The Adoption of Electric Vehicles: Behavioural and Technological Factors

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ABSTRACT

This research explored the preferences and attitudes towards the adoption of Electric Vehicles (EVs) in Perth, Western Australia (WA).

EV has distinct properties when compared with Petrol vehicles. EV has zero tail-pipe emissions and noise and low running cost compared to the internal combustion engines. This is because EV uses electricity as a transport energy source. However, the limited driving range and the time to recharge the battery (at the fast charging stations about 20-30 min) are currently considered substantial barriers for adoption. Currently, home charging stations are provided with a new EV, but the public charging infrastructure is limited in Western Australia (WA).

Previous studies either used only consumer behaviour models or used only discrete choice models for exploring EV adoption, however a few recent studies explored EV adoption using a combination of these two. Using three stages of data collection (driver survey, household mail out survey and PureProfile online survey, all including revealed and stated preference data) and applying discrete choice modelling with attitudinal constructs, this research explored the potential enablers and barriers of adoption of Plug-in EV in WA.

The research found the following:

- Drivers of EVs considered the driving experience of an electric vehicle very similar to an internal combustion engine and identified the environmental effect (zero tail pipe emissions) as the main benefit of EV. Many of them (members of a state EV Association) converted their own ICE cars into EVs and are passionate advocates of the EV technology; they prefer to charge at home for convenience and because many use renewable solar energy, they have a high level of environmental concerns and a marked interest in new technologies;
- The interest they expressed in EVs (perhaps combined with the awareness of a WA EV trial, where 11 organisations purchased EVs and encouraged their employees to use them) has led to a social desirability predisposition in the household survey; the mail-out household sample indicated bias towards highly educated, older participants, with higher levels of environmental

concerns, social norms, and perceived use of EV technology. The initial choice analysis of the data from this sample showed substantial non-trading behaviour and an important sign reversal, for the range parameter of EVs (in contrast to previous studies which indicate that extended driving range increases the utility of an EV). A potential reason for this effect may also have been the substantially different driving range (four-five times larger) between ICE and EV;

- In order to further test the trading behaviour, to minimise the social desirability bias, and obtain a better representation of Perth's population, a second household survey was conducted using an online panel (PureProfile). This latter sample, with equal quotas from the North and South parts of the city, with equal distribution of males and females, and more representative coverage of the population age groups, showed a significantly lower non-trading behaviour, lower scores for environmental concerns, social norms and technology adoption scales, and corrected the negative sign reversal for driving range. The hybrid choice models confirmed the association between preference for EV and higher attitudes for energy conservation, but equally importantly the role of low running cost in the purchase of an EV, as well as the presence of a high-speed EV charging infrastructure.

From the methodological point of view, the research has shown that using the Best-Worst stated choice scenarios (providing the most preferred and least preferred options) is beneficial and provides more reliable parameter estimates. In addition, using experiments with two EVs in the same choice set is more appropriate in situations where technology is largely unknown (not experienced), but there is a positive outlook towards its adoption. Results from mixed logit models confirmed preference heterogeneity within the sample, further distinguishing EV enthusiasts from the population at large.

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I dedicate my PhD to my Grandmother Lodhri, a lady full of wisdom, who advocated Women Education throughout her life until she left at the age of hundred and ten. I saw her devotion for learning in my childhood and she was a source of inspiration.

AUTHORSHIP DECLARATION: CO-AUTHORED PUBLICATIONS

This thesis contains work that has been published.

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Student contribution to work: 95%
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Student signature: Date: [07/11/16]
I, John Taplin certify that the student statements regarding their contribution to each of the works listed above are correct. Coordinating supervisor signature: Date: [07/11/16]

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CHAPTER 1

1 INTRODUCTION TO THE RESEARCH

1.1 TRANSPORT ENERGY SOURCES

Transport energy sources, in Australian household vehicles, include petrol, diesel, liquefied petroleum gas (LPG), dual petrol and electricity, and electric only. The first two are commonly used, while the rest make up 3% of total usage (Australian Bureau of Statistics, ABS, 2014). The transport sector in Australia accounted for 26% of net energy consumption in 2012-2013 (Bureau of Resources and Energy Economics, BREE, 2014).

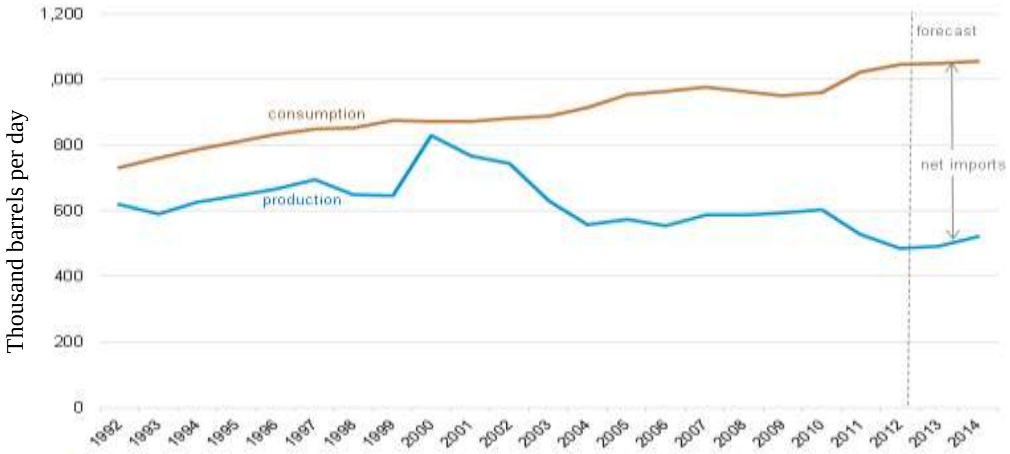

Figure 1.1: Australia's total oil production and consumption, 1992- 2014 (EIA, 2013)

Globally an increase in car use has placed great pressure on energy resources. In 2010 global oil production dropped to 2 million b/d (barrels per day) below consumption (BP, 2010); the shortfall in supply leading to increases in oil price. In 2011, Australia was the world's second largest coal exporter based on weight and it became the third largest exporter of liquefied natural gas (LNG) in 2012 (US Energy Information Administration, EIA, 2013). Although rich in these energy resources, Australia needs to import crude oil; the difference in oil production and consumption is depicted in Figure 1.1 and indicates an increase in net oil imports of more than 500 thousand barrels per day after 2012 (EIA, 2013).

With the rising price of petrol and depletion of oil reserves, there is a need to dedicate other energy resources to transport – and this requires alternative fuel vehicles and technologies as indicated more than a decade ago by Dagsvik, Wennemo, Wetterwald, & Aaberge (2002). Alternative fuels include ethanol, biodiesel, LPG and compressed natural gas (CNG); but their selection mainly depends on fuel availability in a particular country. The electric vehicle (EV) is an alternative fuel vehicle that relies on electricity as energy resource. As such a large share of the automobile market will mean that there is a robust energy mix driving the cars of the future.

EV is environment friendly, with zero tail-pipe emissions, but it relies on various sources of electricity generation. For EV to be ‘green’, the electricity should be generated from renewable energy sources. In the case of Australia black and brown coal are the major fuels used for electricity generation. Although the renewables’ share has risen from 8% in 2003-04 to 13% 2012-13, it still forms a small proportion of total electricity generation (Figure 1.2).

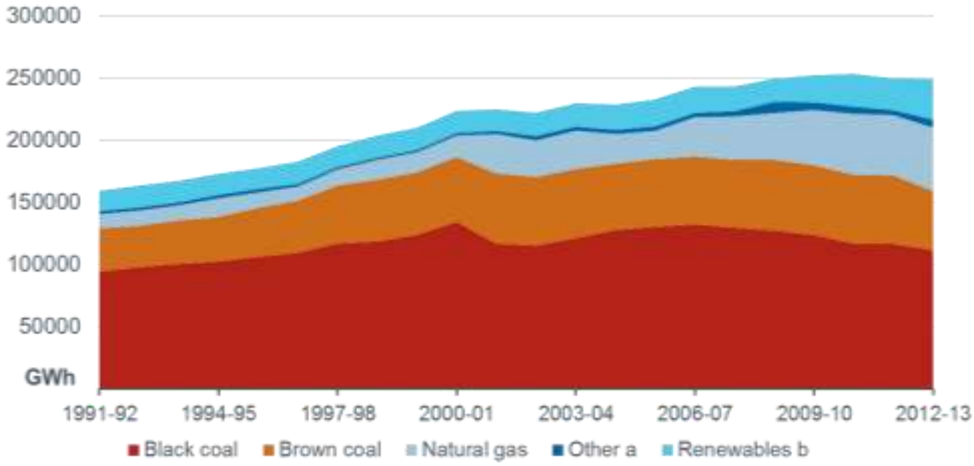

Figure 1.2: Australian electricity generation, by fuel-type (BREE, 2014)
a: includes oil and multi-fuel fired power plants.
b: includes wind, hydro, solar PV, bioenergy and geothermal.

Given that they do not depend on petrol and their power can be generated from renewable energy sources (in small quantities at this stage), EV allow for the establishment of a green transport infrastructure. By 2020, 20% of electricity generation will be from renewable energy sources, and the Bureau of Resources and Energy Economics (BREE) projects that Natural gas would account for 36% of electricity generation by 2035 (EIA, 2013). According to 2011-2014 count of solar panel installations, a total of *144,363 solar panel installations* across the area of *641,786 hectares in Greater Perth* (ABS Western Australia 2017). Considering this use of solar panels, EV batteries can be recharged at home making EV a green vehicle for people having solar panels at home and using EV for their daily short trips.

This thesis aims to explore the propensity to adopt EVs in Perth, the capital city of Western Australia. EV history is presented in the next section, followed by a review of types of EV technologies.

1.2 ELECTRIC VEHICLE: HISTORY

The electric vehicle (EV) competed with conventional cars until about 1920: "*...electric automobiles were competitive with petroleum-fuelled cars particularly as luxury cars for urban use and as trucks for deliveries at closely related points,...*" (Encyclopaedia Britannica, 2009). Subsequently there were intermittent attempts to win acceptance for EVs (Bureau of Transport Economics, BTE, 1974; Kurani Turrentine, & Sperling 1996; Rajashekara, 1994). Wakefield, in his book - *The Consumer's Electric Car* (1977) - mentions the "re-birth of interest" in EV with then modern technology, signalling that EVs had again emerged with slight enhancements in the 1960s. Rajashekara (1994) summarises the EV history of General Motors, presenting a review of a number of electric and hybrid vehicles developed by GM in the previous three decades. GM focused EV research efforts on environmental concerns and began the development in 1916 before gradually slowing down, but then resurrected the initiative on EV and propulsion systems in 1960. In the late 1970's interest declined due to a reduction in petrol prices, but GM continued research in EV technology. Despite the development initiatives by GM, one of its EV models was withdrawn and destroyed as shown in a documentary film (Sony Pictures, 2006). This case may seem to indicate 'some kind of conspiracy', but throughout this period other models continued to be available in the market (Buckley, 2006; Ford, 2009; Tesla, 2009).

Tesla Motors (Tesla, 2009) based their ideas on the original Tesla model in 1882, and since 2004 Tesla has been working to enhance and increase their EV production in California, distributing worldwide. Enfield Automotive (Buckley, 2006) was an electric car manufacturer founded in the UK in the 1960s; the car was a market failure, and production ceased in 1977 but a few are still in use (Chan, 1993; Vyas, Santini, & Johnson, 2009). Recent successes may demonstrate that people are changing the way they use their cars and becoming more concerned about the environment and the need to better preserve non-renewable energy sources.

Yet, current EV technology depends primarily on battery size and whether the battery can be plugged in or not.

The potential adoption of EV technology has been explored in different geographical areas and is discussed in detail in Chapter 2.

1.3 TYPES OF ELECTRIC VEHICLE TECHNOLOGIES

Pure EVs use electricity as their propellant, while hybrid EVs use electric technology to improve their efficiency. Types of EVs are: hybrid electric vehicle (HEV), plug-in hybrid (PIH) or extended range EV, fuel cell electric vehicle (FCEV), and pure EV or plug-in EV.

Any form of EV contains a battery to store power and an electric motor for propulsion except the Fuel Cell EV. While there is widespread public awareness of hybrid vehicle technology, EV technology is not well understood. An ordinary internal combustion engine vehicle (ICE) can be converted to an EV by installing an electric motor and battery to replace the engine; these EV conversions are similar to a factory EV. In 2008, the Renewable Energy Vehicle (REV) project at the University of Western Australia converted a petrol Hyundai Getz to a full EV as a proof of concept using available technologies. The infrastructure for EVs being developed at UWA (Mullan, Whitely, Harries, & Bräunl, 2010) is associated with the conversion to EV of an ICE vehicle. Considerable literature on the operating characteristics of EVs (e.g. Voelker, 2009) and the work at UWA has established that standard car models transformed to EVs can deliver excellent performance. A group of 11 organisations participated in the Western Australian EV (WAEV) trial, where each organisation had a variable number of converted EVs. These Ford Focus conversions provided a driving experience similar to that of the ICVs, with the additional benefit of being quiet and having low running-cost. A study of the operating experience with these vehicles is reported in Chapters 4 and 5.

The following sections present a comparison of types of electric vehicle technology.

Hybrid Electric Vehicle

A conventional Hybrid EV (HEV) primarily uses the internal combustion engine as its drive technology. The electric motor and battery are typically smaller than that of the Plug-in hybrid EV or the plug-in EV. As shown in Figure 1.3, architecture comparison of HEV and PIH shows that hybrid vehicles do not allow for external charging (Bradley & Frank, 2009). HEV batteries are recharged by regenerative braking or by an ICE or other propulsion source (Alternative Fuels Data Centre, AFDC, 2014).

An HEV captures energy lost during braking, with the electric motor generating power to store in batteries. HEV is fuel-efficient in city driving because the vehicle will keep charging itself and then switching from fuel source to electricity on slow speeds, thus saving fuel. This switching method from fuel source to electricity relies on one of two types of HEV internal configurations: parallel and series (AFDC, 2014).

Parallel hybrids are relatively cheap to buy and the configuration enables the HEV, with sufficient battery charge, to be propelled by both ICE and electricity. They are also called mild/micro hybrids because, in this case, the ICE only shuts off when the vehicle is stopping at street-lights or is delayed by traffic; electricity is used to support the engine in acceleration.

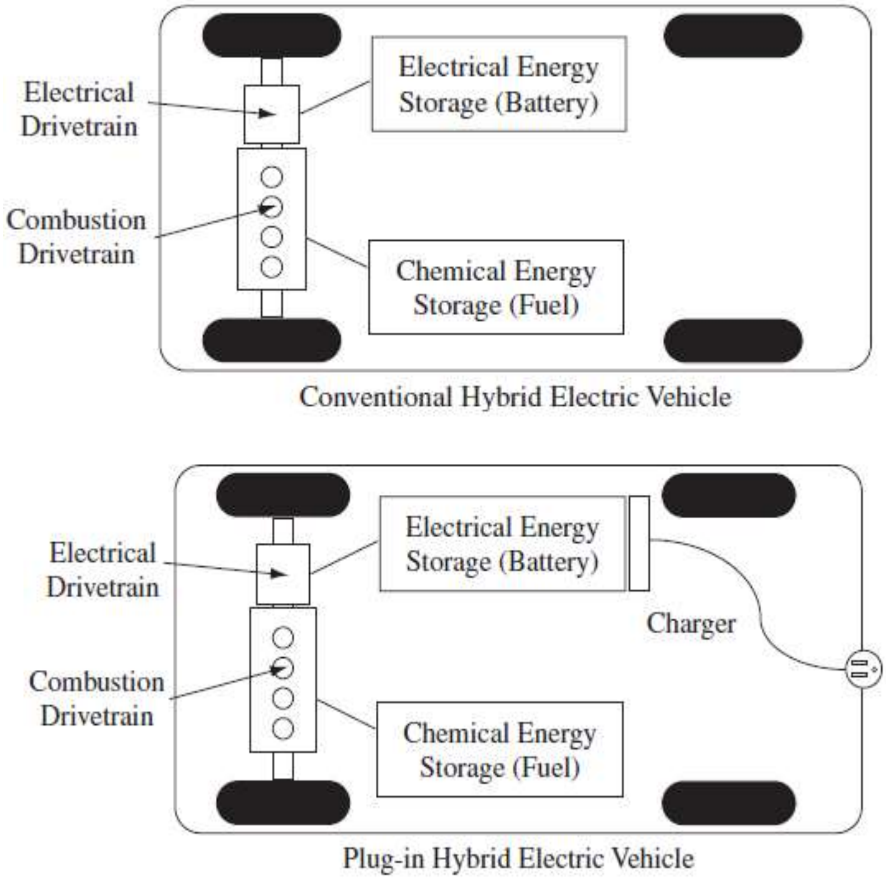

Figure 1.3: Architecture of conventional hybrid and plug-in hybrid Electric Vehicles (Bradley & Frank, 2009)

Series hybrid configuration allows the HEV to be propelled by an ICE or electricity. When the battery is charged sufficiently, the ICE shuts off and the electric motor propels the HEV. These are also called full hybrid vehicles, providing high fuel efficiency, but at a high purchase cost. Series hybrid configurations are also found in some plug-in hybrid vehicles. The engine automatically shuts off when electricity is being used as the power source (Fuel Economy, 2014).

In comparison to EVs, HEVs have a lower purchase price and eliminate range anxiety, but the running cost of an HEV is higher than for an EV/PIH. A number of HEVs exist in the Western Australian market; for example, the Toyota Prius and Toyota Camry.

Plug-in Hybrid Electric Vehicle

The plug-in hybrid (PIH) vehicle is different to the HEV in that the PIH has an option to recharge the battery using a charger, as shown in the architecture in Figure 1.3 (Bradley & Frank, 2009). Battery size or capacity for PIHs is greater than HEVs (AFDC, 2014) and the PIH's electric motor is more powerful than HEV's electric motor to support all-electric drive at higher speeds. Batteries in PIHs can be recharged by plugging-in or by regenerative braking and ICE (Fuel Economy, 2014), but PIH being Hybrid makes them not limited in range. PIHs uses an all-electric drive that could cover a substantial portion of daily travel (Samaras & Meisterling, 2008), while at the same time removing the range anxiety, which is a significant barrier for plug-in EV.

Although the terms PIH and extended range-EV are used interchangeably, technically they represent the two slightly different configurations already mentioned: parallel (PIH) and series (extended range-EV) (Fuel Economy, 2014; DeLucchi, Yang, Burke, Ogden, Kurani, Kessler, & Sperling, 2014).

Parallel plug-in hybrids or '*blended plug-in hybrid*' allow both the engine and the electric motor to propel the vehicle, both being mechanically connected to the wheels (Fuel Economy, 2014). Driving conditions determine whether the vehicle is driven in electric mode; for example electric-only driving is possible only at low speeds (AFDC, 2014).

In series PIHs that form extended range EV, the electric motor performs the drive operation, while the internal combustion engine is only responsible for generating electricity that is stored in the battery. When the battery needs to be recharged, the engine generates electricity, using fuel to power the electric motor. For short driving trips, this type of PIH might not use fuel at all and rely only on electricity stored in batteries. Series PIHs are also called extended-range electric vehicles (EREVs) as they eliminate the range barrier while allow reliance on electricity for short daily trips (Fuel Economy, 2014).

The Holden Volt is an example of an extended range EV, having all the features of a PIH, and can be switched to an electric mode whilst being driven. General Motors (GM) uses a slightly modified version of this series design in the Chevy Volt, where the vehicle is driven by electric motor all the time but can be switched to operate like a parallel hybrid at high speeds, when the battery is depleted. GM refers to this design as an *extended range electric vehicle* (AFDC, 2014).

Table 1.1 compares salient features of EV technologies, which were explored while designing stated-choice experiments for a household study as discussed later in this chapter. With the main aim being to determine potential drivers for adoption of electric vehicles, plug-in electric vehicles and PIHs are compared, as both share the property of battery charging. Hybrid EV, and Fuel cell EV are different from Plug-in EV as they do not require battery charging. The attributes of the vehicles were further identified based on previous studies of EV/alternative fuel vehicle uptake and adoption, in different parts of world.

Table 1.1: Comparison of Electric Vehicle Technologies

Characteristic	Hybrid EV (HEV)	Plug-in Hybrid (PIH)	Fuel cell EV (FCEV)	Plug-in EV (Plug-in EV)
Electric motor	Less powerful than PIH/EV	More powerful as compared to HEV	Electric traction motor	EV solely rely on electric motor
Battery Size	Small batteries	Battery size is greater than HEV	Small batteries	Battery size is greater than PIH
Tailpipe emissions	Less tailpipe emissions as compared to ICV	Less tailpipe emissions as compared to HEV	Zero tailpipe emissions	Zero tailpipe emissions
Running cost	Lower cost as compared to ICV	Lower cost as compared to HEV and ICV	Lower cost as compared to PIH	Lower cost as compared to PIH
Purchase price	Expensive compared to ICV	Expensive compared to HEV	Expensive compared to HEV	Expensive compared to HEV
Time to recharge batteries	Same as ICV; Cannot recharge batteries	Same as ICV, Fast charger can charge to 80% battery capacity in 30 mins	Same as ICV; Hydrogen fuel tanks are replaced	Fastest charger option: 15 mins to 30 mins Other options: 1.5 hours-8 hours
Home charging	No	Yes	No	Yes
Range anxiety	No range limitation	No range limitation	No range limitation depends on fuel tank size	Limited range
Brands available in WA	Toyota Prius, and Toyota Camry	Holden Volt	N/A	Nissan Leaf; Mitsubishi iMiEV

Fuel Cell Electric Vehicle

This vehicle uses hydrogen gas as fuel and generates electricity from hydrogen. One of the benefit of FCEV that is comparable to EV is their zero tail-pipe emissions (Fuel Economy, 2014). The main limitatation of FCEV is that these Fuel cell vehicles require special infrastructure as they require hydrogen fuel cell to be refilled similar to conventional fuels but they require to setup pumps to refuel FCEV (AFDC, 2014). Since FCEV were in their infancy stage in the year 2011 with no FCEV infrastructure/vehicle available in Western Australia this is the main reason that FCEV were not further explored for this study.

Plug-in Electric Vehicle

An EV, also called "Battery EV" or "Plug-in EV", uses an electric motor for propulsion and the battery gives this vehicle a limited range (AFDC, 2014). Battery recharging is characteristic of plug-in EVs; instead of going to a petrol station, plug-in EVs need to be re-charged from an electric power source, and regenerative braking also helps to restore energy while stopping. Battery charging can be done at home or at a specialised station. It is usual to recharge the battery at home during the night.

Plug-in EV has a large capacity battery as it relies solely on electricity. The high purchase price of an EV/PIH is largely due to the battery cost. Nissan Leaf and Mitsubishi iMiEV are examples of plug-in EVs available in the Perth metropolitan market, but the total number of plug-in EVs purchased and driven in the city remains low. A total of 81 registered plug-in EVs were being driven in Perth in March 2014, with a large proportion of them being fleet vehicles. In this thesis term EV refers to "*plug-in EV*" for simplicity. The resale value of EVs dropped within a year from $51,500 to $39,000 (CARSGUIDE, 2013) with the main reason being EV battery life. Battery chemistry or technology plays an important role in EV cost, as discussed in detail in next section.

1.4 ELECTRIC CAR PURCHASE – BATTERY CHEMISTRY DETERMINES EV BATTERY COST AND RANGE

The type of battery used by most manufacturers of EVs and HEVs nowadays is the lithium-ion battery (Mierlo, Maggetto, & Lataire, 2006; DeLucchi *et al.*, 2014). As a side comment, Australia is the second largest producer of lithium (Dunstan, Usher, Ross, Christie, & Paevere, 2011), integral to battery manufacture.

The cost of an EV is increased by the expensive battery in the vehicle. But the battery has a limited life-span, depending on the use and operating temperature of the car (Fraunhofer Research News, 2012). This is a major reason that the demand for used EV is weaker than for new EV (The Detroit News, 2015).

Novel mechanisms for cooling the EV battery while driving the car have been devised in recent research (Pistoia, 2010; Fraunhofer Research News, 2012). Väyrynen & Salminen (2012) designed a battery management system (BMS) that can maintain battery temperature below a specified limit, optimising battery lifespan and allowing safe EV driving.

Gerssen-Gondelach, & Faaij (2012) compared battery performance between five battery technologies and found that it is difficult for one battery technology to meet all required characteristics (for example: energy density, efficiency, operating temperatures, safety, and cost). Only lithium-ion batteries were expected to achieve these goals in the next 5-20 years. The type of battery used in the Nissan Leaf and Mitsubishi iMiEV is a lithium-ion battery (LIB).

Battery types exist in different sizes and weights, depending on their battery chemistry (Figure 1.4; Amine, 2010).

