get Ready: Initial Electric Vehicle Plan. Retrieved May 15, 2018, from: http://www.virginiaev.org/wp-content/uploads/2010/11/EV-VGR-FINAL-October-13-2010.pdf

Vyas, S. & Kumaranayake, L., (2006). Constructing socio-economic status indices: how to use principal components analysis. Health Policy and Planning, 21(6), 459-468. https://doi.org/10.1093/heapol/czl029

Wang, C., Covic, G.A. & Stielau, O.H., (2004a). Investigating an LCL load resonant inverter for inductive power transfer applications, IEEE Transactions on Industrial Electronics, 19(4), 995-1002. https://doi.org/10.1109/tpel.2004.830098

Wang, C., Covic, G.A. & Stielau, O.H., (2004b). Power transfer capability and bifurcation phenomena of loosely coupled inductive power transfer systems, IEEE Transactions on Industrial Electronics, 51(1), 148–157. https://doi.org/10.1109/tie.2003.822038

Wang, Q. & Mompo, S., (2014). Electric-road freight transport, Arlanda - Rosersberg: Logistic flow and environmental analysis. Master's thesis, KTH - Royal Institute of Technology.

Washington, S.P., Karlaftis, M.G. & Mannering, F.L., (2011). Statistical and Econometric Methods for Transportation Data Analysis (2nd ed.). Boca Raton, FL: Chapman & Hall.

Welch, F., (1973). Education, Information, and Efficiency. Working Paper No. 1 (pp. 1-132), Working Paper Series. National Bureau of Economic Research, Inc. https://doi.org/10.3386/w0001

Whitehead J.C., Pattanayak S.K., Van Houtven G.L. & Gelso B.R., (2008). Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the state of the science, Journal of Economic Surveys, 22(5), 872-908. https://doi.org/10.1111/j.1467-6419.2008.00552.x

Wikipedia contributors, (2018). Orange Line (Los Angeles Metro). In Wikipedia, The Free Encyclopedia. Retrieved May 15, 2018, from: https://en.wikipedia.org/wiki/Orange_Line_(Los_Angeles_Metro)

Wikipedia contributors, (2018). Transportation in Los Angeles. In Wikipedia, The Free Encyclopedia. Retrieved May 14, 2018, from: https://en.wikipedia.org/w/index.php?title=Transportation_in_Los_Angeles&oldid=839963865

Williams B., Onsman A. & Brown T., (2010). Exploratory factor analysis: A five-step guide for novices. Journal of Emergency Primary Health Care, 8(3), 1-14. Available at: https://www.scribd.com/document/153912844/Exploratory-Factor-Analysis-A-Five-step-Guide-for-Novices

Wilmink, K., (2015). A study on the factors influencing the adoption of Hybrid and Electric Vehicles in the Netherlands. Master Thesis. Business Information Management, Rotterdam School of Management, Netherlands, EU: Erasmus University.

Wozniak, G.D., (1984). The Adoption of Interrelated Innovations: A Human Capital Approach. The Review of Economics and Statistics, 66(1), 70-79. https://doi.org/10.2307/1924697

Wu, H. H., Boys, J.T. & Covic, G.A., (2010a). An AC processing pickup for IPT systems, 25(5), 1275–1284, IEEE Transactions on Power Electronics. Retrieved from: https://ieeexplore.ieee.org/document/5340583

Wu, H.Y., Trappey, C.V. & Feinberg, R.A., (2010b). The diffusion of innovation and perceived risk for the adoption of alternative energy vehicles. International Journal of Innovation and Learning, 8(3), 296-314. https://doi.org/10.1504/ijil.2010.035032

Yetano Roche, M., Mourato, S., Fischedick, M., Pietzner, K., & Viebahn, P. (2010). Public attitudes towards and demand for hydrogen and fuel cell vehicles: A review of the evidence and methodological implications. Energy Policy, 38(10), 5301–5310. https://doi.org/10.1016/j.enpol.2009.03.029

Zaheer, M., Patel, N. & Hu, A.P., (2010). Parallel tuned contactless power pickup using saturable core reactor (pp. 1-6), in Proc. of International Conference on Sustainable Energy Technologies. https://doi.org/10.1109/icset.2010.5684407

Zero Emission Urban Bus System, (2016). An overview of electric buses in Europe. ZeEUS , eBus Report. Retrieved from: http://zeeus.eu/uploads/publications/documents/zeeus-ebus-report-internet.pdf

Zijlstra, W.P., van der Ark, L.A. & Sijtsma, K., (2011). Outliers in Questionnaire Data: Can They Be Detected and Should They Be Removed?, Journal of Educational and Behavioral Statistics, 36(2), 186–212. https://doi.org/10.3102/1076998610366263