LIB: Lithium-Ion Battery
LPB:Lithium-Polymer Battery
Ni-Cd: Nickel Cadmium
Ni-MH: Nickel-Metal Hydride
Ni-Zn: Nickel Zinc, Wh/kg: Watt-Hour per Kilogram, Wh/L: Watt-hour per Litre

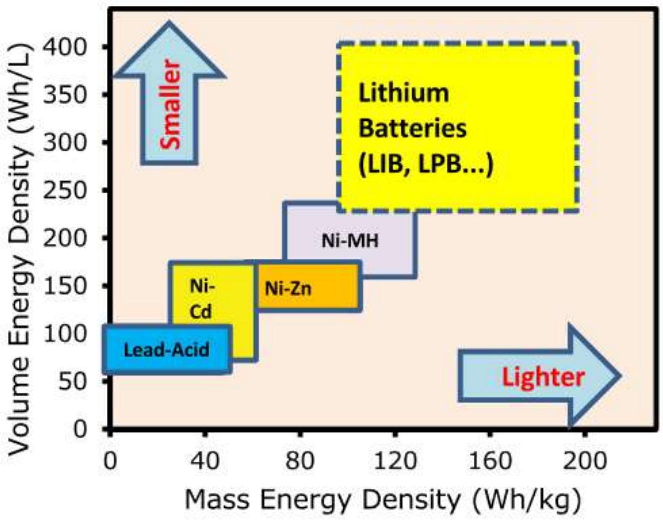

Figure 1.4: Volume Energy Density versus Mass Energy Density for various battery types (Amine, 2010)

The EV battery, which is better than the lead acid battery in terms of size, weight, and power, provides enough power and energy for driving (Scrosati, 2005; Amine, 2010). The feasibility of using alternative lithium compounds has been explored in efforts to decrease cost and toxicity. First generation lithium-ion batteries used lithium cobalt dioxide ($LiCoO_2$), and later lithium manganese oxide ($LiMn_2O_4$) was also used. Lithium iron phosphate ($LiFePO_4$), used more recently (DeLucchi *et al.*, 2014), has several advantages compared with $LiCoO_2$ batteries (Ritchie, 2004; Scrosati & Garche, 2010; Väyrynen & Salminen, 2012). $LiFePO_4$ is less toxic, the battery is environmentally safe over the full battery life cycle, and it is less expensive.

EV driving range depends on a number of factors that are related to battery capability, driving conditions, climate effects, and driving habits (AFDC, 2014). EVs would be ideal for city driving and short distances; while driving in extreme ambient conditions more power consumption occurs, thus reducing the driving range. In addition to this, speedy or aggressive driving might also result in decreased available range. Considering these factors for driving range, an EV is ideal for city driving. Continuing technology development has seen the production of a concept car, the Chevrolet Bolt introduced in 2015 (Chevrolet, 2015) and expected to appear in US market by 2017 (Brian & Jerry, 2015). This vehicle has a range of approximately 321 km and is offered at a price of $30,000, lower than previous EV cars, with battery chemistry for this new concept car defined as an 'advanced lithium-ion battery'. In terms of energy density, Tesla Models (Tesla Motors, 2014) have the highest energy density giving a storage capacity of 85 kWh (Tesla Model S[1]) as compared to 24 kWh for the Nissan Leaf. Range for this Tesla Model S is 502 km, thus greater than the Chevrolet Bolt. These models have a liquid cooling system (Tesla Motors, 2014) for batteries, providing higher levels of safety, whereas the Nissan Leaf relies on air-cooling technologies. Although the latest models from Tesla appear an attractive option among EVs in terms of battery features giving more range and improved safety, they are expensive with a price higher than $100K (The Motor Report, 2015).

[1] http://www.teslamotors.com/en_AU/models

1.5 RESEARCH OBJECTIVES

Acceptance of new fuels and vehicles are determinants of the EV's place in the ensemble of vehicle technologies. Two kinds of individual behaviour are covered in this study: driving and purchase decisions.

Initially, the study aims to find the perceived barriers to the use of EV for the purpose of travel and driving. This might include the number of kilometres travelled on one charge, the need for frequent charging, and where to charge; these factors influence the purchase and use of an EV, along with the efficiency of the vehicle ($ amount spent on travelling per week) and duration of charging. Individuals are likely to trade-off these features, their decision also being affected by attitudes, preferences, and habits. Driving experiences of EV drivers in the Western Australian Electric Vehicle (WA EV) trial are explored to determine factors that influence satisfaction of driving an EV, along with accessibility of charging stations and cost of recharging an EV (Chapter 3).

For the purpose of buying behaviour, the analysis includes the purchase price, maintenance, and pattern of usage. Many Australian households use more than one car (ABS, 2008) so that the range limitation of EVs may not be considered an issue when there is a second car available for long distance trips. The low travel cost means EVs can be used for all short trips within the city, but the charging requires considered trip planning. The location of charging stations is therefore crucial to ensure that the destination is reached, when unexpected detours become necessary. These elements were investigated through stated choice experiments where drivers and households were asked to compare a set of optimally designed scenarios with various vehicle and fuel alternatives (including the EVs) and choose the preferred alternative. In order to achieve the research objectives, the following questions have been addressed:

- Which elements determine EV use and induce acceptance of the electric car on a large scale? Which characteristics of EVs are appealing to the public and what are the barriers to EV uptake?
- What trade-offs do people make when choosing to purchase an electric car?
- What are the public attitudes towards more sustainable vehicle technologies, how can they be influenced and what is the expected effect of sustainable technologies on vehicle choice?

1.6 CONTRIBUTIONS OF THIS THESIS

The contributions or achievements of this thesis are as follows:

- *Findings from investigating drivers' perceived behaviour*. The experiences of drivers in the WA EV trial revealed that an EV is driven in a similar fashion to the same-sized ICE vehicle, but the EV is quieter. A major finding from the study of drivers' experiences is that satisfaction in driving an EV gave them a propensity to recommend and purchase an EV. Drivers who were satisfied with the performance and efficient use of EV energy were more likely to recommend and purchase an EV than drivers who experienced technical difficulties (Chapter 4).
- *Findings from investigating drivers' battery charging behaviour*. It is found that drivers were concerned about the cost and duration of charging an EV; they had a preference to charge EV at night-time. Drivers having solar panels at home showed a strong negative preference for incurring charging costs at public stations (Chapter 5).
- *Findings on household purchase behaviour*. By applying discrete choice modelling techniques it is found that the high purchase price of EVs remains a barrier for EV

uptake. Whereas EV range might not be the key obstacle, short charging duration and low running cost would be key inducements to purchase EV. A large number of pro-environmental people present in this sample biased the results and contributed to a negative estimate for the range parameter (Chapter 6). A second sample, more representative of the population, balanced the findings.

- *Differences between samples*. Analysis using a Mixed Logit (ML) model indicates that people who have a preference for EVs and tend to purchase environmentally friendly products, as well as believing in the usefulness of technology, are more likely to purchase EVs; this may be reinforced by the influence of friends. People who like gadgets or like to learn about new technologies were more concerned about vehicle noise and the operating characteristics of EVs in general. Best-Worst (B-W) stated choice experiments were used to determine whether respondents' preferences were consistent in choosing Best and Worst options and the results indicate that combining B-W is an effective strategy to ameliorate non-trading and social desirability bias (Chapter 7).
- *Two EVs in the same experiment*. Changing the experimental settings by including two EVs in the same scenario allowed respondents in the second sample to make a decision about EV characteristics such as driving range, charging time, and number of charging stations. These experiments were analysed in B-W, and Exploded Logit settings and the overall estimates were more reliable than those obtained in models with only one EV.

  Different willingness-to-pay measures were estimated for Best only, B-W, and Exploded logit data sets with minimal differences in preferences using Exploded Logit and B-W data setups (Chapter 8).

1.7 THESIS ORGANISATION

Chapter 2 presents a review of previous studies about EVs and alternative fuel uptake. Using basic statistics and advanced discrete choice studies, a knowledge gap is identified in previous studies. The organisation of Chapters 4, 5, and 6 is presented in Chapter 3 along with an overview of discrete choice analysis. Two advanced choice models, Latent Class and Mixed Logit (random parameters logit), are also introduced along with a description of how these modelling techniques were applied in this research. Chapter 4 presents findings from a study conducted with EV drivers that explores drivers' perceptions and attitudes towards EV. Chapter 5 also presents findings from a group of drivers in the same trial but this study explores drivers' battery charging behaviour. The household study on EV purchase decisions is presented in Chapter 6, with findings from the closed form choice model; findings from this study using panel ML choice models with Error Components are presented in Chapter 7. Chapter 8 focuses on the findings from the second sample and highlights the benefits of including two EVs in the same choice situation. Conclusions and discussion of future work are presented in Chapter 9.

1.8 CONCLUSION

This thesis aims to explore the propensity of households in WA to adopt an EV as a future vehicle. Vehicle characteristics are considered for the purpose of analysis and individual attitudes are also considered. This is supported by a number of previous studies that explored EVs or alternative fuel adoption in different geographic locations. Chapter 2 presents a review of these studies and attempts to identify a gap in existing research in this area. By applying advanced discrete choice analysis and incorporating attitudinal data into the choice model this thesis identifies factors that influence EV adoption.

CHAPTER 2

2 ELECTRIC VEHICLE UPTAKE: ADOPTING A NEW TECHNOLOGY

2.1 INTRODUCTION

Chapter 1 discussed the differentiating features of plug-in electric vehicle (EV), when compared to petrol or alternate energy sources. Different factors, including the increasing cost of petrol, growing traffic on roads, and associated tailpipe emissions from petrol cars, all contribute to the requirement to explore alternative energy sources for transport. The EV driving experience is similar to that of an internal combustion vehicle (ICV) (Jabeen, Olaru, Smith, Bräunl, & Speidel, 2012), however ownership of an EV requires a change in behaviour as EVs require battery charging instead of refuelling.

The EV offers some advantages, such as a low operating cost, a lower environmental impact and the convenience of charging at home. However, limited driving range may present a worrying barrier for potential buyers, along with the high purchase price. This chapter begins with a discussion of EV benefits and challenges. Currently, buying an EV is a high-cost venture for a family and for fleet owners a significant strategic decision, although EV prices are decreasing each year. For households, this acquisition decision can be compared to the purchase of other high cost new technologies, for example adoption of solar panels for electricity generation at home or high capacity batteries (Ozaki, 2011; Claudy, Michelsen, & O'Driscoll, 2011).

One of the challenges of this research is to assess the reliability of analytical and modelling studies in predicting the uptake of EVs, which can be treated in practical terms as a new technology in the market. This chapter reviews the main theories related to the adoption of new technologies and assesses the relevance of these theories to the uptake of EVs. This is a valid undertaking as adoption theories have typically focussed on the market penetration of low cost technologies and may have little relevance to EVs. Many consumer behaviour models for technology adoption incorporate the psychological (Ajzen, 1985; Mittal, 1995) and marketing factors (Bass, 1969) that influence purchase decision (see Section 2.3). However, this is not a common practice for research into the adoption of new fuel and vehicle technologies; most studies in the choice literature have ignored these psychological factors (as discussed in Section 2.4.2). This research aims to determine whether the consumer behaviour models, in combination with discrete choice analysis, can forecast EV adoption.

This chapter also provides a review of previous studies that explore the adoption of EVs or alternative fuel vehicles by applying different methodologies, classifying findings into two main groups. The first group of studies (Kurani *et al.*, 1996; Golob & Gloud, 1998; Ewing & Sarigollu, 2000; Ozaki & Sevastyanova, 2011; Egbue & Long, 2012) explored EV adoption as "*a new technology adoption*" and explored attitudes, but none of these studies used choice analysis in combination with consumer behaviour models. The second group of studies applied discrete choice analysis, some considering basic discrete choice models (Ewing & Sarigollu, 2000; Dagsvik, Wennemo, Wetterwald, & Aaberge, 2002; Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 2008; Moura, Lopes, Costa, & Silva, 2012; Ito, Takeuchi, & Managi, 2013), while others used advanced discrete choice models (Brownstone, Bunch & Train, 2000; Hess, Train, & Polak 2006; Potoglou & Kanaroglou, 2007; Bolduc, Boucher, & Alvarez-Daziano, 2008; Axsen, Mountain, &

Jaccard, 2009; Hidrue, 2010; Ziegler, 2012; Kuwano, Tsukai, & Matsubara, 2012; Hackbarth & Madlener, 2013). In this second group of studies, apart from the more contemporary examples (Bolduc *et al.*, 2008; Hidrue, 2010) none has incorporated attitudinal data into choice models while exploring EV adoption.

The next section elaborates the benefits and challenges of EV uptake. Section 2.3 discusses consumer technology adoption models, and then in Section 2.4 EV uptake literature is analysed. The discussion section critically analyses and compares this thesis with the existing research. This chapter concludes by identifying a gap in the previous studies, which is then connected with the emphasis and objectives of this thesis.

2.2 ELECTRIC VEHICLES: BENEFITS AND CHALLENGES

DeLucchi, Wang, & Sperling (1989) were among the first to systematically investigate EV performance in terms of life-cycle costs, emissions, and recharging requirements. Their findings revealed considerable progress in development of EV battery technology; they argued that the environmental benefits of EVs could "*practically eliminate HC, CO, NO_x air pollution attributed to highway travel*" (DeLucchi *et al.*, 1989; p. 275) and that the development of fast charging stations might allow EVs to be a viable component of the transport mix. Driving range is a barrier for acceptance, falling far short of the Hess *et al.* (2006) criterion of 353 miles (~560 km) for EV adoption. A full charge currently allows a range of only 100-150 km for most models on the market. Another frequently stated inconvenient aspect of EV use is the long time required for re-charging – compared to the few minutes a consumer needs to fill their tank with liquid fuel. This inconvenience can be resolved by recharging an EV either at home or work, or at a fast public charging station located close to a shopping mall, food vendor, or a coffee shop.

Recent work confirmed the benefits associated with EVs: energy conservation, zero tailpipe emissions, less noise, and low running costs (Mierlo, Maggetto, & Lataire, 2006; Mullan, Whitely, Harries, & Bräunl, 2010; Bühler, Cocron, Neumann, Franke, & Krems, 2014), and home charging (Kurani *et al.*, 1996; Bühler *et al.*, 2014). Due to the push for more efficient and environmentally sustainable vehicles, major automobile manufacturers such as Ford and GM have announced plans to bring EV technology into the mainstream (Ford, 2009).

This thesis analyses the benefits and limitations of EVs as perceived by EV drivers and population at large in a number of sequential studies presented in Chapters 4 to 7.

Energy Conservation

The world oil crisis (Almeida & Silva, 2009) and the environmental concerns (DeLucchi *et al.*, 1989; Ewing & Sarigallo, 2008; Hidrue, 2010; Ziegler, 2012) are the main reasons that alternative fuel resources are being explored for future transport. Yet, the key advantage of EVs (as seen by the market) is lower travel costs, as it consumes relatively inexpensive electricity instead of more expensive non-renewable fuel sources. Chan (2007) compared electric, hybrid and fuel cell as alternative ways of providing energy and found that hybrid and EVs are preferable to liquid fuel and other energy resources, for the purpose of economical (low travel cost) transport.

The cost per km of travel using an EV is reduced to a little over one quarter of the petrol car based on $2.9 per 100km for a small economy EV compared with $10 per

100km for a petrol car in the Australian market, assuming an energy consumption rate of 1.25 MJ/km (iMiEV, 2012). On a yearly basis, EV travel costs of $550 (iMiEV, 2012) compared with $1,900 for a petrol car represent a saving of $1,350 per year. This difference can further increase with a rise in petrol price, thus increasing the EV savings. Lidicker, Lipman, & Shaheen (2010) also suggested that petrol prices could have a dramatic effect on the EV savings (purchase and running).

Zero Tailpipe Emissions and Less Noise

From an environmental perspective, the use of conventional motor vehicles in Australia remains a major source of carbon dioxide (CO_2) and noxious pollutant emissions.

In regard to GHG, CO_2 emissions from the transport sector accounted for 17.3% (92.8 Megatons CO2 emissions) of Australian net emissions in 2013 (Australian National Greenhouse Accounts, 2013). Road transport represents the major source of emissions from transport (85% of transport emissions in 2012, according to the Australian National Greenhouse Accounts, 2014). From 1990 till 2012 road transport emissions increased by 44.7% and are still on the rise. Therefore EV are a vehicle technology option able to curb this trend. Naturally, the magnitude of benefits depends on the source used for producing electricity and full lifecycle assessment of vehicles (Pistoia, 2010).

Mierlo *et al.* (2006) suggested that EVs are an optimum solution for urban mobility, as they do not produce exhaust fumes. A study of vehicle and fuel full lifecycle greenhouse gas emissions showed that EVs have a positive balance when compared with ICE vehicles or hybrid electric vehicles (Ma, Felix, Tait, Xavier, & Andrew, 2012).

However, in Australia, the use of coal fired power stations to generate electricity will leave CO_2 emissions little changed (Garnaut, 2008; Albrecht, Holyoak, Raicu, Pudney, Taylor, Zito, & Groves, 2009; Ehsani, Gao & Emadi, 2010; Thomas, 2012; Hawkins, Singh, Majeau-Bettez, & Strømman, 2013). Pistoia (2010) concluded that EVs can lead hybrid cars in signficantly increasing environmental sustainability, if electricity is produced from renewable energy sources. Granovskii, Dincer & Rosen (2006) also came up with a similar finding that the environmental impact associated with EVs depends on the source of electricity. This is further confirmed by a study in Texas by Nicholas, Kockelman, & Reiter (2015) where they found that EVs reduce GHGs, NO_x, PM_{10}, and CO, but generate much more SO_2 at the point of power generation from coal. Nicholas *et al.* (2015) further suggest that in case of EVs powered by electricity from coal source, emissions occur at the point of electricity generation; thus EV shifts the emission exposure to the point of power generation instead of on the road, while conventional vehicles generate higher emissions during driving as compared to EVs.

The electric motor produces very little egine noise as compared to a conventional car engine – thus reducing noise pollution. Yet, sound coming from road friction and the low sound of the electric motor can be sufficient for a pedestrian to hear an EV approaching.

Home Charging

The fact that the battery can be charged at home is the most convenient feature of an EV (Kurani *et al*., 1996). Home charging stations and installation of a home-charging unit usually comes with the purchase of an electric vehicle (iMiEV, 2012). Most Australians own more than one car (ABS, 2008) and an EV can be effectively used as a second car in a multicar household, given its low-running cost for short trips within the city. In such a scenario, an EV can be recharged overnight and used for the daily chores in a limited distance range on a daily basis. Effective trip planning may obviate the need for public-charging stations at all. This might also result in a change in refuelling behaviour for the drivers. For example, for an EV Project in USA, 85% of Volt charging and 80% of Leaf charging events occurred at home (Smart, 2014). On the other hand, the trip can be extended if required by re-charging from the public charging stations.

Limited Driving Range

The limited driving range of EVs does represent a challenge to their acceptance in the market (Hess *et al*., 2006). Thomas (2012) commented that EV market penetration potential has not been explored in the context of American drivers, and doubts that Americans, fond of driving long distances, would take up these limited range vehicles. In the metropolitan area of Perth, in Western Australia, average daily driving distance is 30km, composed of average round-trip commuting distance of 25km (Bureau of Infrastructure, Transport and Regional Economics, BITRE, 2010) and 5km for contingencies. Thus, limited driving range need not be a barrier as the EV is ideal for short distance travel under 50 km. But more importantly, the EV has a promise of being a truly competitive alternative in city driving for households that own multiple cars (Kurani *et al*., 1996). In this setting, household travel needs can easily be satisfied by dedicating the EV to short trips and using the other car(s) for longer distances.

High Purchase Price

Another challenge for EV uptake is their high purchase price compared to ICE vehicles. The cost of an EV is largely determined by the battery cost; lithium (along with other metals) is the resource consumed in the production of EV batteries. A number of EV manufacturers use lithium-ion batteries (e.g., Nissan Leaf, iMiEV, and Tesla Road Motors). Scientists are working on improving the characteristics of lithium-ion batteries as this type is expected to remain in the market (Andress, Das, Joseck, & Nguyen, 2012). The improvements in battery characteristics might allow the cost of battery packs to gradually decrease in future.

There has been a slight decrease in the average EV price. In Australia, in 2013, the cost of a five-seater ordinary car size 2012 model EV was $39,990 (CARSGUIDE, 2013), and the cost of a conversion car from petrol to EV (100 km maximum range) was $15K to $20K (EVWORKS, 2013). Although this is expensive when compared with ICE cars, when total costs (purchase and running) are considered together, an EV becomes more cost-efficient, especially in the long-run. By applying a life-cycle approach, Lipman & DeLucchi (2006) found that an EV is competitive if the petrol price rises above $1.46 (USD)/gallon, i.e., well below the current price of $2.14 (USD)/gallon. Mullan *et al*. (2010) also did a cost analysis of EV batteries, and their results showed that over a period of eight years the reduction in travel cost will offset the added battery cost.

To study differences in preferences towards EVs compared with conventional cars, this thesis explores adoption of EV as “new technology”. Adoption of new technologies in the literature of marketing, psychology, agriculture and sustainable energy is discussed in the next section.

2.3 CONSUMER BEHAVIOUR MODELS ON ADOPTING NEW TECHNOLOGIES

EVs are not a new idea but the latest developments in EV make it a contemporary new technology. Thus it is pertinent to explore acceptability of EVs as “new technology” adoption. A variety of devices like smart phones, tablet PCs, notebooks, and a variation of Internet applications etc., are examples of innovations. Even if they are small items, representing lower investment costs, their adoption is dependent on individual behaviour and attitudes. In the household context, for example, the decision to use solar panels (Ozaki, 2011) is regarded as an adoption of green electricity that can be influenced by green values, social norms, personal relevance, and inconvenience of switching. Studies exploring the adoption of new technologies (Table 2.1) investigate different social and psychological factors that can influence decisions.

From the literature it is apparent that technology adoption has been studied from various perspectives, market intervention, or in the field of information technology (IT), or both (Gatignon & Robertson, 1985; Huh & Kim, 2008; Son & Han, 2011). Various psychological factors can potentially have impact on the marketing of a new product (Ajzen, 1985, 1991; Mittal, 1995, Parasuraman, 2000; Huh & Kim, 2008; Ratchford & Barnhart, 2012). This section discusses consumer behaviour models and the adoption of new technologies.

Theory of Planned Behaviour

Human behaviour is determined by a number of complex factors (Ajzen, 1985; 1991). Three decades ago Ajzen (1985) presented the theory of planned behaviour (TPB), suggesting three predictors for intention: attitudes towards specific behaviour, subjective norms, and perceived behaviour of control (Table 2.1). Intentions along with perceived behaviour of control were suggested as independent predictors of the behaviour of an individual (Figure 2.1).

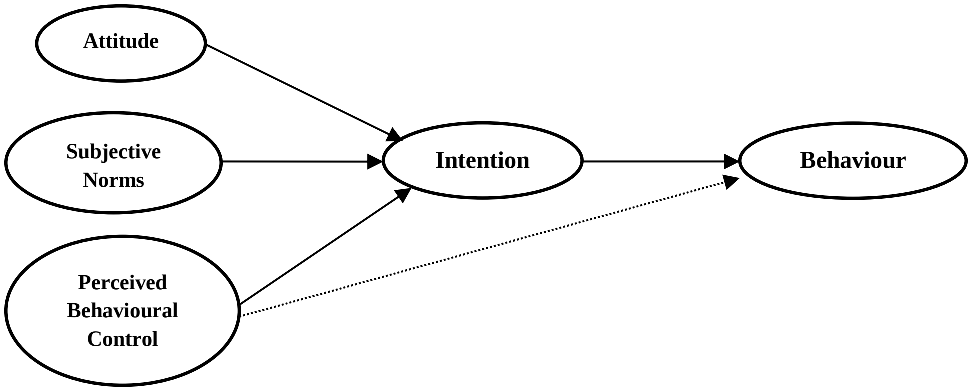

Figure 2.1: Theory of Planned Behaviour (Ajzen, 1985)

The three quintessential predictors were defined in Ajzen (1991) as follows: the first, attitude towards the behaviour, *"…the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question…"*; the second, subjective norm, *"… the perceived social pressure to perform or not to perform the behaviour"*; and the third perceived behavioural control is defined as *"…the perceived ease or difficulty of performing the behaviour and it is assumed to reflect past experience as well as anticipated impediments and obstacles …"* (Ajzen, 1991; p. 188). The three predictors of intention in TPB indicate that an individual is influenced by the attitudes towards a specific behaviour of family or friends, and the perception of resources or knowledge to use the technology. TPB has been applied in various fields, for example:

- Adoption of e-commerce (Nasco, Toledo, & Peter, 2008), electronic services (Liao, Chen & David, 2007), mobile shopping (Yang, 2012), and online banking technologies (Nasri & Charfeddine, 2012),
- Drivers' speeding behaviour with an addition of cognitive constructs into basic TPB model for accident prevention (Elliot *et al.*, 2012),
- Farmers' intentions to purchase agriculture machinery (Feng, Fu, Zheng & Mu, 2010),
- Adoption of green electricity by consumers at home (Ozaki, 2011).

Nasco *et al.* (2008) reported attitudes and subjective norms as significant predictors, but perceived behavioural control was not a significant predictor of intentions to adopt e-commerce by enterprises in Chile. Liao *et al.* (2007) established subjective norms and perceived behavioural control as significant motivators for intentions towards the use of online services; their study combined TPB with technology acceptance model (TAM) model, as did Yang (2012), and Nasri & Charfeddine (2012), (discussed in Section 2.3.2).

In an accident analysis and prevention study, Elliott *et al.* (2013) used TPB to explore drivers' speeding behaviour. In this longitudinal research implemented over two stages, the authors used basic TPB in the first study, and added cognitive constructs such as moral norm, anticipated regret, and self-efficacy for drivers later in their second study. Their results confirmed the relationships proposed in TPB.

The application of TPB in agricultural economics was used to determine farmers' decision-making and explore agriculture machinery purchase behaviour. Development of high-cost agricultural machinery is dependent on farmers' needs and their purchase behaviour. Farmers' decisions for high-cost machinery can be compared with household purchase behaviour for high-cost EVs (Feng *et al.*, 2010).

Technology adoption studies, in the context of information technology, mobile phones or drivers' speeding behaviour, require a decision by an individual but not necessarily by a household. For this reason, adoption of green electricity or solar panels at home (Ozaki, 2011) is comparable to the adoption of EV by a household. These two decisions are similar because, in addition to high-purchase price, both support energy conservation and a green environment, as well as sharing the characteristic of a new technology for a household.

Technology Acceptance Model

On the technology acceptance model, Davis (1989) theorised that intention to use a system is determined by two factors: perceived usefulness and perceived ease of use (Table 2.1). Here, the 'system' is viewed as an information system, and perceived usefulness is the extent to which an individual believes that the system will help to enhance individual performance. The perceived ease of use indicates the extent to which an individual believes that using the system will not require extra effort to learn it first. A theoretical extension of the model, TAM2 (Venkatesh & Davis, 2000) added a social influence construct and also explored how the perceived ease of use can be increased by helping the user to learn the system. This model has been used in various studies, as in Lee, Kozar, & Larsen (2003), who summarised its use in the literature from 1986 to 2003.

Yang (2012) extended the TPB model by adding two new constructs to TAM, perceived usefulness and perceived enjoyment, to explore the attitudes towards mobile shopping adoption. The subjective norm, perceived behavioural control, and perceived enjoyment were found to be strong determinants of consumer adoption decisions for mobile shopping (Yang, 2012). Nasri & Charfeddine (2012) also used a combination of TAM and TPB models and their results confirmed the validity of these constructs for exploring adoption of Internet Banking in Tunisia. Aubert, Schroeder, & Grimaudo (2012) effectively used perceived usefulness and ease of use constructs (from TAM) in combination with product diffusion (as discussed in Section 2.3.4) to determine farmers' adoption of precision agriculture technologies.

In this research, constructs from both TAM and TPB are considered. However, this thesis relies more on perceptions than on intentions to purchase (as discussed in

Chapter 3) with the idea that people who believe that new technologies enable them to benefit from the latest developments are more likely to adopt an EV.

Product Involvement

Zaichkowsky (1985) defined involvement as "*a person's perceived relevance of the object based upon inherent needs, values, and interests*", and defined 20 scale items to measure involvement using four latent constructs, namely *importance/significance, relevance/essentials, hedonic, and attitude* (Table 2.1). A theoretical framework, based on the concept of "involvement", was later established by Mittal & Lee (1989). They identified three sources or causes of involvement:

- Utilitarian,
- Sign, and
- Hedonic.

The product might be important due to its *utility* or *sign* (the social influence on consumers to buy a specific product) or *hedonic* value (a measure of interest or excitement a consumer might have for the product). Later Mittal (1995) analysed product involvement defined by Zaichkowsky (1985), and replaced relevance with importance, "*a person's perceived importance of the object based upon inherent needs, values, and interests*". Bian & Moutinho (2011) referred to product involvement focusing on the consumer's enduring perceptions, while exploring consumer purchase behaviour when buying counterfeit branded products.

The scale items in these product involvement constructs (perceived importance, sign, and hedonic) are useful in determining the behavioural motivations for EV purchase, thus supporting the conceptual model (Chapter 3 discusses this in detail) for this thesis.

Word of Mouth and Innovation Diffusion

Mahajan, Muller & Bass (1990) reviewed numerous product diffusion models in the marketing literature (Fourt & Woodlock, 1960; Mansfield, 1961; Bass, 1969). The Bass model asserts that the adopters of an innovation are initially persuaded in two ways: mass media or word of mouth (WOM) (Bass, 1969). People influenced by mass media were termed "*innovators*", while the others influenced by communications from other people (WOM) were termed "*imitators*". Rogers (2003) further broadened this classification, dividing innovation adopters into five categories:

- Innovators,
- Early adopters,
- Early majority,
- Late majority, and
- Laggards.

From a marketing perspective, Martin & Lueg (2011) found that WOM influences attitudes towards product recommendations. WOM communication has an influence on the purchase decision as well as consumer expectations about a product (Bruyn & Lilien, 2008).

The diffusion of innovation theory (Rogers, 2003) is similar to WOM in that both believe communication influences the adoption or purchase decision. Furthermore diffusion theory demonstrated that the adoption decision is positively affected by the "observability" of innovation, i.e., an innovation that is more communicable (higher *perceived ease of use*) is more likely to be adopted. This theory has been applied in a number of studies, for example, adoption of agricultural technology, solar panels, and microgeneration technologies.

Aubert *et al.* (2012) used this theory in combination with a TAM model to analyse farmers' adoption of precision agricultural technology. Their findings suggest that farmers' expertise plays a key role in this adoption decision. Ozaki (2011) used the diffusion of innovation framework in combination with TPB to find the factors that affect consumers' adoption of solar panels. Perceived ease of use, along with access to information, were found to affect solar panel adoption (Ozaki, 2011). Another study, by Claudy *et al.* (2011), found that *perception of advantages* about micro-generation technologies (for example, solar panels, micro wind turbines, solar water heaters, wood pellet boilers etc.) has a positive effect on the homeowners' willingness to pay. The advantages were environmental benefits, energy cost savings, and independence from conventional sources of energy.

These diffusion theories are considered in relation to the objective of this thesis to study behaviour with respect to EV acceptance, which can be viewed within the wider context of new technology adoption. By exploring motivations to adopt and by accounting for heterogeneity of preferences, this research moves beyond many preference models that assume well-defined and stable purchasing patterns. This thesis also aims to predict the number of potential adopters of EV, and classify them on the basis of the constructs. For instance, individuals subject to social influences may tend to choose and buy an EV in the near future if their friends have bought an EV. In this regard, the literature in product diffusion helps to determine the possible ways to classify the respondents into groups or clusters based on their attitudes (results are provided in Chapter 7).

Technology Adoption Scales

Technology readiness (Parasuraman, 2000) refers to people's propensity to embrace and use new technologies to accomplish goals in home life and at work. A technology readiness index (TRI) scale was designed with four dimensions, two positive - *Optimism* and *Innovativeness* - classified as drivers, and the other two, negative - *Discomfort* and *Insecurity* - considered inhibitors (Table 2.1). The TRI scale (36 items) is used in various studies to explore individual propensity to use new technology (Meuter, Ostrom, Bitner and Roundtree, 2003; and Gelderman Ghijsen, and Diemen, 2011). Both TAM and TRI consider the positive drivers of technology but TRI incorporates constructs with a negative effect on the adoption of new systems. Son and Han (2011) point out that the TRI of a consumer indicates the impact on post adoption behaviour – how well a consumer is prepared for the new technology to help in determining her or his re-purchase intentions.

Table 2.1: Consumer Behaviour Models and their scales

Consumer Behaviour Models	Scales
Theory of planned behaviour (TPB)	Attitudes towards specific behaviour, Subjective norms, and Perceived behavioural control.
Technology acceptance model (TAM)	Perceived usefulness, and Perceived ease of use
Product involvement	Utilitarian, Sign, and Hedonic
Word of mouth WOM, and product diffusion	Mass media or word of mouth Classified technology adopters
Technology adoption scales	TRI: two positive – Optimism and Innovativeness, and two negative – Discomfort and Insecurity
	TAP: two contributing – Optimism and Proficiency, and two inhibiting – Dependence and Vulnerability

Ratchford and Barnhart (2012) developed a technology adoption propensity (TAP) index containing 14 scale items. TAP is similar to TRI, in that it contains two contributing factors – Optimism and Proficiency, and two inhibiting factors – Dependence and Vulnerability. They reported on the assessment of consumer propensity to adopt new technologies, indicating that the purchase decision is based on benefits and the time and effort required in learning and absorbing the new technology. Thus, the precise forecasting of technology products requires measurement of positive and negative attitudes towards the technology. Gatignon and Robertson (1985) suggested that diffusion of technological innovations depends on the consumer's ability to learn and experience the latest knowledge about innovations. TAP and TRI provide useful scales for technology adoption, and they investigate consumer behaviour and directly determine the purchase behaviour. Thus scale items from TAP and TRI are adapted in designing attitudinal questions for survey instruments in this thesis (Chapter 3 discusses this in detail). These scales further provide a useful measure of propensity to adopt EVs by assessing excitement for new technologies, and positive and negative attitudes towards new technologies.

In summary, consumer adoption models indicate that the adoption of new technologies depends on human attitudes and perceptions. TPB and TAM identify the predictors or factors that help to determine the intentions of an individual. Product involvement, word of mouth, and product diffusion are also based on similar constructs but defined on slightly different scales that have been used to assess consumer purchase behaviour in the marketing literature as given in Table 2.1. Studies using technology adoption scales (TRI/TAP) rely on positive and negative experiences, and excitement of consumers to adopt new technologies.

In the context of driver assistance systems Adell, Varhelyi, and Nilsson (2014, Chapter 3) tested a unified theory of acceptance and use of technology (UTAUT) model for understanding driver assistance systems. They used *performance expectancy, effort expectancy,* and *social influence* to predict behavioural intentions.

The authors found *performance expectancy*, and *social influence* important for defining behavioural intentions while *effort expectancy* was not significant.

There have been several methodological advances in exploring people's behaviour towards EV adoption in the past ten years. This thesis explores behaviour using advanced discrete choice modelling techniques with the contribution of looking at the perspective of adopting EVs as a new technology.

In the next section, previous studies exploring the adoption of EVs are presented. Studies in the past applied consumer adoption models, such as TPB or product diffusion, to explore attitudes and perceptions towards hybrid EVs and plug-in EVs, but these relied on basic statistical analysis such as chi-square tests or exploratory factor analysis. These studies are considered in Section 2.4.1. A number of studies applied advanced discrete choice modelling but did not incorporate consumer adoption models (Section 2.4.2). Only a few studies added attitudinal data into advanced discrete choice models (Section 2.4.2) to explore EV/hybrid vehicle technologies but again, with a few exceptions (Bolduc *et al.*, 2008; Hidrue, 2010), have not explored the important construct of "*new technology*" adoption for EV adoption.

2.4 PREVIOUS STUDIES ON THE UPTAKE OF ELECTRIC VEHICLES

Studies to explore the potential demand for EVs started with a marketing perspective. In the late 1990's studies in California started to assess EV acceptance (Kurani *et al.,* 1996; Golob and Gloud, 1998). Later these studies stretched across the globe including Canada, Switzerland, Germany, Japan, Denmark, Korea and Norway, exploring consumer preferences using choice models. Recent studies have investigated consumer preferences for EVs using advances in discrete choice modelling.

Marketing Studies

Kurani *et al*. (1996) were among the first researchers to incorporate attitudinal data in their design. Attributes of EVs that differ from petrol cars are home charging, driving range, and emissions (as given in Table 2.2) but the purchase prices of the two types of vehicle necessarily overlap. The driving range levels were established by creating three classes of EV, each with a specific range: "*neighbourhood EVs*" with a range of 40 miles, "*community EVs*" with a range of 60 or 80 miles, and "*regional EVs*" with a range of 120 or 140 miles. The findings of Kurani *et al.* (1996) indicated that environmental concerns may not have had much influence on the market initially, though they are a motivating feature for choosing an EV. Home charging seemed to be a successful feature of EV and half of the respondents in multi-vehicle households said that they would buy an EV as their next new vehicle. In addition, EV purchasers may not see "*driving range*" as a barrier since 37% of households chose vehicles with range less than 130 miles, and 65% with range less than 180 miles. Similar to Kurani *et al.* (1996), Lieven, Muhlmeier, Henkel & Waller (2011) found price ranked as a top priority for both conventional and EV cars, with range coming second. They applied correspondence analysis with a large sample size (1,152 individuals) and found that 4.2% of "*first vehicle for all uses*" buyers chose EVs. These buyers rated price and range as a lower priority than non-EV potential buyers.

In contrast to the findings discussed above, Golob & Gould (1998) suggested that in competition with petrol, an EV is likely to be used only if average vehicle mileage of the household vehicle is less than 28 miles/day. Considering their study was conducted more than fifteen years ago, the concern was relevant, because, at that time, the driving range was 100 miles under the optimal conditions for EVs. Moreover, the small sample size (69 individuals) of their study limited their ability to understand the individual factors that *"facilitate or inhibit consumer demand"*. Heffner, Kurani & Turrentine (2007) took semiotics, the study of symbols, as a basis for a study to explore consumers' preferences. Less than half of the buyers indicated that the reason they bought a vehicle was: "*it makes a statement about who they are"*. The interview results showed that the current hybrid EV owners purchased the vehicle due to factors like "*preserving environment, opposing war, saving money, reducing support for oil producers, and owning the latest technology*" (411-412).

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Table 2.2: Marketing Studies on Alternative Fuels

Source (article/ report)	Location	Data and Methodology	Fuels Compared	Attributes of Vehicle Considered/ Constructs
Kurani *et al.* (1996)	California	- 454 households - reflexive survey, interactive stated response, ISR methods in purchase intention, and range estimation games (PIREG) to develop the hybrid (conventional and EV) household hypothesis - household lifestyle and activities - attitudinal data Descriptive and multivariate stats applied (log-linear models)	Petrol, CNG, hybrid EV, two types of freeway capable electric, and one neighbourhood battery EV	Driving range, speed, emissions, and price
Golob & Gould (1998)	California	- 69 individuals - RP, SP data and observation - 3 sources: travel diary records, pre-trial, and post-trial surveys (2-week trial) Descriptive statistics, t-tests, and regression analysis	Petrol and EV	Prototype EV (approximately 161 km) under optimal conditions
Heffner *et al*. (2007)	California	- 25 households, who purchased hybrid vehicles in California from the year 2001 to early 2005 Semi-structured ethnographic interviews	Different brands of hybrid electric vehicles (HEV)	Benefits of HEV, purchase cost, fuel saving embracing new technology, better for environment
Ahn *et al.* (2008)	South Korea	- 280 households - SP data Conjoint analysis, Multiple Discrete Continuous Extreme Value (MDCEV) model is used Bayesian procedure used for estimation	Petrol, diesel, CNG, LPG, hybrid	Fuel type, vehicle body type, maintenance cost, engine displacement, fuel efficiency, fuel price
Lieven *et al.* (2011)	Germany	- 1,152 individuals - SP data Correspondence analysis applied to rankings of 8 types of cars (e.g., city, small, van, sports, luxury, etc.) for 6 types of uses (e.g., first vehicle for all uses, second, leisure, etc.)	Conventional and EV	Purchase price, maximum cruising range, environmental impact, performance, durability, and convenience
Ozaki, & Sevastyanova (2011)	London	- 1,263 individuals - Likert scale question - Innovation diffusion theory by Rogers (2003) Exploratory Factor Analysis (financial incentives, social norms, knowledge of technology)	Hybrid (Toyota Prius)	Respondents were buyers of Toyota Prius.
Egbue & Long (2012)	USA	- 481 responses - Likert scale & ranking question - Theory of planned behaviour Descriptive statistics and chi-square test	Hybrid EV, Plug-in hybrid EV, Battery EV	Battery range, cost, charging infrastructure, reliability, safety, style, and comfort
Hutchins & Delmonte (2012)	UK	- Respondents were fleet managers - 20 structured telephonic interviews Qualitative content analysis, categorised fleets according to decision making structure	Conventional, Plug-in hybrid EV, Battery EV	CO2 emissions, efficient fuel consumption, reputable brand, comfort, safety, whole life cost, availability of vehicles

Source (article/ report)	Location	Data and Methodology	Fuels Compared	Attributes of Vehicle Considered/ Constructs
Schuitema *et al*. (2013)	UK	- 2,728 participants - Likert scale question - Theory of planned behaviour Regression models analysed with/without mediating effect	Conventional hybrid EV, Plug-in hybrid EV, Plug-in EV	Only Constructs: Instrumental, hedonic, symbolic, pro-environmental identity, car-authority identity
Peters & Dütschke (2014)	Germany	- 969 respondents - Likert scale questions - Diffusion of Innovation Principal Component Analysis; MANOVA and Regression models analysed to predict intentions to purchase and use an EV	Electric Vehicles	Only Constructs: Relative advantage, compatibility, ease of use, Trialability, Observability, Social Norms
Noopers *et al.* (2014)	The Netherlands	- 109 respondents for study 1 (electric car) - Direct and Indirect questionnaire Correlations and regression analysis to predict interest and intention to buying an EV	Electric car	Only Constructs: Environmental, Instrumental, and Symbolic
Bailey *et al.* (2015)	Canada	- 1,739 respondents - focused on public charging infrastructure Bivariate analysis Regression analysis interest in EV is determined from the EV readiness, and socio-demographics	Pure EV, plug-in hybrid, hybrid, petrol	EV interest and awareness of EV charging infrastructure; EV readiness, and socio-demographics

Ahn, Jeong, & Kim (2008) identified petrol as the consumer's first preference and CNG the next most preferred among alternatives (*gasoline*, *diesel*, *CNG*, *LPG*, *hybrid*). They applied conjoint analysis – which is not a discrete choice experiment (Louviere, Flynn & Carson, 2010) – and a multiple discrete continuous extreme value model (MDCEV) using Bayesian procedures, to explore use of various fuel and vehicle technologies. To take account of multiple cars in a household, Ahn *et al*. (2008) allowed respondents to choose as many hypothetical vehicles as they like, and respondents also mentioned how they would use this vehicle. While forecasting the alternative fuels, their study noted that hybrid EVs also require liquid fuel consumption, thus their market is influenced by fuel price; yet, hybrid and compressed natural gas vehicles have a green impact with low emissions, which may make them more attractive to consumers than petrol or diesel fuelled vehicles.

Another aspect of the EV market is decision-making by fleet managers. Hutchins & Delmonte (2012) analysed a large number of organisations and their sample mapped on the Nesbitt & Sperling's (2001) categorisation. That means decision-making by fleet managers fits with the formalisation and centralisation found in autocratic and bureaucratic hierarchies. Their findings indicate that fleet managers lacked a clear understanding of EV attributes, a possible reason for resistance to being early adopters. Fleet managers' perceptions about EV advantages included environmental, financial (in terms of low-running cost), and business factors as they differentiate an organisation from its competitors, while main barriers for EVs were range and availability of infrastructure. An interesting benefit identified by fleet managers in the context of improving their business was that EVs offer quiet and responsive driving with automatic transmission, thus reducing demands from drivers (Hutchins & Delmonte, 2012).

Some researchers applied consumer adoption models for EV/hybrid vehicle adoption (Ozaki & Sevastyanova, 2011; Schuitema, Anable, Skippon & Kinnear, 2013; Egbue & Long, 2012). Although these studies did not use discrete choice methodology to model the EV market, they offered useful scale items to investigate intangible constructs and used fairly large sample sizes (see Table 2.2). Ozaki & Sevastyanova (2011) analysed a sample of hybrid vehicle drivers and found financial incentive to be a strong construct, followed next by social influence and knowledge about an innovation. These results were supported by Rogers' (2003) model and might have been different with a non-restricted sample including people who did not intend to purchase a hybrid vehicle as well as those who do. In terms of explanatory power, many of the studies are inconclusive. For example, the amount of variance explained by the regression models in Schuitema *et al.* (2013) was low, with 27% being the highest measure of fit when testing relationships between perceived instrumental attributes and intention to adopt battery EV.

Sample selection bias was also a problem. Egbue & Long (2012) explored a number of EV attributes, with a sample from "*technological minded group towards EV*"; although biased, their findings suggest that individual perceptions about EV performance and cost affect the decision to be an early adopter. Peters and Dütschke (2014) compared the attitudes of several groups of people who were either actual EV users, intended EV buyers, individuals with general interest in EVs, and EV non-users. They found that compatibility with own needs had a significant relationship with intention to purchase an EV by all groups, while for less interested people social norms and a higher share of EVs on the streets could have a positive effect on intention to purchase an EV. A study (Noppers, Keizer, Bolderdijk, & Steg, 2014) in The Netherlands investigated adoption of EVs and sustainable technologies in two experiments. Environmental attributes were found to be important indicators for EV adoption, but the study sample was small (109 respondents).

In Canada, Bailey, Miele, & Axsen (2015) analysed EV interest from different perspectives. First, a bivariate analysis showed that EV interest is associated with awareness about charging infrastructure. Second, using multivariate regression analysis, they found that socio-demographics and EV readiness (access to EV charging), predicted the interest in EV. Although Bailey *et al.* (2015) investigated the *interest in EV* from an EV charging awareness perspective, they did not consider fast/slow charging stations or the time it take to recharge at different places.

In general, studies reviewed in this section identified the main EV market influences as price and range of the vehicle. Studies discussed above dealt mainly with the EV, hybrid, or alternative fuel vehicle's market analysis, instead of individual preferences for these vehicles. The attitudinal data used by Kurani *et al.* (1996) appears useful by not only identifying home-charging as a good feature of EV, but also by reaching the conclusion that EVs could be useful as a second car in a multi-car household.

In the next section, studies that explore consumer preferences or behaviour using discrete choice models are discussed.

Studies Using Choice Models

There have been several methodological advances in the methods assessing consumer preferences for alternative fuels, hybrid or EVs. One of them is Discrete Choice Modelling (DCM), widely used in exploring consumer preferences in economics, marketing, and transport (Ben-Akiva & Lerman, 1985). Choice modelling methods are presented in detail in Chapter 3 (Section 3.2) as this thesis mainly applies DCM techniques to explore preferences for EV adoption. Before applying DCM, previous studies are reviewed to reveal the extent to which choice modelling has been applied to explore consumer preferences for alternative fuels.

A number of DCM can be applied: Multinomial Logit Model (MNL) is the basic and most commonly used choice model; Nested Logit (NL) is an improved form of MNL as it resolves some assumption errors, while Mixed Logit (ML), and Latent Class (LCM) models are examples of more sophisticated choice models that provide more accurate estimation. These choice models vary in complexity and are further elaborated in Chapter 3.

Most of the studies use DCM with stated preference (SP) data to forecast the alternative fuel, hybrid, or EV consumer demands. This is primarily due to the fact that EV is an emerging technology in the market. Studies using closed form choice models with SP and revealed preference (RP) data are discussed first, followed by a discussion of studies using advanced choice (latent class, mixed logit and mixed probit) models.

Closed form choice Models

Studies using choice models that include Multinomial Logit Models (MNL), and Nested Logit Models (NL) are shown in Table 2.3. Ewing & Sarigollu (2000) used MNL to model consumer choices, and following Kurani *et al.* (1996), they added attitudinal data into the model. Their findings revealed that consumers showed a preference for clean-fuel vehicles, but with an assumption that vehicle performance is delivered at the same price. Respondents were tolerant of performance, losses in acceleration, range, and refuelling time being accepted. Government intervention (in the form of subsidies/levies) was suggested to improve consumers' preference for clean-fuel vehicles. Ewing & Sarigollu (2000) also used cluster analysis to model heterogeneous attitudes, but preference heterogeneity could be captured better by simultaneously estimating DCM and latent constructs, as done by Bolduc *et al.* (2008).

Dagsvik *et al*. (2002) also identified range as a major hurdle for EVs, with the next attribute of key importance being purchase price. An important finding of their study is that alternative fuel vehicles (AFV) can compete with petrol cars *if maintenance and refuelling infrastructure for alternative fuel vehicles are well established*. Another interesting finding of the study is that females showed more interest in AFVs than males. Mau, Eyzaguirre, Jaccard, Collins-Dodd & Tiedemann (2008) conducted a study of consumer preferences for new vehicle technologies using MNL and found that consumer preferences for hybrid petrol electric vehicles (HEVs) were dynamic and dependent on their availability on the market. Their study explored market shares for hybrid vehicles. Moura, Lopes, Costa, & Silva (2012) studied EV adoption by using decision trees; they created respondent profiles indicating which group can potentially buy EVs depending on their income, parking bays, number of cars owned, and kilometres of travel. They found only 2% to 7% would qualify to buy an EV, and as 63% of households did not have a parking bay at home, this indicated a requirement for public charging infrastructure. Out of 465 respondents, 122 specified their ranges above 250km, with rather inconsistent decisions on EV purchase. Thus analysis of only 343 respondents was conducted using MNL and NL, with results indicating no significant market share for EV in then current (2012) technical and economic circumstances.

In the study by Ito, Takeuchi, & Managi (2013), a stated preference methodology was used to explore the infrastructure requirements for alternative fuel vehicles in Japan. With a web-based survey, Ito *et al.* (2013) found that the infrastructure for battery exchange could be efficient only when EVs established 5.63% of market share. One of their counter-intuitive findings is that WTP for range decreases as the infrastructure improves; the parameter estimate for range of the EVs charged at home was also negative in their study.

Studies discussed so far deliver interesting findings, but do not investigate preference heterogeneity in their model specifications. Consequently, advanced choice models are required to improve models' predictive accuracy. The next section continues this discussion with advanced discrete choice models.

Table 2.3: Studies Using Closed Form Choice Models

Source (article/ report)	**Location**	**Data and Methodology**	**Fuels Compared**	**Attributes of Vehicle Considered**
Ewing & Sarigollu (2000)	Canada - Montreal	- 881 individuals - SP experimental design - 4 focus group sessions conducted with drivers to find the relevant vehicle attributes for choice experiments Multinomial logit (MNL) used to model consumer choice, cluster analysis used to model the heterogeneous attitudes	Petrol, alternative fuel vehicles (AFV), and EV	Purchase price, repair and maintenance cost per year, cruising range, refuelling time, acceleration, pollutant emissions, commuting time and cost
Dagsvik *et al.* (2002)	Norway	- 922 individuals - SP survey Various probabilistic choice models applied (Luce model for ranking, random utility models with taste persistence)	Electric powered, hybrid, LPG, and petrol	Purchase price, top speed, driving range, fuel consumption or energy consumption
Mau *et al.* (2008)	Canada	For HEV - 916 completed surveys - SP experiment MNL model is used Maximum likelihood estimators for each parameter in MNL estimation, parallel studies for HEV and HFCV	Conventional hybrid gas-electric vehicle (HEV) OR hydrogen-fuel cell vehicle (HFCV)	For HEV vehicle purchase price, fuel cost, government subsidy, warranty coverage; range
Moura *et al.* (2012)	Portugal Lisbon (Metro Area)	- 465 valid responses - SP data Screening of potential EV adopters using decision trees MNL, and NL model estimations, then profiles compared	Petrol, diesel, LPG, hybrid and pure electric	Energy used, price, operational costs, number of makes and models in the market, maximum speed, range and refuelling/charging time
Ito *et al.* (2013)	Japan	-1,531 respondents - 8 choice sets for each respondent NL (Nested Multinomial Logit) WTP calculated using Kinsky and Robb's procedure Scenario forecasts of market shares of Toyota's subcompact/compact cars	Petrol vehicle, Hybrid Electric Vehicle (HEV), Electric Vehicle (EV), Fuel Cell Vehicle (FCV)	Fuel type, body type, manufacture, range (km), refuelling rate, carbon dioxide, fuel availability, purchase price, annual fuel cost

Studies Using Advanced Choice Models

Most of the EV acceptance studies are based on SP experimental design. In the next chapter, the RP and SP experiments will be discussed in detail, using joint RP/SP data for the prediction of alternative fuels. A few studies (Brownstone *et al*., 2000; Axsen *et al.*, 2009) discussed in this section have used the RP-SP combination in their experimental design. This section presents a review of studies using advanced choice models such as Mixed Logit, Stated and Revealed choice Nested Logit, Mixed Probit, and Latent class Models.

Although conducted 16 years ago, Brownstone *et al.* (2000) used advanced methods to forecast uptake of alternative fuels. In addition to using joint RP/SP data, they compared the parameter estimates using MNL and an advanced DCM: mixed logit (ML) model. A number of additional vehicle attributes were considered in addition to purchase price, range, and size (Table 2.4) and their findings indicated that SP models gave high forecasts of non-petrol car shares: 20% with MNL specifications and 42% with ML specification. SP models also showed a higher forecast percentage for sports cars as compared to the results from joint models. Design of RP data was found a difficult task because an attempt to cover a real market with a large "*universal choice set*" containing numerous makes, models, and vintages might not be sufficient. The joint RP/SP models for non-petrol vehicles gave a 6% share with a MNL specification and 18% with a ML specification. ML models provided better goodness-of-fit measures as compared to MNL, and accounted for the heterogeneity in respondents' preferences for alternative fuels. Thus, ML models were suggested as a feasible class of model for joint RP/SP choice data. Axsen *et al.* (2009) used joint SP/RP data in models similar to those of Brownstone *et al.* (2000), but they used only MNL models for estimation. The attributes in the SP experiments were similar to the attributes in Bolduc *et al.* (2008) except that Axsen *et al.* (2009) added subsidy on purchase price and performance. The estimation of joint models proved superior for modelling vehicle choice, with the best performance from the SP-dominant data. The RP only and the equally weighted RP/SP joint models predicted highly optimistic penetration scenarios, while SP/RP with greater SP influence were more realistic and consistent with previous empirical research.

Another study in California (Hess *et al.*, 2006) used Modified Latin Hypercube Sampling (MLHS) in the ML model estimation. Their study indicated that information campaigns for awareness about EVs were necessary, as preference for ICV and hybrid vehicles were dominant. EVs appeared competitive at unrealistically high ranges (>353 miles) making driving range the main barrier to EV acceptance. In contrast, Potoglou & Kanaroglou (2007) did not consider range as an attribute in their study; instead for every respondent they customised purchase price, annual fuel cost (product of kilometres travelled per year and fuel cost per kilometre), and maintenance cost (type and size of vehicle). A nested logit (NL) model was estimated with SP data, with variations in preferences being captured by differences in the characteristics of individuals. A number of hypotheses were tested through interaction terms between vehicle attributes and three classes of characteristics that include: individual, household, and dwelling location characteristics. Their findings revealed that, all else being equal, the potential vehicle buyers preferred low-cost vehicles; specifically individuals on medium-level incomes considered purchase price more important than did the individuals with a high-income. Female respondents were more inclined towards slower cars and individuals living alone preferred faster vehicles; young people were more eager to buy hybrid vehicles. This study also computed the willingness to pay (WTP) measures: respondents were estimated to be willing to pay between $2,000 and $5,000 USD more for a vehicle that would emit only 10% of their current car's emissions. The parameters of the NL model indicated that reduced purchase costs, purchase tax relief, and low emission rates support the adoption of clean-fuel vehicles. Individuals in households of mainly long-distance commuters would be more hesitant to adopt an AFV due to limited fuel availability.

Bolduc *et al.* (2008) followed Kurani *et al.* (1996) and Ewing & Sarigollu (2000) in using attitudinal data and estimated hybrid choice models which incorporated perceptions and attitudes, referring to environmental concerns and appreciation of new car features. In the SP experiment, like Potoglou & Kanaroglou (2007), they did not consider range as an attribute; capital cost, operating cost, fuel available, and emissions data were the main attributes. The structural and measurement equations for latent variables were estimated together with the DCM. Identification of latent constructs is a contribution of the study; a similar conceptual model is used in this study, as discussed in Chapter 3. The hybrid choice model by Bolduc *et al.* (2008) demonstrated that attitudinal variables have substantial explanatory power in the purchasing decision results. However, the behaviour towards charging of EVs was not discussed.

Ziegler (2012) explored consumer preferences through SP experiments, with taste persistence included in the choice set, but without attitudinal data. An advanced DCM: multinomial probit model (MPM), with inclusion of taste persistence across choice sets, a particularly environmentally friendly aspect, was estimated. Ziegler (2012) brought interesting insights from the sample of the German population; however he did not explore the concept “excitement for new technologies”. Ziegler (2012) found that younger potential car buyers show a higher preference for natural gas vehicles as compared to petrol for their journey-to-work, they usually purchase environmentally friendly products and own a second vehicle (which runs on biofuel). Market shares were predicted for different energy sources: petrol and diesel approximately 20%; hybrid and gas 12%; biofuel 11%; hydrogen 15%; and electric (EV) 8.7%. Younger males preferred environmentally friendly products; consequently they showed a preference for hydrogen vehicles or EVs compared with petrol cars.

Hidrue, Parsons, Kempton, & Gardner (2011) also conducted SP experiments to explore EV acceptance but by using the latent class model (LCM). The main attributes included charging time, fuel cost saving, pollution reduction, and performance. As in the experiments by Brownstone *et al.* (2000) and Hess *et al.* (2006), driving range was included as an attribute by Hidrue (2010). As part of his dissertation, Hidrue (2010) captured preference heterogeneity using latent constructs and also analysed preferences for charging duration and cost. Later, Hidrue *et al.* (2011) found that savings in fuel cost tended to lead to the purchase of EVs. Range anxiety, charging time, and high-purchase price remained consumers' main concerns, and a reduction in the cost of the EV battery appreciably increases EV acceptance.

To summarise, although the studies listed in Table 2.4 provide numerous insights into the decision mechanisms for purchasing EV, they do not assess constructs such as the excitement for new technologies or the influence of social norms, which may affect EV purchase decisions.

Table 2.4: Studies Using Advanced Discrete Choice Models

Source (article/ report)	Location	Data and Methodology	Fuels Compared	Attributes of Vehicle Considered
Brownstone *et al.* (2000)	California	- 7,387 households - Stated and revealed preference data Joint SP/RP used to compare MNL models and mixed logit (ML) models for analysis of demand for alternative fuels	EV, CNG, and methanol/ petrol	Fuel type, vehicle range, purchase price, refuelling time and cost at home and at service station, service station availability, acceleration time, top speed, tailpipe emissions, size, body type, space
Axsen *et al.* (2009)	Canada and USA	- 535 Canadians and 408 Americans - SP and RP data (online data collection) MNL modelling of the SP data, Joint SP/RP choice models estimation	Petrol, hybrid EV	Purchase price, fuel cost (per week), pollution, subsidy on purchase price, performance
Hess *et al.* (2006)	California	- 500 individuals - SP data Modified Latin Hypercube Sampling (MLHS) method used in mixed logit (ML) model estimation An alternative to quasi-random Halton sequences proposed to generate "true" parameters for simulation	Internal combustion engine vehicle (ICV), EV, hybrid vehicle (HV)	Car type, body type, purchase price, operating cost, performance, range
Potoglou & Kanaroglou (2007)	Canada	- 902 individuals with 482 completed the choice experiment, 8 choice sets - SP data Nested logit model used for parameter estimation Willingness to pay (WTP) measures computed on the basis of parameter estimates	Conventional petrol, hybrid, and alternative fuel vehicles	Fuel type, purchase price, annual fuel costs and maintenance costs, fuel availability, acceleration(s), incentives, and pollution level
Ziegler (2012)	Switzerland - German population	- 598 individuals, 6 choice sets, 3,588 observations - SP experiment Econometric analysis performed by applying the multinomial probit models (MP) Simulated maximum likelihood method - used for parametric estimation hypothesis testing	Petrol, diesel, hybrid, gas (i.e. CNG or LPG), biofuel, hydrogen, EV	Purchase price, engine power, fuel costs (per 100 km), CO_2 emissions (g/km), service station availability (% of stations with respective fuel)
Hidrue *et al.* (2011)	Delaware	- 3,029 individuals - SP data Estimated latent class random utility model and used the results to estimate WTP for EV attributes	Consumer preferred petrol, and 2 electric versions of the same preferred car	Driving range, charging time, fuel cost saving, pollution reduction, and performance Attitudinal data *Buying new products, Being Green (Major, Minor, Not)*
Bolduc *et al.* (2008)	Canada	- 866 individuals - SP experiments and attitudinal data Hybrid choice models including perceptions and attitudes used. Structural and measurement equations for latent variables simulated. Simultaneous estimation of DCM and latent constructs	Petrol, alternative fuel, hydrogen fuel cell vehicle, hybrid EV	Capital cost, operating cost, fuel available, express lane access, emissions data, power Attitudinal data *Environmental Concern, Appreciation of new car features*
Kuwano *et al.* (2012)	Japan	- 384 respondents; 1,920 observations - Stated preference data Two stage study: first, formation of vehicle choice set; then SP choice sets analysed using LCM	{ Petrol, hybrid} and { Petrol, hybrid, electric vehicle}	Purchase price, range, charging time, fuel operation cost *Share of EV sales*

Source (article/ report)	**Location**	**Data and Methodology**	**Fuels Compared**	**Attributes of Vehicle Considered**
Hackbarth & Madlener (2013)	Germany	-711 respondents - 10,665 observations -1000 Halton draws Mixed (error component) Logit (ML) Three nests in specification of error components (CVs,HEV, NGVs), (PHEV,BEV), (BVs, FCEVs) WTP measures calculated by ratio from ML and market shares for vehicle technologies predicted	Biofuel vehicles (BVs), natural gas vehicles (NGVs), hydrogen fuel cell electric vehicles (FCEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs)	Purchase price, fuel cost per 100km, CO_2 emissions, driving range, fuel availability, refuelling time/battery recharging time, policy incentives
Jensen *et al.* (2013)	Denmark	- 369 respondents (before and after being EV drivers) - 5,904 observations with 2 wave survey Joint hybrid choice model (mixed logit) A latent variable jointly estimated with two-wave panel stated choice dataset (before and after EV drive). Market share elasticities for EV and ICV WTP for driving range, carbon emissions, top speed, battery life, and charging possibilities	ICV{petrol/diesel}, and an EV	Purchase price, fuel costs, top speed, carbon emissions, driving range Charging possibilities (locations), and battery lifetime for the EV In addition to vehicle attributes: *-environmental attitudes*
Kim *et al.* (2014)	The Netherlands	- 726 respondents - binary choice problems - orthogonal fractional factorial design of the $8^2 \times 4^9$ full factorial design was created in 128 runs Hybrid choice models estimated by maximum simulated likelihood Estimated part worth utilities	EV, Petrol, and Diesel	Attributes: Price, range, maximum speed of car, *social attributes: share of EV among friends and acquaintances, share of EV among colleagues, reviews.* Latent attributes: *Environmental, economic, battery, technological aspects, innovation*

Kuwano *et al.* (2012) used a two-stage model in a vehicle choice study. In the first stage a respondent was given a brief overview of EV features along with social conformity in terms of EV market share, and then the subject was asked whether they would consider EV as one of their feasible options. If the respondent decided to keep EV in the choice sets, a set of scenarios containing petrol, hybrid-electric, and EV was displayed to the respondent. Otherwise, respondents were given scenarios with only petrol and hybrid-electric vehicles. Kuwano *et al.* (2012) captured preference heterogeneity, but social conformity was not necessarily indicated by EV market share. They obtained three latent classes: *EV share rise, EV purchase price reduction, and EV performance improvement* (Kuwano *et al.,* 2012: p. 7). With assumed market shares of 10%, 25%, and 50%, the respondents were presented with choice situations far from market conditions, but acceptable in hypothetical scenarios. Kuwano *et al.* (2012) forecast high EV diffusion rate, as 10% of respondents prefer to own an EV, while 20.2% considered EVs as an alternative in the choice experiments. Their study did not explore attitudes towards the EV's low emissions or appreciation for new technologies.

Hackbarth & Madlener (2013) looked at consumer preferences for alternative fuel vehicles using mixed logit model with error components; defined as three mutually exclusive nests consisting of seven vehicles, a total of 15 choice sets being presented to each respondent. This large number may have led to respondent fatigue. For EVs, Hackbarth and Madlener (2013) computed the WTP measure for 1 km increase in driving range as € 16-33; and suggested an increase in EV market share if their range increases to 750km.

A study by Jensen, Cherchi, & Mabit (2013) compared the preferences and attitudes before and after experiencing an EV. To avoid complicated choice models they chose only one latent variable (environmental concern) among environmental concern, technology interest and perception of the car as a status symbol. With eight choice tasks a complete dataset from 369 individuals in two waves resulted in 5,904 stated choice observations. Their most salient finding is the change in individual preferences after experiencing EV. Understanding driving range, top speed, fuel cost, battery life and charging locations, has led to different WTP values, despite no scale differences in the two datasets. WTP for driving range almost doubled (€34-104 to €91-193) after respondents tried the EV, however this effect was less obvious in multicar households (€16-82 to €48-130). The environmental concern latent variable had a positive value for the coefficient, indicating that individuals who are concerned about environment have high preference for EVs (Jensen *et al.*, 2013). This coefficient was significant in both samples, but not different from each other. As indicated, the attitudes about technology interest and perception of the car were not tested as latent variables.

Jensen *et al.* (2013) used the Best-Worst choice experiments to investigate EV adoption. Although their framework offered an increased number of observations per respondent and also enabled investigation of individual decisions on their least preferred vehicle, their investigation did not incorporate latent constructs.

Instead of using the latent class or mixed logit models, Kim, Rasouli, & Timmermans (2014), used the maximum simulated likelihood to estimate hybrid choice model. They incorporated attitudinal data and their findings revealed that environmental and innovation aspects of EVs have positive impact on intention to purchase EVs, while battery, economic and technological aspects of EVs have a negative impact on intention to purchase an EV.

To conclude, studies of EV acceptance have been increasing since their start more than 15 years ago, with the most recent research in this area being in The Netherlands (Kim *et al.*, 2014), Denmark (Jensen *et al.*, 2013), Japan (Kuwano *et al.*, 2012), USA (Hidrue, 2010), Germany (Lieven *et al.*, 2011; Hackbarth & Madlener, 2013), and Switzerland (Ziegler, 2012). The EV technology embodies significant advances and this thesis has set as its task the assessment of the role of these advances in improving acceptability of EV.

2.5 DISCUSSION

The advantages of EVs, as discussed above, include energy conservation, zero tailpipe emissions, less noise while driving, and home recharging. Most of the previous studies about the uptake of EVs considered the following characteristics: range, purchase price, refuelling time, environmental impact, and performance. However other relevant attributes are top speed (Dagsvik *et al.*, 2002), CO_2 emissions (Bolduc *et al.*, 2008; Ziegler, 2012), home charging (Kurani *et al.*, 1996), acceleration, government subsidy, and warranty coverage (Mau *et al.*, 2008). The limited driving range and the high purchase price were identified as the main hurdles in the acceptability of an EV as a future car. The findings from the research studies in Section 2.4 can be summarised as:

- range is a hurdle for EV uptake;
- purchase price is the next barrier for EV uptake;
- presence of recharging infrastructure is an enabler for EV uptake;
- low emission rates support the adoption of clean fuel vehicles;
- a major incentive to purchase EV is the saving in fuel costs;
- reduction in the cost of the EV battery would help EV acceptance; and
- there are individual characteristics and attitudes that may contribute or otherwise to EV uptake (e.g., gender and environmental concerns). Dagsvik *et al.* (2002) found that females showed more interest in AFVs

than males: "*the possible explanation might be that men are affected more than women by the development of infrastructure for servicing and refuelling for EV in the near future*" (p. 383). Women may also have better trip planning than men; in addition 75% of young females and 60% of young males preferred EVs over petrol cars.

People who prefer to buy environmentally friendly products show a preference for hydrogen powered or electric vehicles.

Studies based on market analysis, exploring consumer preferences, and a number of methodological advancements were discussed in detail. Various DCM forecasted an underlying interest in EVs or alternative fuels, via different types of models. Axsen *et al.* (2009) used MNL, Brownstone *et al*. (2000) used MNL and mixed logit (ML), whereas Ziegler (2012) applied multinomial probit model (MP), and Potoglou & Kanaroglou (2007) applied nested logit (NL). Whereas Ewing & Sarigollu (2000) used cluster analysis to model the heterogeneous attitudes in MNL and Bolduc *et al*. (2008) used latent constructs in hybrid choice model, Hidrue (2010) applied the latent class models to capture the preference heterogeneity of individual behaviours. Although the latent constructs such as environmental concern (Bolduc *et al*., 2008; Hidrue, 2010; Jensen *et al.*, 2013) and appreciation of new car features (Bolduc *et al*., 2008) have already been explored, this thesis contributes by analysing the adoption of EV as a "*new technology*", from a psychological and marketing perspective. A number of constructs or measurement scales from TPB and TAM are assessed along with consumer involvement factors, as discussed in Section 2.3. This research also classifies the respondents or prospective consumers into rationale buyers or trendy/fashionable buyers, similar to the classification by Rogers (2003) in the consumer product diffusion model. The two classes are expected to choose EVs for different reasons: whereas rationale buyers may be interested in saving purchase and fuel costs and minimising the impact on the environment (i.e., their decisions are determined by perceived benefits and technology learning constructs), trendy buyers (who like being seen as avant-garde) are driven to new experiences that are entertaining or modern. Their decisions might be then derived by the social influence or the hedonic constructs. Since trendy users are usually more likely/willing to adopt new technology that has environmentally safe and less noise features, EV may first attract the fashionable buyers.

In summary, the main contribution of this research is that it investigates perceived usefulness, subjective norms, and perceived behavioural control to determine the attitudes towards EV adoption along with the preference heterogeneity via discrete choice models.

The Question of validity

A question was posed at the beginning of this chapter was how reliably can analytical and modelling studies predict the uptake of EVs?

Buying an EV is a high-cost venture for a family. The attraction of low-operating costs may not offset the range limitation barrier, even though a rational assessment of scenarios may indicate likely adoption. The lack of charging infrastructure is another limitation that might hinder the decision to purchase EV. Current reduction in prices for EV ($31,900 by Mitsubishi) in the Australian market could remove the high-cost barrier from the customers' minds. When compared with hybrid electric vehicle technology, plug-in EVs present a solution with less maintenance cost (Ahn *et al.*, 2008; Bühler *et al.*, 2014; Lieven *et al.*, 2011). Discrete choice experiments are applied in various fields to model preferences for products or services. According to Louviere (2006), "*real market stores*" can be simulated using discrete choice experiments, thus these experiments allow prediction of market shares. As discussed earlier, Brownstone *et al.* (2000) found that the MNL model underestimated EV market shares, while ML for the same data gave slightly better results. On the other hand, Kuwano *et al.* (2012) forecast a high diffusion rate for EV, similarly Axsen *et al.* (2009) predicted highly optimistic penetration scenarios, as compared to Brownstone *et al.* (2000).

This thesis aims to explore the take up of EV by employing choice methodologies that incorporate attitudinal data in discrete choice models. The attitudinal data is based on new technologies adoption and planned behaviour theories. These theories usually include a stated intention component that asks the respondent to indicate whether they are 'likely to undertake some behaviour or make a certain purchase'. Similarly, stated choice tasks are stated intentions to undertake a certain behaviour or to choose a product. The advantage of stated choice tasks is that the product is described in detail through a combination of attributes and the respondent states their intention more than once when presented with varying combinations. Both stated intentions and stated choice tasks do not capture observed behaviour in the market place. However, the EV market is virtually non-existent in Western Australia at this time and it is not possible to recruit a sample of EV owners and some form of stated intention is required. Stated choice is preferred because it offers a more realistic description of the choice in the market and it is capable of providing valuations for performance attributes of the EVs.

This attitudinal data is later incorporated into advanced choice models thus analysing adoption of EV as a new vehicle technology.

2.6 CONCLUSION

With the distinct characteristics of having an EV battery, the acceptability of EVs in the market requires further investigation. A number of studies presented in this chapter are more than ten years old or they do not include attitudinal data. Considering the speed of innovation, many studies need re-evaluation, which means that new research is warranted. The gap in the research mostly lies in exploring consumer behaviour towards EVs through a model that contains preference heterogeneity and explains behaviour using latent constructs. For this reason, modelling for this thesis covers a number of latent constructs, including environmental concerns, technology related constructs from TAM and TPB, and consumer purchase intentions involving new technology. The results of this research may help analysts of the Australian market to predict the EV market share or allow them to calculate price elasticities that can be later used by car manufacturers.

The next chapter discusses the literature on choice models and also elaborates the conceptual framework of this research.

CHAPTER 3

3 METHODOLOGY AND CONCEPTUAL MODEL INCLUDING ATTITUDES

3.1 INTRODUCTION

Different methodologies have been applied in transport modelling to explore consumer behaviour regarding the purchase of EVs, plug-in hybrids, and other alternative fuel vehicles, for example: contingent valuation, multivariate methods, and discrete choice modelling (Chapter 2). In this research, discrete choice modelling techniques are applied to analyse decisions for vehicle purchase, accounting for individual preferences and attitudes. The structure of this chapter is provided in Figure 3.1.

The WA EV Trial

A limited number of EVs have been used in the Western Australian Electric Vehicle trial (WA EV) undertaken in Perth. The trial monitored the performance, benefits, infrastructure and practical implications of the EV fleet. There were 11 participant organisations, each owning a number of EVs. Drivers (employees of these organisations) used the EV during the daytime and the vehicle was plugged-in for charging at the organisation's parking bay. Thus drivers in the trial have gained experience in driving and charging electric vehicles, most of which are traditional petrol-fuelled vehicles converted to EVs. After one year of accumulated experience of charging and driving, drivers were recruited for the first part of this research (driver behaviour and charging). The lessons learnt informed the subsequent household study on likely purchase behaviour (second part of the research).

The EV driving experience was explored in a survey of drivers' attitudes and their perceived behaviour towards EV. This helped in designing the household pilot survey, as further elaborated in this chapter. Attitudinal questions were designed from previous studies (as discussed in Chapter 2: Section 2.4) and were tested in this driver survey before being presented in the household pilot questionnaire. In addition, the driver survey helped in the experimental design for the household pilot-study where attribute levels were defined for four different vehicles and fuel technologies: petrol, diesel, plug-in hybrid and plug-in EV. Additionally, drivers' battery charging behaviour was explored in a separate survey that brought several useful insights, as discussed in Chapter 5. Technology adoption studies discussed in Chapter 2 were used to develop a conceptual model for this research (as shown in Figure 3.1). Attitudes towards adoption of new technologies were tested along with stated choice experiments to determine the likelihood of people adopting EVs as their future vehicle. This is further elaborated in Section 3.4 presenting the conceptual model for this study. Thus, there is a strong link between findings from the drivers' survey (presented in Chapter 4) and the design of the household study.

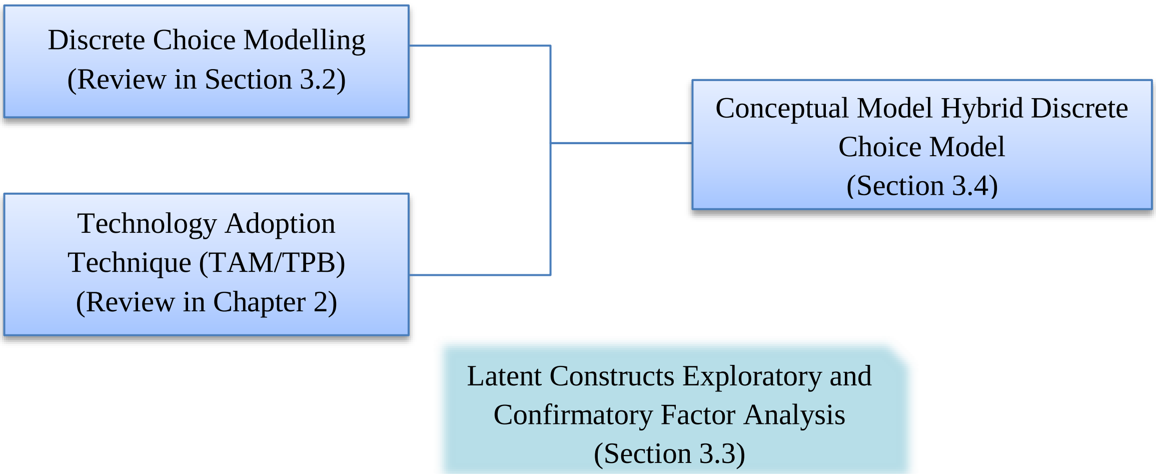


Figure 3.1: Conceptual Model Development and Structure of Chapter 3

This chapter continues with a discussion of discrete choice models, then a confirmatory factor analysis of the attitudinal scales, and concludes with how the modelling approaches were applied in this research. In addition, it presents a conceptual model of the vehicle purchase decision and elaborates on using the drivers' behaviour in the WA EV trial to analyse household behaviour.

3.2 DISCRETE CHOICE MODELLING: THEORY

Discrete Choice Modelling (DCM) is based on random utility theory (RUT) (Ben-Akiva and Lerman, 1985) which posits that rational decision makers, in a homogeneous market segment and having perfect information, choose the most preferred alternative (economic rationality) from a set of alternatives available to them (McFadden, 1980). Their utility functions are a composite of all the characteristics of the alternatives and the choice depends on personal preferences, circumstances, habits, or inertia.

DCM has been successfully applied to explore consumer preferences (Ben-Akiva and Lerman, 1985; McFadden, 1978) in various fields such as economics, marketing, and transport. The domain has evolved and matured in the last few decades, from the simplest and most commonly used model – Multinomial Logit Model (MNL) – to more sophisticated modelling of error structures including Nested Logit (NL), Mixed Logit (ML), and Latent Class Models (LCM).

Multinomial Logit

MNL is the basic discrete choice model assuming the alternatives are uncorrelated and that the decision makers use the same decision processes. The MNL model is estimated using maximum likelihood methods and output includes the estimated utility parameters, statistical significance of the utility parameters, measures of goodness of fit for the model as a whole, elasticities of choice with respect to the various attributes, and valuation of attributes (Louviere, Hensher, & Swait, 2000). The MNL model requires that the decision makers must be able to differentiate among alternatives (McFadden, 1973) which is sometimes difficult. MNL remains the starting point for empirical investigations of data before applying advanced discrete choice models (Louviere *et al.*, 2000).

In a choice model (Hensher, Rose, & Greene, 2005), *"... the choice probability of alternative* i *is equal to the probability that the utility of alternative* i*,* U_{in}*, is greater than or equal to the utilities of all other alternatives in the choice set"*. According to RUT the probability of choosing an alternative is given by:

$$P_{in} = P(U_{in} \geq U_{jn}),\ \forall\, j \neq i$$

Eq. 3.1

where:

U_{in} represents the utility level of the alternative;

i is a potential choice by individual n and C_n is the available choice set.

These utility functions include a systematic component and a random error, accounting for the unexplained elements of choice behaviour.

$$U_{in} = X_{in}\beta + v_{in}$$

$$y_{in} = \begin{cases} 1 & if \quad U_{in} \geq U_{jn} \\ 0 & otherwise \end{cases}$$

Eq. 3.2

where

X_{in} is the row vector of attributes of alternative i and socioeconomic characteristics of the individual n;

β is the column vector of unknown parameters;

υ_{in} is the error term, with certain properties (Gumbel distributed, *independence of irrelevant alternatives*, IIA, and *independently and identically distributed*, IID)

y_{in} is 1 if individual n choses alternative *i* and 0 otherwise.

As mentioned earlier, the output of an MNL includes – in addition to parameter estimates and goodness-of-fit – estimated choice elasticities and valuations of attributes. Hensher *et al.* (2005) define choice elasticity as a unit-less measure that describes the relationship between the percentage change for some variable that is an attribute of an alternative or socio-demographic of a decision maker and the change in the probability of choosing a particular alternative, *ceteris paribus*. These are purely choice elasticities; ordinary market demand elasticities can be derived from them using at least one other economic estimate (Smith & Taplin, 2015). There are two types of choice elasticity: direct and cross elasticities (Louviere *et al.*, 2000), depending on the attribute and alternative chosen. In the context of this thesis, a direct elasticity would be a measure of the percentage change in the utility/choice of an electric vehicle with respect to the percentage change in the running or purchase cost of an EV *ceteris paribus*; a cross elasticity would be a measure of the percentage change in the utility/choice of an electric vehicle with respect to the percentage change in the running or purchase cost of another vehicle (other than EV) *ceteris paribus*.

The valuation of an attribute is an individual's willingness-to-pay (WTP) in money terms to get a one unit change in the attribute. For example, in the driver behaviour study, the dollar value an individual is willing to pay to decrease charging time by 1 min would be calculated as the ratio (Equation 3.3):

$$WTP = \left(\frac{\beta_{time}}{\beta_{cost}}\right)$$

Eq. 3.3

MNL is a commonly used model due to its simple mathematical structure and estimation but, as indicated, MNL relies on the inherent *independence from irrelevant alternatives* (IIA) assumption (Luce and Suppes, 1965; Ben-Akiva and Lerman, 1985). The random part of utilities of different alternatives in the MNL model are restricted by an IID assumption with a type I extreme value or Gumbel distribution (Johnson and Kotz, 1970; Chapter 21). These restrictions imposed by MNL motivate the researchers to apply more advanced discrete choice models, for example the latent class model (LCM), or the mixed logit model (ML) also called the random parameters logit (RPL).

Latent Class Model

The LCM is an advanced discrete choice model that adds taste heterogeneity along with the heteroscedasticity, similarly to ML/RPL (Section 3.2.3). The difference is that LCM is a semi-parametric variation of ML, with the latent classes representing the underlying market segments, each of which is characterised by unique tastes. Because it adds parameter heterogeneity across individuals by using a discrete distribution, LCM is less flexible than ML. At the same time it does not require the analyst to make any assumptions at the time of estimation.

Latent Class Model Applications

LCM has applications in marketing studies (Louviere *et al*., 2000) where it is used to identify or develop market segments (Wen and Lai, 2010), similar to cluster analysis, but adding preference heterogeneity into the classes. In addition to marketing, LCM has been applied to explore individual preferences in transport, health, and environmental and ecological economics.

Latent Class Model Specification

Another important difference between models concerns correlation across the choice situations. The latent class model assumes that the choices are independent and draws from the distribution (Greene and Hensher, 2003). Class choice probabilities of choice *j* by individual *i* in choice situation *t* for latent class *c* (where there are C classes in total) are:

$$P_{jit|c} = \frac{exp(\beta_c x_{jit})}{\sum_{j=\{1,2,\ldots J_i\}} exp(\beta_c x_{jit})} \forall\, c \in C$$

Eq. 3.4

The class membership is unknown and a prior probability is estimated using observable characteristics. The class membership is also a MNL choice function of the form:

$$P_{ic} = \frac{exp(\theta_c z_i)}{\sum_{c \in C} exp(\theta_c z_i)}, \qquad c = 1,2,\ldots\ldots C, \theta_c = 0$$

Eq. 3.5

where:

z_i = all observable characteristics or attitudes which enter the model for class membership;

θ_c = parameter estimates for membership.

One parameter vector θ_c is set to zero for identification. The likelihood for an individual *i* is the expectation over the C possible classes:

$$P_i = \sum P_{ic}.P_{i|c}$$

Eq. 3.6

LCM assumes a fixed parameter vector in each class, with the overall mean being a function of how these are mixed by the class probabilities. These, in turn, may depend on covariates, z_i and parameters θ_c (Greene and Hensher, 2003).

Mixed Logit Model

Mixed logit is a generalisation of the MNL model, accommodating the differences in covariance of the random components and unobserved heterogeneity (Train, 1998; McFadden & Train, 2000; Louviere *et al.*, 2000). As indicated, ML/RPL defines the degree of preference heterogeneity through inclusion of random parameters (the standard deviations of the parameters) and through interactions between the mean parameter estimate and deterministic segmentation criteria (Train, 2003; Hensher *et al.*, 2005: 611). ML/RPL not only adds preference heterogeneity, but also a parameterisation of heterogeneity is achieved (Train, 1998; Greene *et al.*, 2006). These developments depend on the assumptions considered for the distribution of the random term (Train, 2003; Louviere *et al*., 2000).

Whereas a homoscedastic mixed logit assumes that the distribution of the taste parameter is the same for the entire sample, a heteroscedastic mixed logit models allows for increasing variance with respect to one or more characteristic of the individual. Preference heterogeneity captures the differences in individual preferences, i.e. individuals choose an alternative due to a specific preference and this preference can vary due to differences in attitudes/perceptions. Greene, Hensher & Rose (2006) discuss how RPL handles heteroscedasticity.

ML/RPL is used for exploring the behavioural output, elasticity of choice, and valuation of attributes. Revelt and Train (1998) suggested that the RPL interpretation is useful when considering models with repeated choice: RPL '*...allows efficient estimation when there are repeated choices by the same customer* (decision maker)" (p. 647). Given that the multiple integration does not have a closed form solution, numerical techniques are required. Standard Halton sequence draws (SHS) are widely used in RPL because SHS is an intelligent draw method that can obtain good results with a small fraction of the total number of draws required by methods which cover the entire parameter space (Bhat, 2001; Train, 2003). More recently, shuffled uniform vectors (Hess, 2004), have been considered in the simulations (Hensher *et al*., 2015).

An overview of ML presented by Hensher and Greene (2003) highlighted the following empirical ML model issues as significant for an analyst:

1. Selecting the random parameters;
2. Selecting the distribution of the random parameters;
3. Selecting the number of points in the distributions;
4. Accounting for observations from the same individual (correlated choice situations);
5. Preference heterogeneity around the mean of a random parameter;
6. Accounting for correlation between parameters;
7. Understanding the willingness-to-pay challenges.

The ML model has applications in various areas, for example to explore behavioural heterogeneity in transport (Bhat & Castelar, 2002; Hensher & Greene, 2003; Brownstone Bunch, & Train, 2000), environmental studies (Bjørner, Hansen, & Russell, 2004), agricultural economics (Alfnes, 2004), health (Johnson, Banzhaf, &

Desvousges, 2000; Hall, Fiebig, King, Hossain, & Louviere, 2006), and residential location (Bhat & Guo, 2004).

Mixed Logit Model Specification

The class choice probabilities remain the same for ML as for MNL, that is choice probability of choice *j* by individual *i* in choice situation *t* is:

$$P_{jit} = \frac{exp(x'_{it,j}\beta_i)}{\sum_{j=\{1,2,..J_i\}} exp(x'_{it,j}\beta_i)} = P_{jit}|\beta_i$$

Eq. 3.7

The model parameters are continuously distributed across individuals:

$$\beta_i = \beta + \Delta z_i + \Gamma\boldsymbol{\gamma}_i$$

Eq. 3.8

where:

$z_i =$ vector of individual characteristics that affect the mean of the random parameter distribution;

Δ= associated parameter matrix;

$\boldsymbol{\Gamma\gamma}_i$ is the noise or random component; assumed to (the mean=0) be normally distributed; and variance according to:

$$Var[\boldsymbol{\gamma}_i] = \Sigma = diag[\sigma_1, \dots, \sigma_k]$$

Eq. 3.9

For the total number of observations T, the conditional contribution to the likelihood is:

$$P_i|\boldsymbol{v}_i = \prod_{t=1}^{T_i} P_{it}|\,\boldsymbol{v}_i$$

Eq. 3.10

To get unconditional likelihood, $\mathbf{v}_i$ is integrated as follows:

$$P_i = \int_{\boldsymbol{v}_i} P_i | \boldsymbol{v}_i h(\boldsymbol{v}_i) d\boldsymbol{v}_i$$

Eq. 3.11

where:

$h(\mathbf{v}_i)$ is the density of the standardised random vector $\mathbf{v}_i$.

The mixed logit model holds the random vector $\mathbf{v}_i$ constant in all choice situations, which induces the correlation across choice settings. Once again, this is part of the deeper parameterisation of the mixed model versus the less detailed specification of the latent class model (Greene & Hensher, 2003).

LCM and ML/RPL both have their own properties and applications in different fields. There are no set rules that prioritise the use of one over the other. As indicated, LCM adds parameter heterogeneity across individuals by using a discrete distribution as opposed to the assumption of continuous random variations in taste parameters used by the ML/RPL model (Wen, Wang, & Fu, 2011). By applying both of these models in a household study this thesis aimed to determine which model fits best for the study purpose. Comparison of parameter estimates across models does not provide information due to scale differences; it is however meaningful to compare the derived willingness to pay indicators, elasticity, and simulations.

Error Components Panel Mixed Logit Model

An advantage of discrete choice experiments is that each individual completes multiple-choice tasks, hence providing a greater level of information on the decision generating process. However, to make good use of these data the model specification will need to take into account the quasi-panel nature of the observations. The following general utility expression assumes that each respondent maintains a core set of preferences throughout the entire experiment; but may differ from other respondents in terms of taste parameters (i.e., heterogeneity), correlations between error terms for each vehicle type (i.e., substitution patterns) or by the magnitude of the error (i.e., random effect). Incorporating the panel effect into the choice model estimation is achieved by including at least one choice task (period) invariant random parameter in the utility expression below:

$$U_{jtn} = ASC_j + \sum_{k=1}^{K} (\bar{\beta}_{jk} + \gamma_{jnk}) X_{jtnk} + \sum\nolimits_{1}^{J} \theta_{vn} \delta_{jv} + \omega_{jn} + \varepsilon_{jtn}$$

Eq. 3.12

where *j* represents the alternative,

t= choice task,

n= the decision maker, and

k= the attribute.

U_{jtn} is the utility provided by the j^{th} vehicle alternative for respondent n as expressed for choice task t = 1,…T_n; T_n being the total number of completed choice tasks. The k^{th} attribute X_{jtnk} varies over respondent and choice task[2]. The taste parameters associated with the vehicle *j* and choice task *t*, have a distribution of mean, $\bar{\beta}_{jk}$ and a random component $\gamma_{jk} \sim N[0, \sigma_\gamma]$. The error components $\sum_1^J \theta_{vn} \delta_{jv}$, model

[2] In the EV choice experiment herein, the attribute levels are not conditioned or pivoted on revealed choice data and respondents see only one of two *partitioned* choice surveys. The attribute levels are experimentally controlled to vary over choice tasks (t), but the variation across respondents is only due to which version of the survey instrument was presented to each of them.

correlations between two or more alternatives by taking a simultaneous draw from $\theta_{vn} \sim N[0, \sigma_\theta]$ across all alternatives that belong to a *nest*, v, where δ_{jv} is an indicator variable set to one if alternative j belongs to nest v and zero otherwise. Finally $\omega_{jn} \sim N[0, \sigma_\omega]$ decomposes the unobserved utility (error) into a choice task invariant component and choice task specific term, ε_{jtn}. The standard deviations $\sigma_\gamma, \sigma_\theta \; and \; \sigma_\omega$ are to be estimated by the model. The choice task specific error term is modelled as an extreme value type 1 distribution, meaning that the choice models based on the utility expression (Equation 3.12) fall under the mixed logit family.

The panel effects are captured by any of the following random parameters γ_{jnk}, θ_{vn} or ω_{jn}; whilst each is modelled as a random variable for the population they are nevertheless constants in the utility expression for each individual (they do not vary over choice tasks). Perhaps the easiest to model is $\omega_{jn} \sim N[0, \sigma_\omega]$, being a decomposition of the unobserved utility (error term) into a constant for each vehicle type (J-1, for normalisation purposes) and a choice task specific error term ε_{jtn}. This has the effect of locating the unobserved utility at different values, ostensibly, by allowing for individual and alternative specific parameters (invariant over choice tasks) to reflect comparative propensity of the respondents to select one alternative as opposed to another for a given set of attribute levels.

Setting the other two random parameters γ_{jnk} and θ_{vn} to zero (i.e. making the remainder of the systematic utility non-random) the resulting model is the **random effects panel mixed logit:**

$$U_{jtn} = ASC_j + \sum_{k=1}^{K} \bar{\beta}_{jk} X_{jtnk} + \omega_{jn} + \varepsilon_{jtn}$$

Eq. 3.13

The estimation of the model can be achieved by standard choice modelling software – such as NLogit – by setting J-1 alternative specific constants to be random parameters and estimating non-random parameters for all preference weights.

The **error component panel mixed logit** uses a similar mechanism as the random effects model, but take simultaneous draws for the alternatives within an identified nest. Taking simultaneous draws has two effects. Firstly, as before, the task invariant component of the unobserved utility captures a comparative propensity to choose from the alternatives within the nest. Secondly, the error for each choice task is decomposed into a constant shared across some alternatives and a random term resulting in correlated error terms for alternatives within the nest. The utility expression is:

$$U_{jtn} = ASC_j + \sum_{1}^{J} \beta_j X_{jtn} + \sum_{1}^{J} \theta_{vn} \delta_{jv} + \varepsilon_{jtn}$$

Eq. 3.14

To estimate the choice models, the analysts have to collect information on both chosen and not chosen alternatives. Two approaches are adopted in the literature: revealed preference (RP), and stated preference (SP) data collection.

Revealed Preference vs. Stated Preference Data

The revealed preference data reflects the choices in the actual market (Hensher *et al.*, 2005). According to Louviere *et al.* (2000), RP data depicts the current market equilibrium, and has high reliability and face validity. The limitation to RP data collection is that it relies on existing alternatives that are available in the market; thus, one may not experimentally test an option or attribute that does not yet exist. Furthermore, in some markets the attributes of the alternatives may not vary sufficiently, hence model estimation is difficult. However, RP data is most reliable for forecasting because it reflects observed market behaviour and subsequently accounts for the constraints faced by the household.

The stated preference (SP) data, on the other hand, reflects choices in hypothetical or virtual situations. Here the analyst means to generate realistic and plausible scenarios by manipulating the levels of the attributes considered to affect the choice.

The benefit of SP data is that it allows the analyst to efficiently create scenarios that combine existing attributes with novel attributes, testing for characteristics that are not currently available. SP data are rich in attribute trade-off and, although the contextual realism may sometimes be low, RP may be more useful in forecasting changes in behaviour. A combination RP and SP results in "*data enrichment*" (Louviere *et al.,* 2000), increasing the confidence in predictions. SP parameter estimates adds a richer understanding of the trade-off between attributes but the RP data forms the base level for market predictions. As EVs are not readily available in the market yet, most of the EV acceptance studies are based on SP experimental design (Ahn, Jeong, & Kim, 2008; Ewing and Sarigollu, 2000; Bolduc *et al.*, 2008; Dagsvik *et al.*, 2002; Ziegler, 2012). A few (Brownstone *et al.*, 2000; Axsen *et al.*, 2009) have used the RP-SP combination in the experimental design. Brownstone *et al.* (2000) found that SP models gave higher forecasts of non-petrol cars and sport cars, as compared to joint models. Axsen *et al.* (2009) reported that joint models with more influence from SP data, gave the best performance, and the estimation of joint models was found superior for vehicle choice modelling.

Best-Worst Data Scaling

Best-worst choice analysis was developed by Louviere and Woodworth (1990) and, as described in its first application (Finn & Louviere, 1992), the best-worst (B-W) scaling allows for richer information. For a set of three alternatives, B-W provides a complete ranking, whereas with four alternatives, a partial ranking can be achieved. Despite its continuous use, the formal statistical and measurement properties of B-W were demonstrated only in 2005 (Marley & Louviere, 2005). As shown by several recent studies in marketing (Auger, Devinney, & Louviere, 2007; Cohen, 2009) and health economics (Flynn, Louviere, Peters, & Coast, 2007), Best-Worst scaling is considered better than complete ranking, because it is easier for a respondent to choose the Best and Worst. By marking/choosing two option (Best and Worst) instead of one option, thus it is expected to provide greater information content.

Best and Worst is not only a manner of data collection, but also a behavioural paradigm (Flynn and Marley, 2014) because people are using distinct decision mechanisms to select the Best option and to avoid the least attractive (Worst) option. Many models have been developed, using only Best data, then the Worst data, determining the maxdiff difference between the two scores for the two options, or considering pairs of best-worst alternatives (Coote, 2014; Flynn and Marley, 2014). All Best and Worst models are considered to meet the conditions for the weighted utility ranking models (Flynn and Marley, 2014).

Many recent models found scale differences across Best and Worst options chosen by respondents (for example, Collins and Rose, 2013). This has implications for the data pooling, which is deemed the main advantage of the Best-Worst approach.

Given the reduced cognitive burden and the added data set they provide, Best-Worst data collection and scaling is applied in this study.

Best-Worst (B-W)

There are three types of B-W analyses (Rose, 2013): 1) comparing alternatives without attributes (e.g., airlines, clothing brands, policy interventions); 2) comparing statements chosen randomly from a pool of statements; and 3) multi-profile case (similar to a discrete choice experiment, but selecting two alternatives, the most preferred and least preferred. The last of these is B-W.

According to Marley & Flynn (2014), let P denote a finite set of alternatives that are part of design D. D(P) defines a set of choice task alternatives that could occur in a study; while Y represents one choice task with two or more alternatives. *The Best choice MNL model assumes there is a difference in scale u in the systematic utility such that for all y ∈ Y∈ D(P),*

$$B_Y(y) = \frac{e^{v(y)}}{\sum_{z \in Y} e^{v(z)}}$$

Eq. 3.15

The value *v(y)* for an option *y* is interpreted as the systematic/observable utility for that option. *The Worst choice MNL model assumes there is difference in scale -u such that for all y∈ Y∈ D(P),*

$$W_Y(y) = \frac{e^{-u(y)}}{\sum_{z \in Y} e^{-u(z)}}$$

Eq. 3.16

Marley & Louviere (2005) present theoretical arguments for *–u(y)* representation for negative sign with the Worst choice. Depending on the order applied to setup the data and perform the analysis, we distinguish between: BEST, then WORST and WORST, then BEST.

BEST then WORST: *assuming the best choices satisfy* (3.15) *and the worst choices satisfy* (3.16), *the Best then Worst, MNL model assumes that for all x, y∈ Y∈ D(P), x ≠ y,*

$$BW_Y(x, y) = B_Y(x)W_{Y-\{x\}}(y)$$

WORST then BEST: In this case, *MNL model assumes that for all x, y∈ Y∈ D(P), x ≠ y,* $BW_Y(x, y) = W_Y(y)WB_{Y-\{y\}}(x)$

B-W and Exploded Logit

Maximum difference (max-diff) takes into account all possible pairs of alternatives in each choice task, thus increasing the number of observations in the data set (Flynn, Louviere, Peters, & Coast, 2008). Marley & Flynn (2014) discuss a number of different possible ways for dealing with B-W choice data; in partial ranking cases respondents indicate only their most preferred or least preferred choice. In terms of data setup, the most preferred and least preferred options are set up in two alternate ways in this thesis: B-W data, and Exploded Logit data (Chapter 7: Section 7.5).

Data setup for B-W choice data takes a block with positive sign for attributes and Best choice = 1 and after removing the Best alternative, the next block is created with a negative sign for attributes and Worst choice = -1. Data setup for Exploded Logit data is defined as the B-W choice comparing the best option (i.e. the choice) with all the other alternatives, then after removing the Best alternative, comparing the remaining options (chosen alternatives) with the Worst alternative.

Experimental Designs

Stated Choice experiments are designed to present sampled respondents with different choice situations that contain a set of alternatives, each alternative defined on a number of attribute dimensions. *"A designed experiment is therefore a way of manipulating attributes and their levels to permit rigorous testing of certain hypotheses of interest."* (Louviere *et al.*, 2000: p.84). Experimental design for stated choice experiments involves a systematic process in which attributes and their levels are pre-defined without measurement error and levels are varied to create choice preference.

Steps in Experimental Design

Hensher *et al.* (2005; Chapter 5) discuss eight stages in the experimental design process. They include: *i) problem refinement, ii) stimuli refinement, iii) experimental design consideration, iv) generate experimental design, v) allocate attributes to design columns, vi) generate choice sets, vii) randomise choice sets, viii) construct survey instrument*.

The first two stages, problem refinement and stimuli refinement, involve a clear understanding of the problem and identification of alternatives, attributes, and attribute levels. This could be done by analysing previous studies and/or by conducting focus groups with the relevant subjects. After this, a number of considerations are taken into account: whether choice experiments will be labelled or unlabelled, number of levels for each attribute, size of experimental design, whether to block the design or not. Then experimental designs are generated and attributes are allocated to design columns, which could be done by generating a full factorial design or a fractional factorial design. Full factorial design implies that each attribute level is combined with every attribute level of all other attributes; statistically this design allows the generation of *treatment combinations* where attributes are independent of each other, but it is hard to cope with a full set of treatment combinations for experiments with large number of attributes and attribute levels. For a relatively small experiment having only three attributes with each attribute having four levels, there would be 4x4x4 that is 64 combinations, but for five attributes where two attributes have seven levels, two have four levels, and another eight, the number of full factorial combinations would be $7^2 x 4^2 x 8$, which equals 6,272. It is not practical to test such a large number of combinations with even a large set of sample respondents. For this reason, fractional factorial designs are generated, where a subset is chosen from the full factorial. Next, choice sets are created in the form hypothetical scenarios so that the decision maker can select their preferred option based on the attributes. In order to cover most of the treatment combinations by respondents, blocks of choice sets are randomised so that each block is presented at least once to any of the respondents. Once choice sets are finalised, it is important to locate them in the survey either in the beginning or middle of the survey, so that a respondent does not get bored and attempt to make a choice without carefully observing the attribute levels. In this research, 6-8 choice sets/stimuli were generated for the driver and household surveys by attaching cognitive meanings to attribute levels.

Efficient Experimental Designs

As already indicated, full factorial designs are only realistic for problems with small numbers of attributes and levels. In larger designs fractions are used and their selection is not trivial.

Experimental designs for SP surveys have continuously evolved to match the complexity of the discrete choice models. In orthogonal experimental designs the attribute levels between different attributes are uncorrelated (Louviere *et al.*, 2000). Although widely used in stated choice experiments, orthogonal experiments are not statistically efficient. Discrete choice models are different from the linear regression models and their variance-covariance matrices are obtained in a different manner. McFadden (1973) indicated that the asymptotic variance–covariance (AVC) matrix of the multinomial logit (MNL) model could be derived from the second derivatives of the log-likelihood function of the model. Whereas traditional standards of orthogonality, balance and non-dominance have prevailed, recent scholarly work questioned those design characteristics and proposed efficient designs, aimed to produce stable and reliable parameter estimates in a fractional design setting. Optimal designs may be achieved by minimising at least one property of the AVC matrix: determinant, trace, and variances. Numerous authors (e.g., Rose & Bliemer, 2005 a,b; Sándor & Wedel, 2002; Carlsson & Martinsson, 2003; Ferrini & Scarpa, 2007; and Bliemer, Rose, & Hensher, 2009a) have investigated the efficiency or optimality of these designs for various models and types of experiments.

Researchers face two challenges when designing efficient experiments for DCM: i) the requirement for known or previously estimated parameters when deriving the AVC; ii) the size of the experimental design, which even at a small number of attributes and values quickly becomes excessive. Some studies (Street & Burges, 2004; Grasshoff, Grossmann, Holling, & Schwabe, 2003) consider null values for previously estimated parameters, that is null priors; while other studies with a focus on efficiency prefer known prior values (Bliemer *et al.*, 2009a; Ferrini & Scarpa, 2007; Sándor & Wedel, 2002). Priors are commonly obtained from literature reviews or pilot studies.

GA Optimised Design

Despite the substantial attention devoted to experimental designs in the past decade, optimality has been demonstrated only in a limited number of situations (for simpler experiments and models). This is because of the large size of the space of potential solutions for experimental designs (NP-hard problems). Hence, searching heuristics are necessary to find efficient choice sets in reasonable time and this research relies on designs optimised using genetic algorithms (GAs) (Olaru, Smith, & Wang, 2011). GAs are inspired from biological evolution (Holland, 1992) and have been very successful in numerous optimisation problems (Taplin *et al.*, 2005; Olaru, Smith, and Wang, 2011). The algorithm starts with an initial random population of solutions (parents), then by applying genetic operators such as crossover and mutation, new solutions are obtained. Best solutions (here designs) are kept in the pool of solutions, whereas poor performers tend to be discarded from generation to generation. This is similar to the survival, elitist strategy of evolution.

The literature presents numerous other algorithms. Ferrini & Scarpa (2007) and Bliemer *et al.* (2009a) described the construction of various types of experiments including the systematic row- and column-based algorithms (modified Fedorov) and the RSC (relabelling, swapping, and cycling) algorithms. Meyer & Nachtsheim (1995) described the cyclic coordinate-exchange algorithms for constructing D-optimal and linear-optimal designs using a mix of qualitative and quantitative attributes for GLM (in quality improvement). Street, Burgess & Louviere (2005) provided strategies for obtaining "*quick and easy choice sets*" for paired comparison designs when the attributes have the number of levels being equal to powers of two. Wang & Li (2002) proposed uniformly scattered solutions in the problem domain.

As indicated, the search space is not the only challenge of finding the most efficient experimental designs. Considering the importance of priors, Bayesian designs have also been proposed (Sándor & Wedel, 2001; Kessels, Jones, Goos & Vandebroek, 2008), by specifying prior parameter distributions instead of fixed priors. In setting the best designs, Dp measures are calculated as expected values over numerous draws taken from the probability distributions of the priors (Sándor & Wedel, 2001; Kessels, Jones, Goos & Vandebroek, 2008) (ibid.).

3.3 FORMULATION OF LATENT CONSTRUCTS FOR THE CHOICE MODELLING: DRAWING ON PREVIOUS STUDIES

The focus of this research is to apply advanced discrete choice analysis and modelling techniques to predict electric vehicle uptake in Perth, WA. In Chapter 2, it was indicated that a number of previous studies applied multivariate tests, and either discrete choice analysis or advanced discrete choice models (DCM) to explore individual behaviour towards EVs. This thesis also attempts to investigate willingness to recommend and purchase an EV through DCM, combined with the examination of latent constructs (such as environmental concerns, perceived usefulness of EV technology and social norms). Latent variables are defined as hypothetical constructs that cannot be measured directly; rather, each latent variable is represented by two or more measured variables, called indicators or items. A combination of these indicator questions as a whole provides a reasonably accurate measure of the latent construct (attitude) of an individual. To identify and build constructs in this study, previous studies were first explored to determine suitable constructs that could be used to determine the propensity to adopt electric vehicles (Figure 3.1). Chapter 2 also presented studies of the adoption of new technologies, including consumer behaviour models: theory of planned behaviour (TPB), technology acceptance model (TAM), product involvement, technology acceptance scales. In TPB, behaviour is assessed indirectly; that is first finding attitudes, subjective norm, and perceived control behaviour that define intentions. Behaviour is then predicted by intention directly and perceived behaviour of control directly and indirectly as given in Figure 2.1 (Chapter 2) and expanded in Figure 3.2.

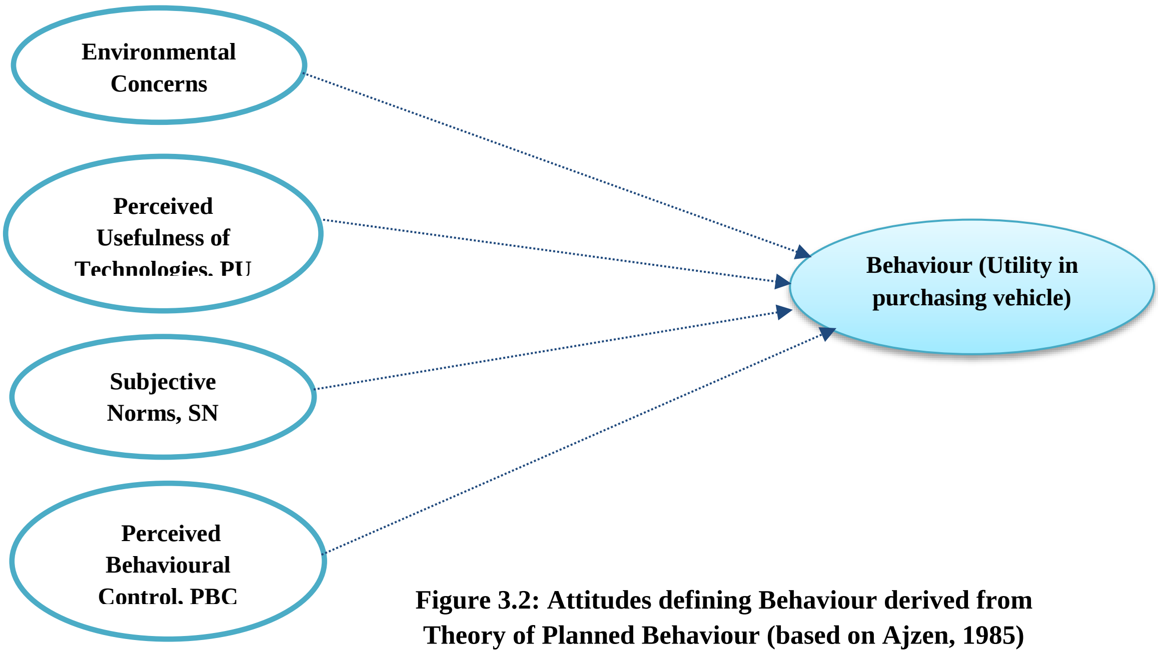


Figure 3.2: Attitudes defining Behaviour derived from Theory of Planned Behaviour (based on Ajzen, 1985)

In TAMs, behavioural intentions to use an information system are defined by perceived usefulness, and perceived ease of use; similarly, product involvement (PI) scales measure importance or relevance of a product by its utility, sign or hedonics. Technology acceptance (TAM) scales directly determine people's propensity to adopt new technologies. Upon exploring these studies, in addition to environmental concerns attitudes, it was found pertinent to investigate more latent constructs from the perspective of adopting EVs as a new technology. These constructs include: social influence or subjective norms and perceived behaviour of control - from TPB, and perceived usefulness - from TAM, attitudes that directly define behaviour as given in Ozaki, 2011; Elliot et al., 2012; Yang, 2012; and Nasri & Chaferddine, 2012. Next, this behaviour or attitudinal data is tested as latent constructs in the utility function. Items for each construct selected from existing literature, were factor analysed and factor scores were included in the hybrid discrete choice model for the household study (Figure 3.3).

Exploratory Factor Analysis

As an initial step, the constructs were determined through an exploratory factor analysis. Environmental concerns, perceived control behaviour, and perceived usefulness were investigated (Figure 3.2). These constructs were first presented to drivers in the WA EV trial with the primary objective to determine drivers' experiences and perceptions about EVs, and attitudes toward the environment and adoption of new technologies (Chapter 4). This driver survey also served as pilot study for the household questionnaire as findings helped in refining the design of household choice experiments, and also to ascertain attitudinal data or to test the reliability of latent constructs required to capture preference heterogeneity in the household study. The attitudinal dimensions that were chosen to be tested were: *Environmental Concerns*, *Perceived Usefulness and Ease of use*, *Electric Vehicle Benefits*, *Willingness-to-recommend and purchase an EV*.

Environmental Concerns

The first construct tested was *Environmental Concerns*, an attitude that has already been used by a large number of studies that explore EV adoption behaviour (Ewing and Sarigollu, 2000; Dagsvik *et al.,* 2002; Hidrue *et al.,* 2011; Bolduc *et al.,* 2008; Ozaki, 2011). Items that were selected for testing in the drivers' survey are the following:

- *"Saving the environment requires our immediate efforts."*
- *"Now is the real time to worry about the effects of air pollution."*
- *"Climate change is a myth."*
- *"Vehicle emissions can destroy our flora and fauna."*
- *"I am concerned that future generations may not be able to enjoy the world as we know it currently."*
- *"I am willing to spend extra time only to save the environment."*
- *"I always recycle products such as: paper, glass, aluminium, etc."*
- *"I am willing to pay more for products or services only to save the environment."*

As expected, most of the items loaded well into this construct for the driver and household surveys. Details of items and factor loadings are presented in Table 4.2 in Chapter 4, where results of the exploratory factor analysis are discussed.

Perceived Usefulness and Ease of Use

The second construct, as determined from TPB literature, was "*perceived behaviour of control*", interpreted as readiness to adopt technology or behaviour that requires learning new technology. To define items for this scale, previous studies were reviewed, some items being taken without change; for example items given in bold italic were taken from Ewing and Sarigollu (2000). In addition to the technology adoption propensity (TAP) index, 14 scale items presented by Ratchford and Barnhart (2012) were also explored while defining *Perceived usefulness and Ease of use*. Items from TAM were also reviewed while identifying items for this latent construct. Items included are:

- *"Using new technologies makes our lives easier."*
- *"New technologies give more control over our daily life."* (Ratchford & Barnhart, 2012)
- *"Taking up new technologies makes one trendy."*
- *"**Things have become so complicated today that it is hard to understand what is going on in this techno-world.**"* (Negative) (Ewing & Sarigollu, 2000)
- *"I learn new technologies without help from others."*
- *"**New technologies cause more problems than they solve.**"* (Negative) (Ewing & Sarigollu, 2000)
- *"I am excited to learn to use new technologies."* (Parasuraman, 2000)

Items that were adapted from technology readiness survey (TRI: Meuter *et al.*, 2003), include:

- *"Being fashionable means having up-to-date knowledge of the techno-world."*
- *"I love gadgets."*
- *"Keeping up with the new knowledge on technologies is necessary."*

The results of the driver survey data however indicated only one construct, named "*excitement for technology learning*"; details of items and loading are given in Table 4.2 (Chapter 4). The motivation may be the sample of drivers: although small in size, the sample included respondents heavily interested in new technologies.

Willingness-to-recommend and purchase an EV

Willingness-to-recommend and purchase an EV was assessed by the following items:

- *"I prefer to use EVs over any other type of cars."* (Adapted from: Schuitema *et al.*, 2012)
- *"I would recommend EV to others."*
- *"I would buy an EV as my next car."* (Consumer Involvement: Bezencon & Blili, 2011; Mittal & Lee, 1989).

Items in this construct loaded well for the driver survey, as expected. Details of items and factor loadings are presented in Table 4.2 in Chapter 4.

Electric Vehicle Benefits and Challenges

Items were designed to test two constructs related to drivers' perceptions about i) *Benefits of EV*; and ii) *Challenges of EV use*. Battery recharging at station, home-charging, and maintenance were identified/designed during a focus group with WA EV drivers in Nov 2011 (as discussed in Chapter 4). Items include:

- *"I believe EV produces less noise during driving."*
- *"I believe EV has problems with acceleration."*
- *"I believe EV goes to a heat-*up*-stage frequently during summer."*
- *"I believe EV is ensuring the proper ambient temperature in winter."*
- *"EV driving reduces my average travel cost/trip."*
- *"I need to do a lot of planning of activities in the day when I drive the EV."*
- *"Battery recharging at home is convenient for my EV."*
- *"Recharging at stations is convenient for my EV."*
- *"I spent a significant amount of money to fix my EV in the last 3 months."*

Findings for this construct are discussed in Section 4.5.3 in Chapter 4 (no items had high factor loadings to form reliable constructs).

Confidence in Driving an Electric Vehicle

As drivers in the WA EV trial had experience of driving EVs, to draw on their knowledge, a number of questions assessing their confidence level, their attitudes about EV benefits and battery charging were tested in the driver survey. In addition, their involvement with EVs (as a product) was also assessed as suggested by consumer involvement studies (Mittal & Lee, 1989; Bezencon & Blili, 2011).

Although the aim was not to build a construct, these items were further used to determine antecedents of EV adoption as discussed in Section 4.7 in Chapter 4. The indicators are as follows.

- *"How confident do you feel driving an EV?"*
- *"How confident are you in the environmental performance and efficient use of energy of EV?"*

Overall Satisfaction in Driving an Electric Vehicle

Considering EV drivers as consumers, their involvement with EVs was assessed through their *Overall Satisfaction* with using an EV; the indicator used to test this behaviour given below:

- *"Overall, how satisfied are you driving the EV?"* (*Consumer Involvement*: Bezencon & Blili, 2011; Mittal & Lee, 1989)

Drivers' overall satisfaction was driven by several factors that influenced willingness to purchase an electric vehicle. This is further discussed in Section 4.7, Chapter 4.

Findings from the exploratory factor analysis on driver data helped to establish the attitudinal constructs for the household study. Some items had high loadings, others low, and the findings from exploratory analysis suggested some changes in the constructs.

Confirmatory Factor Analysis

Confirmatory factor analysis was used to perform construct validation and scale refinement, once attitudinal constructs were established through exploratory factor analysis on driver data (findings are given in Section 4.5, Chapter 4). In order to perform confirmatory factor analysis (CFA) five elements must be specified: 1) the latent constructs; 2) the measured variables; 3) the item loadings on specific constructs; 4) the relationships among constructs; and 5) the error terms for each indicator (Hair *et al.*, 2010).

In the household study, the following five constructs were tested: i) *Environmental concerns;* ii) *Excitement for New technologies;* iii) *Perceived Usefulness;* iv) *Subjective Norms;* and v) *Attitude towards Purchase and Use of EV*. Their structure is given in Section 4.5, and results further discussed in Chapter 6. Constructs including EV benefits and confidence in driving an EV were not presented to households, given that an EV is not a common household vehicle and assuming little or no prior EV experience of the households.

3.4 CONCEPTUAL MODEL

The conceptual model for the household study is presented in Figure 3.3. This brings together the explanatory variables, such as purchase price and range (Table 3.1), and the latent variables considered in Section 3.3 – to be developed further in this section. A hybrid choice model is applied to sharpen our understanding of the elements conducive to EV uptake. Instead of defining behaviour indirectly, as in TAM (where behaviour is defined by intentions), in this study individual behaviour is defined through choice and attitudinal data. Attitudinal data are defined through latent constructs (Section 3.4.1) and then incorporated into the utility function of the choice model as covariates (Section 3.4.2). In this way, a sequential hybrid discrete choice model is applied using as explanatory variables both attributes of the alternatives and characteristics of individuals, as well as the attitudinal data in the utility specification (Figure 3.3).

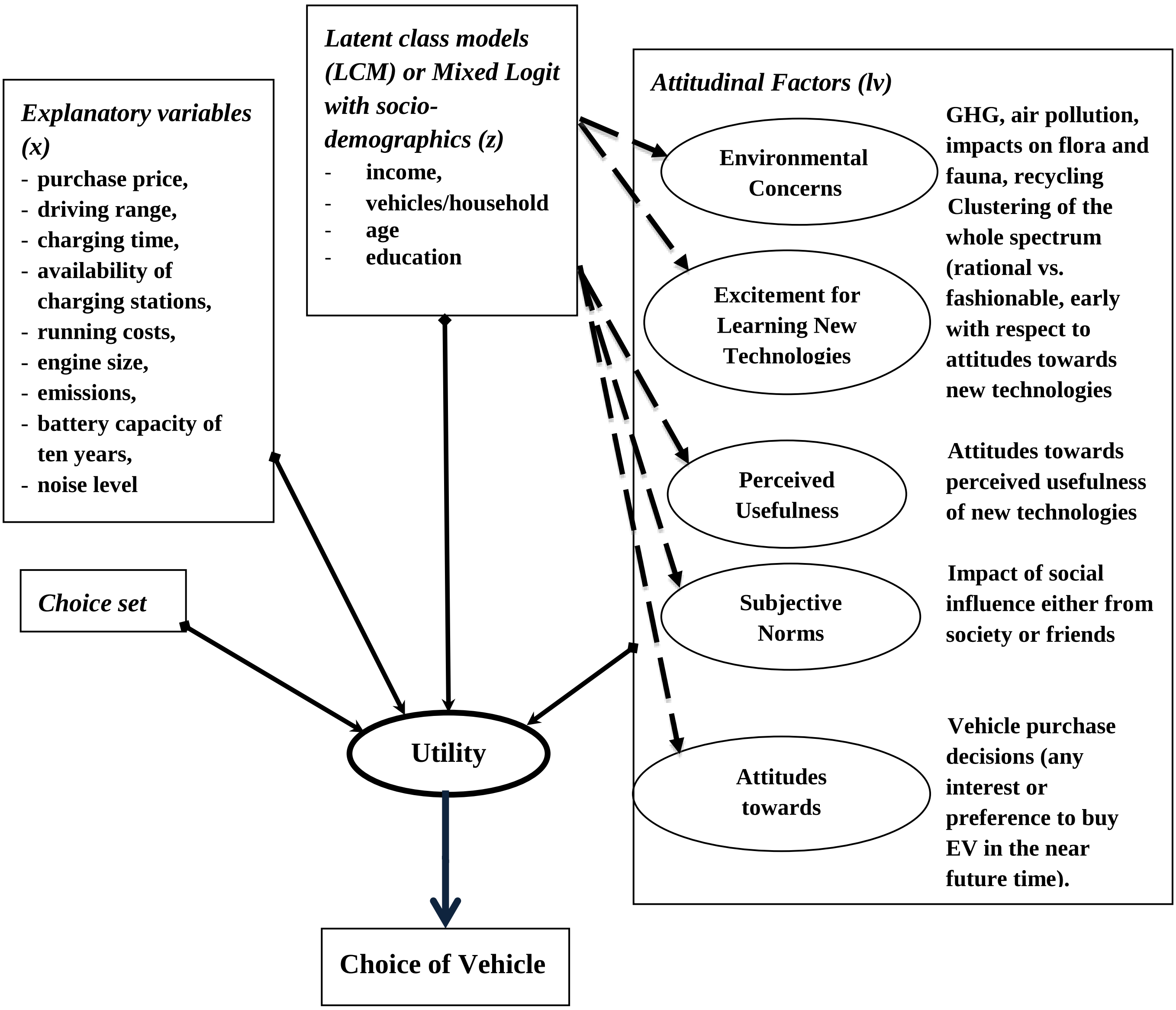


Figure 3.3: Conceptual Model - Hybrid LCM with Attitudinal Factors

Measurement Model

As already indicated, the measurement model was developed through CFA. According to Hair *et al.* (2010: p.632) a measurement model is "*a structural equation model that: 1) specifies the indicators for each construct; 2) enables an assessment of construct validity.*" Measurement theory requires that constructs are defined first. In confirmatory factor analysis (CFA) measurement theory is used to specify *a priori* the number of factors along with variables loading on those factors (Hair *et al.*, 2010: p.694). This specification refers to the way constructs are *operationalised* in a measurement model. Once identified through exploratory factor analysis (EFA), these constructs were assigned items based on EFA results and previous studies, as discussed below.

Environmental Concerns

This construct is defined using the items as specified in the driver survey, with the addition and removal of some items, based on EFA results and the literature. The following items were taken from the driver survey, while the <u>underlined items</u> were removed because of their modest loading (factor loadings are presented in Chapter 4):

- *"<u>Vehicle emissions can destroy our flora and fauna.</u>"*
- *"<u>I am willing to spend extra time only to save the environment.</u>"*
- *"Saving the environment requires our immediate efforts."*
- *"Now is the real time to worry about the effects of air pollution."*
- *"Climate change is a myth."*
- *"I am concerned that future generations may not be able to enjoy the world as we know it currently."*

- *"I always recycle products such as: paper, glass, aluminium, etc."*
- *"I am willing to pay more for products or services only to save the environment."*

Five more items were added into this construct, again looking at the studies in this context (Ewing & Sarigollu, 2000; Dagsvik *et al.*, 2002; Hidrue *et al*., 2011; Bolduc *et al.*, 2008; Heffner *et al.*, 2007):

- *"I prefer to walk/cycle in order to reduce pollution."*
- *"I might join a group, club, or organisation concerned with ecological issues."*
- *"It is acceptable for a modern society to produce a certain degree of pollution."*
- *"Riding public transport helps reduce pollution."*
- *"I prefer driving a car with a powerful engine than a car that emits little CO_2."*

Excitement for New Technologies

In the driver study test of control and technology adoption attitudes, only one dimension appeared significant ("*technology learning*"), therefore to further identify/test more dimensions in this context, more items were added. Three constructs were identified: *1) Excitement for New Technologies; 2) Perceived Usefulness; 3) Subjective Norms*. Items in this context were mostly adapted from studies by Bitner, & Roundtree (2003), Meuter, Ostrom, and Nasri & Charfeddine (2012), Parasuraman (2000).

The following items were taken from the driver study, while the underlined items were removed based on their weak loadings:

- ***"****I love gadgets.****"*** *(Hedonic Component)*
- *"Keeping my knowledge up to date about technology is necessary."* (reworded)
- *"New technologies enable me to resolve my daily tasks."* (reworded)
- *"Using new technologies makes life easier."*
- *"I am excited to learn new technologies.*"
- *"Being fashionable means having up-to-date knowledge of the techno-world."*
- *"Keeping up with the new knowledge on technologies is necessary."*

Four additional items were considered in the household study, based on findings from previous studies:

- *"I never travel without a GPS."*
- *"People often become too dependent on technology to do things for them."* (Negative) (Parasuraman, 2000; Item adapted from the Technology readiness survey)
- *"I prefer to use the most advanced technology available."*(Parasuraman, 2000; Nasri & Charfeddine, 2012)
- *"I enjoy the challenge of figuring out high-tech gadgets."*(Parasuraman, 2000; Meuter *et al.*, 2003).

Perceived Usefulness

From the driver study the following items were further tested for this construct:

- *"Using new technologies makes life easier."*
- *"Things have become so complicated today that it is hard to understand what is going on in this techno-world."*
- *"New technologies cause more problems than they solve."*

Again, drawing on previous studies, the construct was "enriched" with three more items:

- *"I use online maps to plan my travel when I need to visit a new place."*
- *"Exploring new technologies enables me to take benefit from latest developments."* (Meuter *et al.*, 2003)
- *"EV Technology would enable me to cut the running costs."* (Ozaki & Sevastyanova, 2011).

Subjective Norms

Two items, measured on a likert scale, from the driver survey had high loadings and hence were retained in the construct to test the element of fashion/trend:

- *"Taking up new technologies makes me trendy."*
- *"Being fashionable means having up to date knowledge of this techno-world."*

Three additional items were included in the household survey. Items measured on a Likert scale:

- *"People who influence my behaviour think I should buy an EV."* (Venkatesh & Davis, 2000; Ozaki, 2011)
- *"People who are important to me think that I should buy an EV."* (Venkatesh & Davis, 2000; Ozaki, 2011)
- *"I would buy an EV if many of my friends would use an EV."* (Yang, 2012).

Attitudes towards Purchase

Three items were tested in the household survey for this construct. All items are measured on a Likert Scale.

- *"If you were to buy a car within the next five years (independent of whether you really intend to or not), how likely is it that you would buy an electric vehicle?"* (Peters, Popp, Agosti & Ryf, 2011)
- *"Assuming you had an electric vehicle available. How likely is it that you would do without an additional car with an internal combustion engine?"* (Peters *et al.*, 2011)
- *"How often would you use your EV?"* (Mittal & Lee, 1989; Consumer Involvement).

The estimated loadings and percentage of variance explained by items in the constructs and their results are discussed in Chapter 6. These latent constructs were used with the vehicle-related explanatory variables and socio-demographics, in the hybrid choice model (Figure 3.3).

Hybrid Choice Model

As mentioned at the beginning of Section 3.4, this study uses a hybrid choice model. A discussion about the use of attitudinal data to analyse individual behaviour in previous studies was presented in Chapter 2. Ewing & Sarigollu (2000) incorporated the environmental construct in the analysis of EV purchase decision, and hybrid models have been used in previous vehicle purchase studies (Hidrue *et al.*, 2011; Bolduc *et al.*, 2008). In this type of model, the explanatory variables include not only vehicle characteristics and socio-demographics of households (decision maker), but also attitudinal factors, which are all tested inside the utility that drives the choice of a vehicle (Figure 3.3).

The household study concentrates on the latent class model as the modelling strategy to infer lifestyle or attitude impact on choice of EV, along with contribution of its various features. The estimation is broken down into two stages: 1) a structural model of latent constructs; 2) a class specific (conditional) choice probability estimated by the multinomial logit, where the parameter estimates β_c are class dependent. The utility is derived in the same way as given in Equation 3.2 for a choice situation (the class-specific choice probabilities for latent classes c are given in Section 3.2.2, Equation 3.4). The vector of explanatory variables of the class specific choice model includes vehicle characteristics; attributes of the household (decision-maker); and attitudes of the household towards EV, environment, and technology adoption.

The class membership is unknown and a prior probability is estimated using observable household characteristics (current car ownership, income, age, gender, etc.) as well as latent variables formed by using attitudinal questions. The probability that respondent *i* belongs to class *c* makes use of multiple observations for each respondent allowing a better estimate of utility function for each respondent. The class membership is also a multinomial logit choice function (as given in Equation 3.5).

The choice model simultaneously estimated the class membership and the class specific choice probabilities, with a sequential approach applied for the inclusion of the attitudinal responses. Other mixed logit and error component logit model structures were also investigated. The results for these models are presented in Chapters 7 and 8.

Examples of formulated hypotheses derived from this model are the following:

I. People who are concerned about the environment are more likely to buy an EV/Plug-In Hybrid (PIH) vehicle.
II. People who are excited about learning new technologies are more likely to purchase an EV/PIH.
III. People who believe in the perceived usefulness of new technologies are more likely to purchase an EV/PIH.
IV. People who are trendy, or are more receptive to social influences, believe that buying an EV would allow them to be more fashionable/up to date.
V. Young environment enthusiasts are more likely to purchase an EV/PIH.
VI. Highly educated technology savvy people have a stronger preference for buying EV/PIH.

These hypotheses are a subset of what is tested in the household study while exploring behaviour towards buying EV technologies. With an objective to test these hypotheses, findings from the household survey data analysis are presented in Chapters 6 to 8.

3.5 SUMMARY

As discussed in Chapter 2, a number of studies have attempted to determine individual propensity towards the adoption of EV or an alternative-fuel vehicle, and discrete choice models have been successful in gauging the market tendencies in transport studies. A study by Jensen *et al.* (2013) applied a joint hybrid choice model to test preferences for EVs and their findings indicate that individual preferences changed after having "a real EV experience"; for example, in their study, acceptance of limited driving range doubled after having the EV driving experience. This finding further supports the design of this research. Formation of latent constructs was refined using a sample of EV drivers (Chapter 4) to inform the household survey in Chapter 6. The constructs also represent covariates in a hybrid choice model for households.

In the beginning of this chapter, the discrete choice modelling approach was presented along with other advanced discrete choice models; LCM, ML/RPL, and ECM, with their specifications. With some differences, for example in terms of their flexibility and their applications, these structures present a possible solution to explore preference heterogeneity.

Then, a brief description of B-W scaling was provided; B-W is a technique that has recently gained popularity for its ability to better elicit preferences for alternatives, and thus applied in this research. Finally, the attitudinal factors tested in the models were presented.

Figure 3.4 presents the flow of information and also indicates the organisation of the remainder of the thesis. The research started by analysing WA EV trial drivers' behaviour, with findings from the survey serving as a pilot for a household survey, the main focus of this thesis. Drivers' behaviour and their perceptions of EVs were explored to find the factors that can influence the individual towards accepting EVs. Following the factor analysis, a structural equation model analysed the antecedents of EV adoption in Chapter 4 (Jabeen, Olaru, Smith, Braunl, & Speidel, 2012). Chapter 5 explores WA EV trial driver behaviours and attitudes (Jabeen, Olaru, Smith, Braunl, & Speidel, 2013) from a different perspective: battery-charging behaviour. Chapter 6 presents the results of confirmatory factor analysis regarding households' attitudes towards the environment and new technologies, and presents findings from hybrid choice models aimed at finding the drivers for EV acceptance.

Chapters 7 and 8, further examines findings using Best and Worst data from the two samples, mail out and PureProfile.

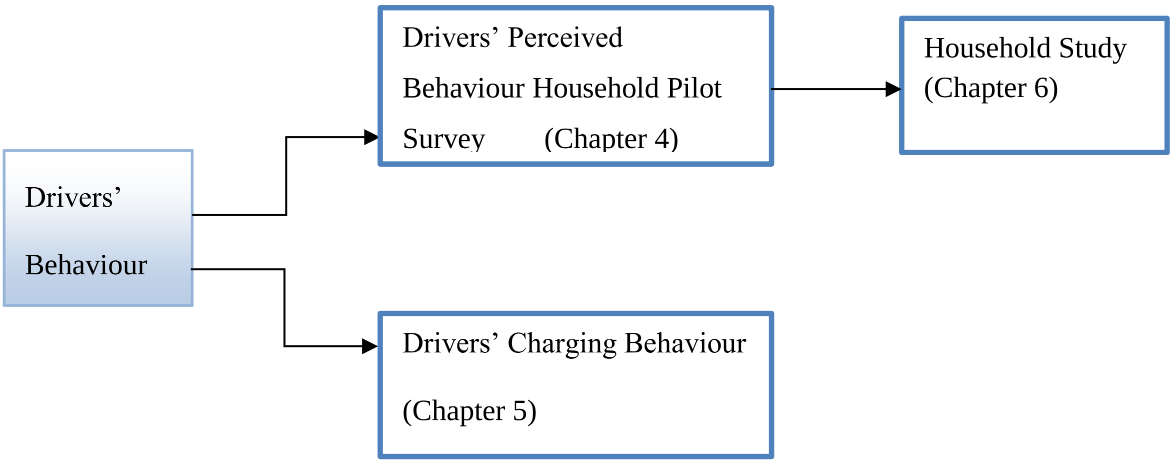


Figure 3.4: Structure of the Information Flow in this Research

CHAPTER 4

4 ACCEPTABILITY OF ELECTRIC VEHICLES: FINDINGS FROM A DRIVER SURVEY

4.1 INTRODUCTION

As indicated in Section 2.2, EVs have distinct characteristics from internal combustion engine (ICE) vehicles: limited driving range, battery re-charging, zero tailpipe emissions, and low running costs. Acceptance of alternative fuel vehicles determines the EV's place in the ensemble of vehicle technologies. The number of kilometres travelled on one charge and the need for frequent charging are factors influencing the purchase and use of an EV, along with the efficiency of the vehicle (weekly travel financial expenditure) and comfort. Individuals are likely to trade off all these features, but their decision is also affected by attitudes, preferences, and habits.

As discussed in Chapter 3 (Section 3.1.1), exploring the WA EV Trial drivers' behaviour helped to design and analyse households' EV adoption behaviour. The first survey in this regard (presented in this chapter) looks at driving experiences. This survey serves as an exploratory study, as well as a pilot for the household study.

Chapter 4 contributes to the overall research by examining in detail drivers' experiences and attitudes. Drawing on previous studies about EV uptake, this study also explores drivers concerns for the quality of the environment, confirming the hypothesis that drivers who are keen to use environmentally friendly products are also more inclined to buy an EV. In addition to this, technology learning and adoption constructs are also tested in this study, before their actual deployment in the household study. Overall, this chapter provides insights into drivers' experiences, and their perceived behaviour and attitudes towards adoption of EVs. Results of this study facilitated the design of the household survey, which aimed to explore EV adoption behaviour at the population level.

Aims and Objectives

This study explores the drivers' behaviour through a survey with the following aims:

- Identifying drivers' perceptions about EVs and their willingness to purchase an EV;

- Ascertaining participants' attitudes towards the environment and adoption of new technologies;

- Informing the research program and assisting in refining the design of the questionnaire for the household survey that was conducted separately. The EV driver survey thus serves as a pilot, testing two sections of the household questionnaire: a stated choice experiment and household attitudes towards EVs. The driver study assisted in distinguishing the most relevant characteristics for EV purchase, as well as testing the reliability of several latent constructs needed to capture households' preference heterogeneity.

The next section discusses behavioural models, followed by a description of the survey instrument. The descriptive statistics of the respondents are given in Section 4.4, after that the results of factor analysis and cluster-analysis are presented. Based on the constructs identified in EFA, regression models are tested in Sections 4.7 and 4.8. In Section 4.9, these models are further affirmed in a structural equation model (SEM), followed by discussions and conclusion of this chapter.

4.2 BEHAVIOURAL MODEL TO DETERMINE ELECTRIC VEHICLE ADOPTION

This research aims to predict the likely uptake of EVs using advanced discrete choice modelling techniques, which include attitudinal questions. In one of the past studies that examined the adoption of sustainable innovations (such as solar panels or green electricity), Ozaki (2011) explored the pro-environmental innovation adoption behaviour, and found that green environment attitudes do matter in the decision to uptake sustainable technologies; but also the strong social influence, and knowledge about perceived use of these technologies affects green electricity adoption. The motivation for exploring attitudinal data is not only that EVs are a comparatively new technology; rather, three main characteristics are distinguishing EVs from ICE: 1) battery charging, while charging infrastructure is in inception phase; 2) distinct features of EVs as compared to petrol cars as mentioned in Chapter 2 (Section 2.2); and 3) the relatively high purchase price of EVs. Those characteristics also emphasise the more environmentally friendly features of EVs, which require nevertheless some “environment commitment” of the users.

In finding which EV features, attitudes and driving experiences are likely to affect propensity to adopt an EV, a number of specific research questions need to be addressed: the direct impact of EV benefits and technical difficulties experienced while driving EV; and the effects of the attitudes towards environment and technology adoption (measured using latent constructs) on overall satisfaction whilst driving an EV. It is hypothesised that latter allows prediction of the willingness to recommend and purchase an EV (Figure 4.1).

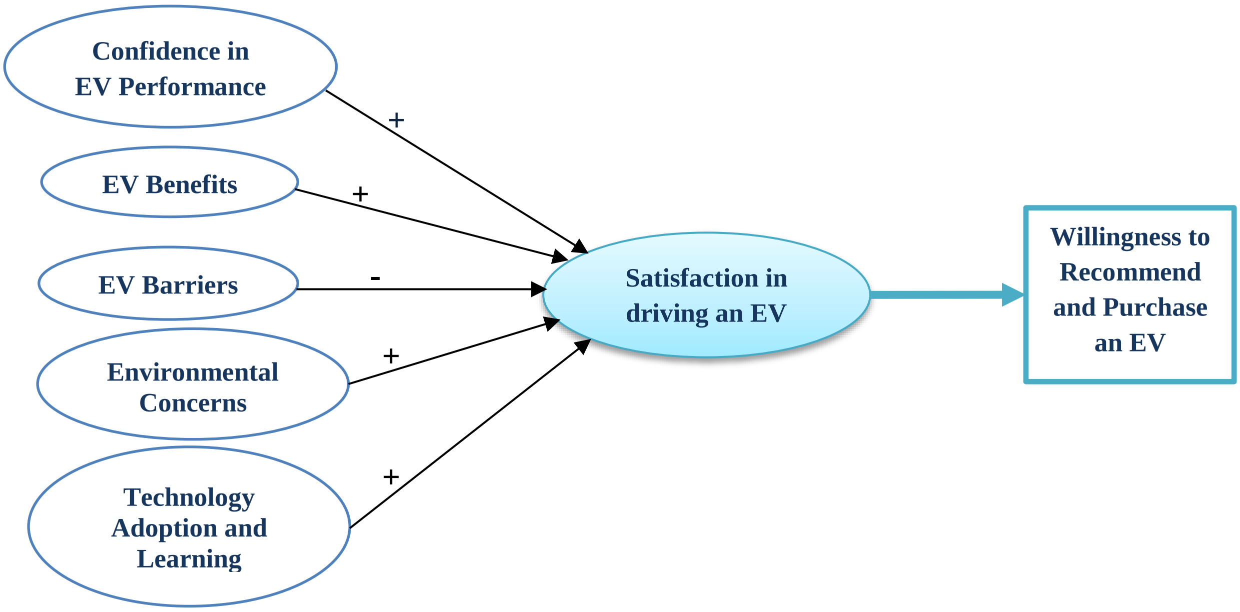


Figure 4.1: Conceptual Structural Model for Adoption

Environmental Concerns have been already been used in number of previous studies and shown to be a strong construct (Ziegler, 2012; Bolduc *et al.*, 2008). Technology Adoption was less tested in the transport literature together with EV benefits, barriers, and confidence in driving. Following on from the TAM model (Davis, 1989) these constructs are tested here as antecedents, considering the experiences of EV drivers in the trial.

In previous studies (Ozaki & Sevastyanova, 2011; Egbue & Long, 2012), consumer adoption models were applied to explore EV/hybrid vehicle adoption. Technology adoption scales developed by Ratchford & Barnhart (2012) were also adapted for this study; they included a technology adoption propensity (TAP) scale containing 14 items as reviewed in Chapter 2. Two items, relevant for the EV context, were included from this TAP scale: "*Technology gives me more control over my daily life*", and "*New technologies make my life easier*". In addition to these, a few other items were also tested here with the aim of exploring the technology adoption and learning construct.

Although the purpose of this study in the research is to test a mediating model (EV Benefits and Barriers, Environmental Concerns, and Technology Adoption and learning impact on the overall satisfaction, while driving an EV, which in turn allows the prediction of Willingness to Recommend and Purchase an EV), a direct model (Figure 4.2) was first hypothesised and tested with all predictors affecting the outcome variable, Willingness to Recommend and Purchase an EV.

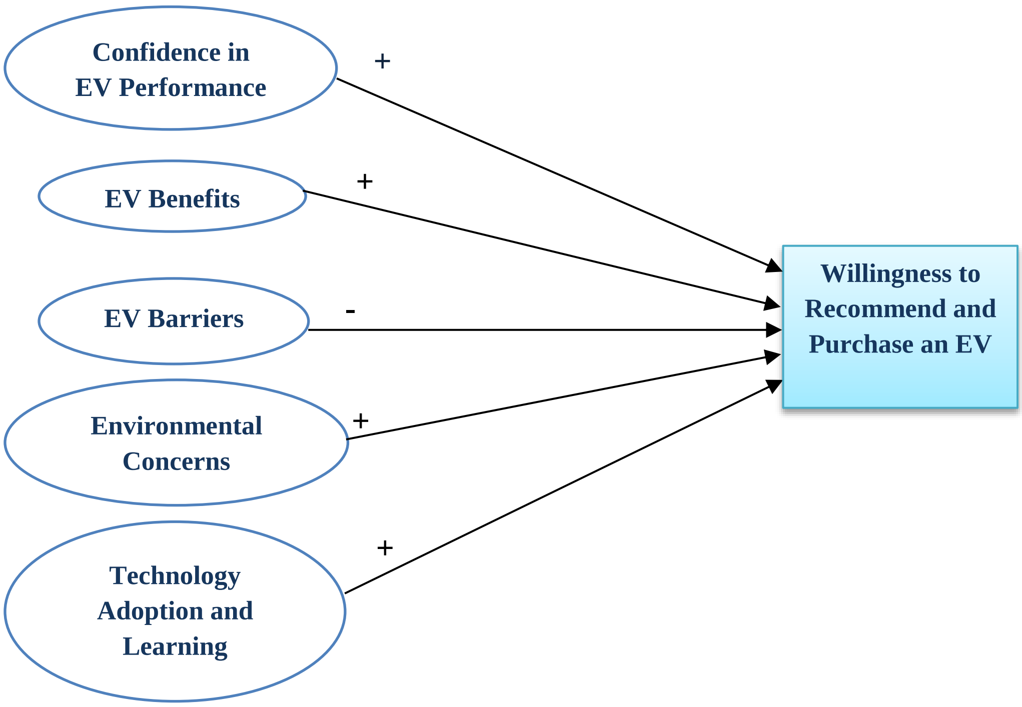


Figure 4.2: Direct Model

From the perspective of driver study, the primary hypotheses (see Section 3.4.2) include:

H1: Drivers confident in the environmental performance and efficient use of energy of EVs are more likely to recommend and purchase an EV.

H2: Drivers showing concerns for environmental changes are more likely to recommend and purchase an EV.

H3: Drivers ready to adopt and learn new technologies are more likely to recommend and purchase an EV.

H4: Perceived EV benefits influence positively the willingness to recommend and purchase an EV.

H5: Technical difficulties experienced while driving an EV influence negatively the willingness to recommend and purchase an EV.

For the model including the overall satisfaction (Figure 4.1), an additional hypothesis is considered: H6: Drivers' satisfaction with an EV is positively associated with the willingness to adopt an EV as a future car. Moreover, hypotheses # 1 to 5 are modified accordingly, reflecting the relation between antecedents and Satisfaction as response variable, as already shown in Figure 4.1.

4.3 SURVEY INSTRUMENT

A questionnaire was presented to the drivers in the WA EV trial in December 2011 (Appendix A). Because the vehicles in the trial are all converted EVs, only four respondents used manufactured EVs, with one having experience of both a converted and commercially available EV. In terms of sample size, the number of drivers using manufactured EV was small due to the limited availability of EVs in the Western Australian market.

In order to design the survey questionnaire, a focus group was conducted in November 2011 with 11 EV drivers at The University of Western Australia. The drivers discussed their EV driving experiences and perceptions towards EVs as a new technology. Overall, they were satisfied with the trial EV performance and showed confidence towards its acceptance. The participants indicated the pros and cons of EVs in the trial. The advantages of EV as discussed in the focus group included: smooth and quiet operating drive, good torque, resource management, sustainability, being a new technology (innovative) but appearing or driving like a normal car, clean energy with no emissions, low running cost, minimal service cost or no need to go for oil-checks, free reserved parking, and efficiency. The drivers also discussed the drawbacks and concerns that they had while driving an EV: limited range, finding a charging station, recharging time, trip planning, range indicator problems, and technical problems such as regenerative braking, acceleration etc. These barriers also affected the willingness of other drivers to become part of the trial, when the opportunity was presented in the induction process. The focus group participants reached conclusions on the factors that might affect EV performance in the market, such as range, performance, place and time required for recharging, substantial purchase price, limited choice of EV models, and their resale value.

In December 2011, an online survey was then sent to all EV drivers in Perth, WA. The instrument included four sections: 1) EV characteristics; 2) Driver experiences; 3) Attitudinal questions; and 4) Background questions. The socio-demographics in the survey included age, gender, education of the respondents, and number of cars at home. Since the drivers in the trial did not purchase the EVs themselves, an income question was deemed irrelevant. The questionnaire also asked drivers about the technical problems encountered when driving the EV, as well as what did they perceive to be the most and the least desirable features of EV. The overall satisfaction of driving an EV was also included in the questionnaire. A copy of the survey instrument is included in Appendix A.

4.4 DESCRIPTIVE STATISTICS

The drivers in the EV trial filled in an online survey, with 43 respondents completing all behavioural questions. Although this is a small number of respondents, the response rate was high (and the sample appropriate for representing the EV drivers in WA) considering that only a few organisations in the trial have started to use EVs, with not all the respondents using them on a regular basis.

The socio-demographics in the survey showed that the majority of respondents were male drivers (68%). Figures 4.3 and 4.4 indicate that the majority of respondents are over 30 years of age and have a tertiary education.

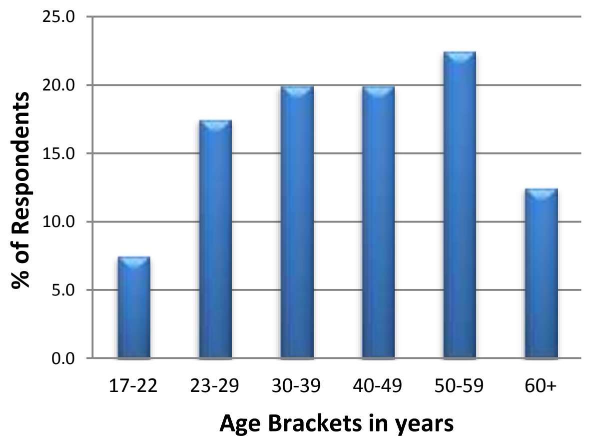


Figure 4.3: Age of Respondents

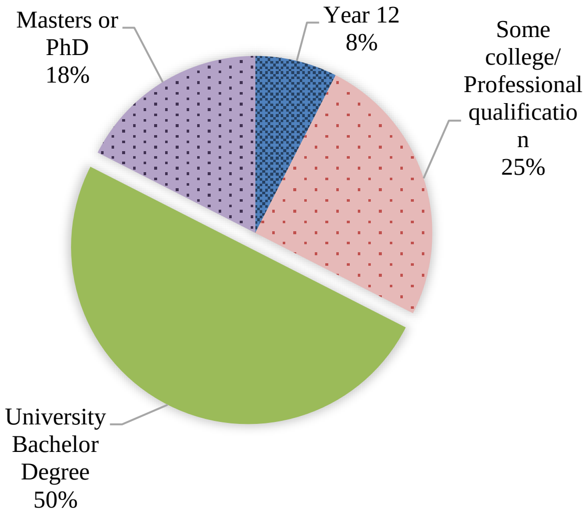


Figure 4.4: Respondents' Education

More than 80% of the drivers showed satisfaction in driving an EV, with 34.1% being extremely satisfied. This is a positive indication of EV acceptance in the WA EV trial, where 24% of respondents drive more than 50km, 39% drive 21-50km, 27% drive 10 to 20km, and only 11% drive less than 10km in a single trip.

Table 4.1: Levels of Desirable Features, and Perceived Barriers as indicated by Drivers

Desirable Features	**Levels of Desirability**
"*Zero-tail-pipe emissions*"	1st: First desirable feature
"*low running cost*",	2nd
"*reliability*",	3rd
"*low-maintenance*"	4th
"*home-charging*". "*low level of noise*"	5th: Last desirable feature
Perceived Barriers	**Levels of Seriousness**
"*limited range*" and "*purchase cost*"	1st: Most Serious barrier
"*recharging infrastructure*" and	2nd
"*recharging time*", and "*reliability*"	3rd: Least serious barrier

Table 4.1 shows that "Zero-tail-pipe emissions" was considered the most desirable feature, suggesting that the drivers are concerned about the environment. While "home-charging", and "low level of noise" appeared as the last deriable feature in the ranking done by drivers. In terms of perceived barriers for EV uptake, the respondents indicated "limited range" and "purchase cost" as the most serious barrier towards EV uptake, followed by "*recharging infrastructure*". While "*recharging time*", with "*reliability*" were marked as the least serious barrier.

As suggested by the focus group, the questionnaire presented a list of technical problems, from which the participants had to select the ones they encountered while driving an EV. Forty-two respondents answered this question, 52% indicating "*power-steering failure*", "*no regenerative braking*" and "*range indicator errors*" as the most frequent issues associated with their EVs. Other faults related to charging, braking, motor overloading and gearbox problems were reported by 10 respondents.

Since the objective of this survey was to investigate and test the role of the latent constructs against the willingness to purchase an EV, the analysis was conducted in two stages: i) exploratory factor analysis to test the validity of the latent constructs (latent factor scores were derived for use in the subsequent analysis); ii) multiple linear regression and structural equation modelling, for simultaneous assessment of the linear interrelationships between predictors for willingness to purchase EV.

4.5 EXPLORATORY ANALYSIS OF ATTITUDES TO ELECTRIC VEHICLES

Items reflecting the five latent constructs presented in Figures 4.1 and 4.2 were included as a set of five-level *Likert-Scale* questions ranging from strongly agree to strongly disagree. Some of these constructs did not converge at that stage but were tested later in the household study, with more items chosen after a review of previous studies. After the EFA stage, uni-dimensional constructs were tested. During the analysis of the constructs, a few items were found weak and consequently the constructs were redefined for the household survey. Each construct is discussed in detail below.

Environmental Concerns

This construct showed strong relationships among the variables. The basic assumptions of factor analysis are satisfied, with a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of ***0.701*** indicating a mediocre to sound underlying covariance matrix for performing factor analysis. The KMO statistic is a measure of how cleanly the data loads into the specified number of factors. The *alpha factoring* extraction method was used to maximise construct reliability; factor loadings of each element in this construct are above 0.5 (Table 4.2).

The analysis of results showed that 90% respondents agreed that "*Now is the real time to worry about our environment and this requires our immediate efforts*" and a large number (69.8%) believed that climate change is not *"a myth"*, thus indicating concern about climate change and air pollution effects. Approximately 63% of respondents showed willingness to spend extra time or pay more for products and services that can save the environment. For this construct, the reliability coefficient, Cronbach's Alpha has a value ***0.839,*** suggesting consistency of the entire scale (Hair *et al.,* 2010). Cronbach's alpha is a measure of how closely related a set of items are. It is a measure of reliability for the factors reported in the results of the model.

Technology Adoption

This important construct has been tested in previous work on the adoption of EVs as new technology (Ewing & Sarigollu, 2000). This study showed that multiple constructs may have emerged (the items were not correlated significantly for a uni-dimensional factor), thus the strongest one – *"technology learning"*, with a scale reliability of ***0.702***, was selected for further analysis and reporting.

In the survey responses about the relevance of technology adoption in EV uptake, 90% of respondents believed that "*using new technologies makes our life easier*", and 70% respondents felt that "*new technologies give more control over our daily life*". Nearly 77% of respondents showed excitement for learning new technologies, while 80% of the drivers agreed that "*keeping up with the new knowledge or technologies is necessary*".

With regard to the tendency to be fashionable, it was found that almost 30% of respondents are savvy-trendy adopters, based on their responses to "*taking up new technologies makes one trendy*", and "*being fashionable means having up-to-date knowledge of the techno-world*". Approximately 44% of respondents did *not agree* that "*new technologies cause more problems than they solve*".

The sampling adequacy (KMO) value of ***0.669*** and loadings above 0.59 indicated that this structure for the one-dimensional *Technology Learning* construct is appropriate.

EV Benefits and Challenges

The most important EV benefits, identified by respondents, included: convenience of home battery recharging and reduced average travel cost per trip. The respondents were also comfortable with recharging their EV at public stations, although almost half of the respondents mentioned that they need to do a lot of planning of activities when driving an EV.

In regard to EV technical difficulties, only 20% of the respondents believed that EVs have problems with acceleration while 29% did not agree that EVs incur significant maintenance costs.

Neither of the constructs, *EV Benefits* and *Technical Problems Associated with EV* had adequate reliability in this sample, and consequently they were not used further in the structural analysis.

Willingness to Recommend and Purchase an EV

This construct showed strong relationships among the variables (KMO=***0.726***). Factor loadings of the elements in this construct (all above 0.8) are given in Table 4.2. The Cronbach's Alpha had the highest value of all constructs, ***0.905***.

Table 4.2: Factor Loadings: Environmental Concern, Technology Learning, and Willingness to Recommend and Purchase an EV

Attitudes towards EV: Factors and their respective factor loadings		
Environmental Concern	**KMO*=0.701**	**Cronbach's Alpha=0.839**
Items		**Factor Loadings**
Now is the real time to worry about the effects of air pollution.		**0.804**
I am concerned that future generations may not be able to enjoy the world as we know it currently.		0.765
Saving the environment requires our immediate efforts.		0.746
I am willing to pay more for products or services only to save the environment.		0.704
I am willing to spend extra time only to save the environment.		0.603
Vehicle emissions can destroy our flora and fauna.		0.565
Technology Learning	**KMO=0.669**	**Cronbach's Alpha=0.702**
Items		**Factor Loadings**
I am excited to learn to use new technologies.		0.703
Reverse (Things have become so complicated today that it is hard to understand what is going on in this techno-world.)		0.716
I love gadgets.		0.591
Willingness to recommend and purchase an EV	**KMO=0.726**	**Cronbach's Alpha=0.905**
Items		**Factor Loadings**
I prefer to use EV over any other type of cars.		**0.963**
I would recommend EV to others.		**0.838**
I would buy an EV as my next car.		**0.837**
**** Measure of sampling adequacy (Kaiser-Meyer-Olkin)***		

The results of the analysis show that approximately 65% of respondents would recommend EVs to others. Buying an EV as a next car is chosen by 27.9% of respondents, while 35% of respondents would prefer to use an EV over any other cars. This percentage of driver's showing a preference for EV over any other type of car indicates a positive attitude towards EV and acceptability of the electric car.

Following the factor analysis, factor scores were calculated for the three constructs, based on their score coefficients.

4.6 TYPOLOGY/TAXONOMY OF WA EV SUBJECTS

The factors or latent constructs identified have been used to group respondents/subjects with similar behaviour. *"Cluster analysis is a group of multivariate techniques whose primary purpose is to group subjects based on the characteristics they possess"* (Hair *et al.*, 2010: 508). This typology construction method is used here to group EV subjects based on their socio-demographics (age, gender, education, number of cars at home) and attitudes (as identified above: Environmental Concerns, Technology Learning, and Willingness to Recommend and Purchase an EV).

In order to classify the respondents, hierarchical clustering was first used to determine the number of clusters in this sample. Ward's method was used as an agglomerative algorithm (Hair *et al*., 2010) starting with individual observations as clusters and grouping them together by their similarity (Euclidean distance). The criterion used to decide on the number of clusters is the loss of homogeneity in the newly formed cluster, compared to the clusters that are combined. Ward's method is ideal for a small number of observations. After determining the number of clusters, the K-means non-hierarchical clustering algorithm was applied to get the final cluster solutions. The combination of hierarchical and non-hierarchical clustering algorithms indicated the existence of three clusters.

All clusters indicated a pro-environment behaviour, but they varied in technology learning behaviour and in their willingness to recommend and purchase an EV. The first group of subjects labelled *Unlikely to Recommend and Purchase an EV* comprises 14 subjects, with slightly more males (8 out of 14), higher proportion (8) having a University Bachelor Degree, and most of them (10) owning at least two cars. This group represents educated drivers, with environmentally friendly attitudes, neutral on learning new technologies, and unwilling to recommend and purchase an EV, although they do not rely on only one vehicle. The second cluster consists of 13 subjects, only two being female, with more than half having a University Bachelor Degree and being above 40 years of age (8). Ten subjects in this cluster have two or more cars. They represent *Supporter EV-Environmental* people who are willing to recommend and purchase an EV because they are concerned about the environment, although they are not technology savvy.

The third group comprises 15 subjects who are relatively young (seven less than 30 years old) and includes six females. Ten of the 15 had at least two cars at home. In this comparatively young group, seven out of 15 completed Year 12 or some college/professional qualification. This group, named *Technology Promoters-Environmental*, shows pro-environmental behaviour, and an excitement to learn new technologies; they are neutral in their willingness to recommend and purchase an EV.

Profiling of the clusters in their attitudes (expressed as factor scores) and willingness to recommend and purchase an EV is given in Figure 4.5.

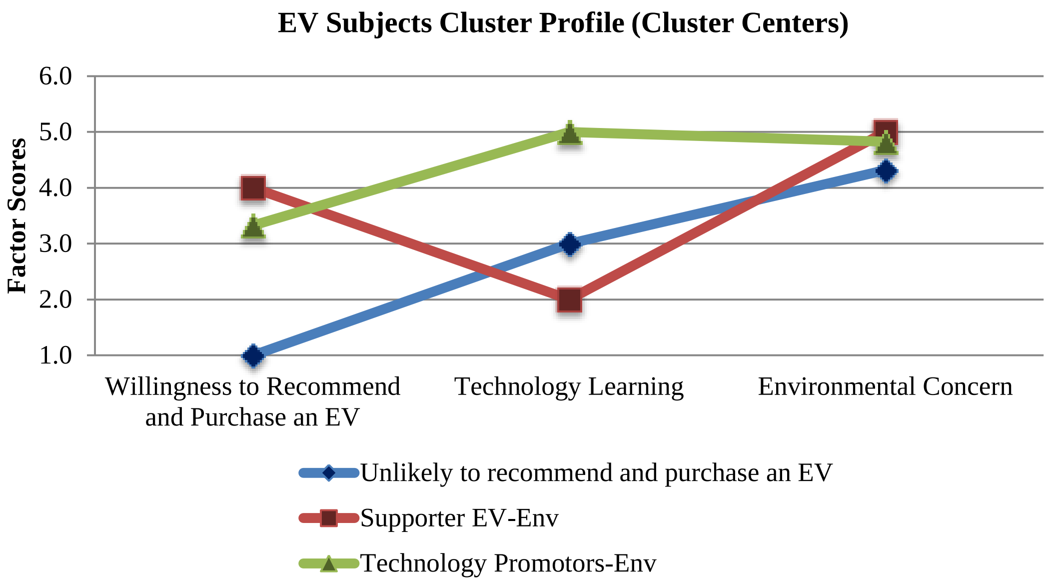


Figure 4.5: Taxonomy of WA EV Subjects

The analysis suggests that even in this small group of EV drivers, there is heterogeneity in attitudes towards the environment, new technologies, and EVs. Ignoring this aspect, may incorrectly lead to conclusions that "one-size" policy options can be successful in the uptake of EVs. The household surveys (Chapter 6) target a variety of different population groups to achieve a more comprehensive assessment of attitudes.

4.7 ANTECEDENTS OF EV ADOPTION

Once all the possible factors were identified, the next step was to quantify the effect of different factors in the willingness to adopt EVs. As suggested in the hypotheses, the set of independent variables identified for this model include: *Environmental Concerns*, attitudes towards *Technology Learning*, *EV Benefits*, *EV Technical Barriers*, being a savvy-trendy adopter (*Technology Adoption*), and having *Confidence in EV Performance* (Figure 4.6). In order to explore their impact on the willingness to adopt EVs, the latent constructs were tested in a multiple regression model.

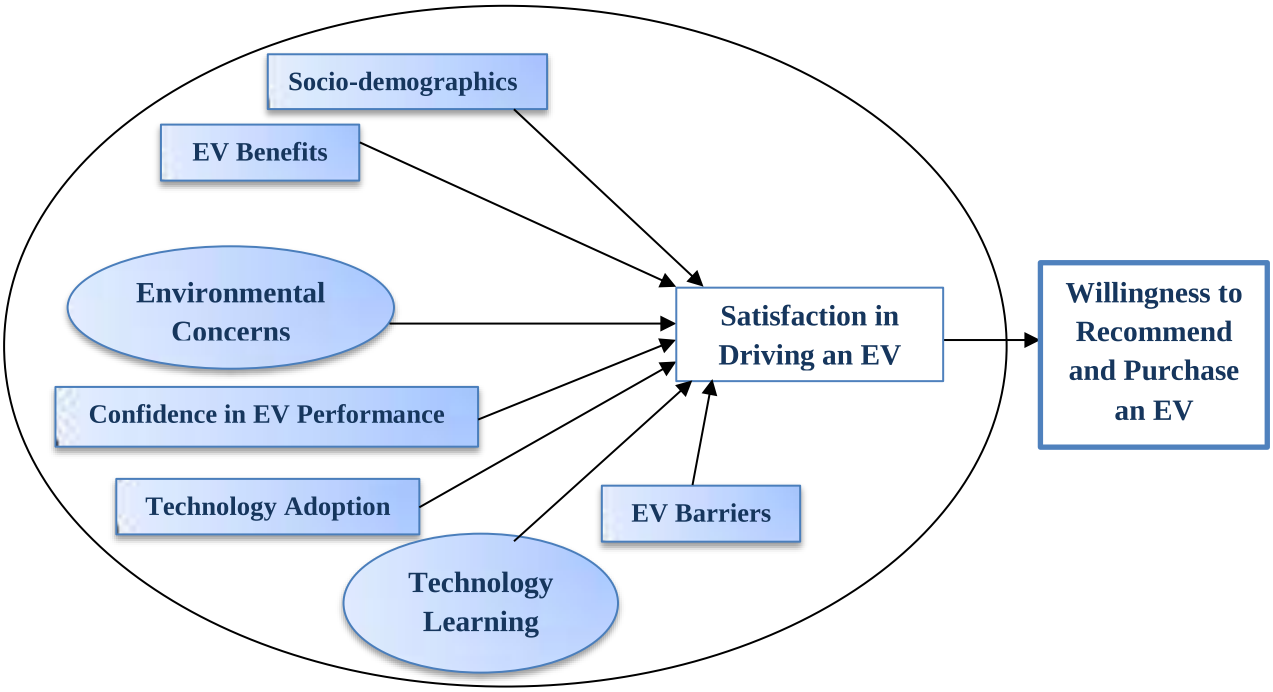


Figure 4.6: Antecedents of EV Adoption

The regression model initially tested all the independent variables, but the high correlations among the explanatory variables resulted in multicollinearity issues (Hair *et al.*, 2010). The correlations between independent variables and the willingness to purchase and recommend an EV are given in Table 4.3.

Table 4.3 shows that all independent variables (Confidence, LessMoney, EV_B1, EV_B2, OvSat) have moderate correlations with each other. Overall satisfaction in driving an EV (OverallSat) is related to EV Benefits (EV_B1, EV_B2), and to being confident in environmental performance and efficient use of EV energy (Confidence). Similarly, a lower amount of money spent to fix an EV in the last 3 months (LessMoney) has a positive impact on the overall satisfaction (OverallSat), and perceived EV benefits (EV_B1, EV_B2).

Table 4.3: Correlations between Independent Variables and Willingness to Recommend and Purchase an EV

	Independent Variables	***Willingness to Recommend and Purchase an EV*** **Correlation Coefficients**	**Significant Cross Correlation Coefficients between Potential Explanatory Variables**
AGE	What is your age (years)?	0.143	
HE	What is your highest level of education?	-0.152	
TechL	*Technology Learning construct*	0.157	
EnvC	*Environmental Concern construct*	*0.250*	
Confidence (in EV Performance)	How confident are you in the environmental performance and efficient use of energy of EV?	**0.561****	**EV_B1 (0.448*), EV_B2 (0.434*), OverallSat (0.475**)**
AdoptTech Tech_B	New technologies give more control over our daily life.	-0.004	
TFashion	Being fashionable means having up-to-date knowledge of the techno-world.	0.077	
LessMoney	Reversed (I spent a significant amount of money to fix my EV in the last 3 months).	**0.476****	**Acceleration (0.454*), EV_B1 (0.482**), EV_B2 (0.449*), OverallSat (0.441*)**
Acceleration	I believe EV has no problems with acceleration.	**0.346***	**LessMoney (0.454*)**
Home Charging EV_B1	Battery recharging at home is convenient for my EV.	**0.594****	**Confidence (0.448*), LessMoney (0.482**), EV_B2 (0.509**), OverallSat (0.552)**
Driving Cost EV_B2	EV driving reduces my average travel cost/trip.	**0.491****	**Confidence (0.434*), LessMoney (0.449*), EV_B1 (0.509**), OverallSat (0.560**)**
Overall Satisfaction OverallSat	Overall, how satisfied are you driving an EV?	**0.634****	**Confidence(0.475**) , LessMoney (0.441*), EV_B1 (0.552**), EV_B2 (0.560**)**
*** p<.05**	**** p<.01**		

One of the remedies for multicollinearity is to omit one or more highly correlated variables, and identify other independent variables to help the prediction (Hair *et al.*, 2010). To address multicollinearity and given the reduced sample size, a backwards elimination procedure was applied. Two different models were tested, with overall satisfaction and EV benefits being the response variables (results presented in Tables 4.4 and 4.5).

4.8 DETERMINANTS OF WILLINGNESS TO RECOMMEND AND PURCHASE AN EV

With a coefficient of determination R^2 =0.643, the regression model presented in Table 4.4 confirms a subset of the hypotheses formulated in Section 4.2. The standardised coefficients indicate the relative importance of predictors in the same units or standards, regardless of the measurement scale used for the independent variables (Hair *et al*., 2010). When considering the socio-demographics, age played a significant positive role in the model, with younger people less likely to recommend and purchase an EV (β for AGE is 0.185; Table 4.4). This might be explained by the sample structure, with more than 30% of respondents being 50 years of age or older. However, this may reflect a correlation between age and income and subsequently the capacity to purchase the higher priced of an EV. The AGE variable is even more significant in Table 4.4 where β is 0.260.

The first hypothesis of this study *("Drivers confident in the environmental performance and efficient use of energy of EV are more likely to recommend and purchase an EV"*), is confirmed with a standardised coefficient of 0.262. The third hypothesis shows mixed results with one positive coefficient (Technology Learning 0.198) and a negative one (Control given by technologies -0.287). Hypotheses 2 and 4 were not tested in this model because of the multicollinearity issues (Table 4.4) and lack of variability of the construct variables: *Environmental Concerns* and *Perceived Benefits of EV*. Hypothesis 5 is also confirmed with a significant negative coefficient and the highest β in absolute terms (0.367). The satisfaction variable (OverallSat) comes next (0.336), confirming hypothesis 6 that overall, drivers' satisfaction with EV reflects the willingness to adopt EV as a future car.

Table 4.4: Regression Model including the Satisfaction Variable as an Independent Variable

	Dependent Variable: ***Willingness to Recommend and Purchase an EV***	**Unstandardised Coefficients**		**Standardised Coefficient**	**Significance Level p**
	Independent Variables	**B**	**Std. Error**	**Beta**	
	(Constant)	-0.716	0.815		0.385
AGE	What is your age (years)?	**0.127**	**0.072**	**0.185**	**0.086**
Confidence (H1)	How confident are you in the environmental performance and efficient use of energy of EV?	**0.370**	**0.177**	**0.262**	**0.044**
TechAdoption Tech_B (H3-A)	New technologies give more control over our daily life	-0.371	0.146	-0.287	0.016
TechL (H3-B)	*Technology learning construct*	0.281	0.174	0.198	0.114
Tech_Diff Money (H5)	I spent a significant amount of money to fix my EV in the last 3 months	**-0.387**	**0.125**	**-0.367**	**0.004**
OverallSat (H6)	Overall, how satisfied are you driving an EV?	**0.338**	**0.131**	**0.336**	**0.014**

As discussed in more detail in the next section, Satisfaction is considered a mediator between the EV Benefits, EV Barriers, and Technology Learning constructs, and the Willingness to Recommend and Purchase an EV.

The regression model in Table 4.5 tests the hypotheses after excluding the Overall Satisfaction from the list of predictors. Independent variables that were not significant were removed from the model, one at a time, while exploring the impact of the remaining variables. The regression model, containing significant variables, is given in Table 4.5. It has an R^2 value of 0.592, indicating that variables in this model explain 59.2% of the variability in the Willingness to Recommend and Purchase an EV.

The second hypothesis in this study *("Drivers showing concerns for environmental changes are more likely to recommend and purchase an EV")* is not confirmed by the model, but this may be due to the sample size and limited variability in the construct (the average factor score is 3.71, with a standard deviation of 1.02).

Again, hypothesis 3 does not have full support with the question on *"technology's control over lives"* displaying a negative relationship. This negative coefficient was unexpected, however it might be due to the fact that most of the respondents in this study have experience of driving converted EVs, not commercially manufactured EVs. Another possible reason might be the word "control". This item was reconsidered for the household survey and instead of "control over our daily life", the question was reformulated using a positive tone and phrases (for example "*Using new technologies in our daily lives makes life easier*.")

Table 4.5: Regression Model for
Willingness to Recommend and Purchase an EV

	Dependent Variable: *Willingness to Recommend and Purchase an EV*	**Unstandardised Coefficients**		**Standardised Coefficient**	**Significance Level p**
	Independent Variables	**B**	**Std. Error**	**Beta**	
	(Constant)	0.411	1.416		0.773
AGE	What is your age (years)?	**0.180**	**0.082**	**0.260**	**0.036**
EnvC (H2)	*Environmental Concern Construct*	0.224	0.172	0.150	0.201
TechAdoption Tech_B (H3-A)	New technologies give more control over our daily life	-0.382	0.172	-0.299	0.034
TechL (H3-B)	*Technology learning construct*	0.387	0.178	0.278	0.037
EV_B1 (H4-A)	Battery recharging at home is convenient for my EV.	**0.266**	**0.124**	**0.308**	**0.040**
EV_B2 (H4-B)	EV driving reduces my average travel cost/trip.	**0.284**	**0.147**	**0.268**	**0.062**
Tech_Diff Money (H5)	I spent a significant amount of money to fix my EV in the last 3 months.	**-0.305**	**0.151**	**-0.289**	**0.051**

Hypothesis 4 of the study *("Perceived EV Benefits influence positively the Willingness to Recommend and Purchase an EV")* is confirmed, with EV_B1 (home charging) and EV_B2 (reducing cost) having β coefficients of 0.308 and 0.268, among the highest in the model. This demonstrates that perceived EV benefits (low driving cost and home charging) positively influence the willingness to recommend and purchase an EV. This is consistent with the previous literature: e.g., Kurani *et al.* (1996) identified the home-charging as a key benefit of EV.

Hypothesis 5, regarding the relationship between experienced Technical Difficulties while driving an EV and the Willingness to Recommend and Purchase an EV, is confirmed as well, with a negative coefficient and a β value of -0.289. Technical difficulties are a deterrent for EV uptake. This is well supported by the literature. Dagsvik *et al.* (2002) indicated that *alternative fuel vehicles can compete with petrol cars if maintenance and refuelling infrastructures for alternative fuel vehicles are well established*. It is expected that these coefficient values could be different if there were a greater number of respondents driving commercially manufactured EVs (with less technical difficulties) instead of converted EVs.

4.9 STRUCTURAL EQUATION MODEL

As discussed in Section 4.7, high correlations among independent variables lead to multicollinearity issues. While testing the determinants of EVs it was found that the Overall Satisfaction variable may have had a mediating role. For this reason, a structural equation model (SEM) approach (Meyers, Gamst, & Guarino, 2006) was used to determine the role of Overall Satisfaction as a mediator between socio-demographics, EV Benefits, Barriers, Environmental Concerns, Confidence in Environmental Performance, Technology Learning and the Willingness to Recommend and Purchase an EV. This model was tested using AMOS software. Given the limitation of small sample size (N=43), the structural model was estimated using factor scores and also applying bootstrapping. The conceptual model is presented in Appendix B.

The results of SEM supported the model presented in Figure 4.7, the negative sign of EV Barrier (i.e., *I spent a significant amount of money to fix my EV in the last 3 months*) further supports theory that Overall Satisfaction decreases with an increase in the maintenance cost. Among socio-demographics, education appeared to be significantly related with Overall Satisfaction.

Table 4.6: Estimates of Structured Equation Model (SEM)

Parameter Estimates			Regression Weight	Standardised Regression Weight	Significance Level p
Overall Satisfaction	<---	EV driving reduces my average travel cost/trip (low running cost)	**0.348**	**0.339**	**<0.001**
Overall Satisfaction	<---	Confidence in Environmental Performance of EV	**0.269**	**0.196**	**<0.001**
Overall Satisfaction	<---	Battery recharging at home is convenient for my EV (home charging)	0.269	0.330	0.011
Willingness to Recommend and Purchase an EV	<---	Confidence in Environmental Performance of EV	**0.352**	**0.262**	**<0.001**
Willingness to Recommend and Purchase an EV	<---	Battery recharging at home is convenient for my EV	**0.269**	**0.338**	**<0.001**
Willingness to Recommend and Purchase an EV	<---	Overall Satisfaction	**0.352**	**0.359**	**<0.001**
Model Fit: χ^2 (6)=13.55, p<0.05; Goodness of Fit Index (GFI)= 0.89; Root Mean Square Residual (RMR)= 0.189					

A number of competing SEM models were tested according to theory, and items statistically non-significant were removed. The model presented in Table 4.6 had a better model fit compared to the small sample size. Chi-square value of X^2 (6)=13.5, p<0.05 is significant and CMINDF=2.25, GFI index=0.89, and RMSR (root mean square residual) = 0.189 suggest that the hypothesised model is acceptable (reasonable fit to the observed data), given the small sample size (N=43). The path diagram of the SEM model is given in Appendix B. With nine parameters, direct and indirect effects were tested here for EV benefits, Confidence in EV Performance against Overall Satisfaction and Willingness to Recommend and Purchase an EV. EV home-charging benefit and Confidence in EV Performance positively affect Overall Satisfaction and Willingness to Recommend and Purchase an EV (β=0.338, β=0.262 respectively); thus they had direct and indirect effect (β=0.330, β=0.196 respectively) on Overall Satisfaction and then Willingness to buy an EV. Overall Satisfaction thus partially mediates the relation between Confidence in EV Performance and EV home charging benefit, against Willingness to Recommend and Purchase an EV. The low running cost benefit only directly affects Overall Satisfaction (β=0.339) with no direct influence on Willingness to buy an EV. Overall Satisfaction thus totally mediates between low running cost and Willingness to Purchase and Recommend an EV. This mediation indicates a trade-off between low running cost, and high purchase price of EV. That is, on buying an EV, one might be willing to pay a higher price because it will allow the use of the EV with a low running cost. This trade-off was included in the experimental design for households where SP respondents were given scenarios that contained these two variables (running cost, and purchase price) as vehicle attributes.

From these results it was further indicated that running cost and recharging time must be added as attributes of vehicles compared in the household survey.

4.10 DISCUSSION AND FUTURE RESEARCH

The independent variables taken into account in this study were derived from the literature and were further refined after the focus group research. This study primarily explored the behaviour and experiences of drivers already using an EV in the WA EV trial. With a restricted number of respondents (N=43), only a limited number of hypotheses have been tested and confirmed. One of the limitations of this study is that among the small set of respondents (N=43) the majority of drivers used converted EVs, with only four drivers having experience of driving manufactured EVs. Intuitively one would expect the results to be different if there were more drivers of commercially manufactured EV. Nevertheless, this aspect does not have a negative bearing on the main objective of the study, that is to discover the drivers' perceptions and attitudes towards EVs, and to determine how their experiences might affect acceptability of electric vehicles.

The weakness of the few constructs was also noted as another limitation and these constructs were further revised for the household survey. In the cluster analysis/typology construction, one of the groups consisting of 15 subjects was found to include technology promoters: drivers who showed Excitement for Learning New Technologies and had a pro-environmental attitude. Another group of EV supporters were found to be concerned mainly about the environment. These observations from cluster analysis are indicative of the heterogeneity in drivers' attitudes towards the environment, new technologies, and EVs, providing useful guidelines for exploring drivers' perceived behaviour and looking at households' EV purchase decision in the next experiment.

Since the Overall Satisfaction variable seems to be a mediator between perceived EV benefits, EV technical difficulties, attitudes towards technologies constructs and Willingness to Recommend and Purchase an EV, a structural equation modelling approach was tested, acknowledging the limitation of the small sample size. The results of SEM model confirmed and supported the antecedents of EV adoption identified in Figure 4.7. The mediating role of satisfaction allowed a trade-off between the running cost and purchase price of an EV that is reflected in the household stated preference experimental design.

4.11 CONCLUSION

This chapter explored the EV drivers' behaviour and their perceptions and attitudes towards new technologies. Experiences of drivers in the trial were useful for exploring the impact of EV benefits any technical difficulties inhibiting the acceptance of EV. The drivers showed confidence in the EV's environmental impact and its efficient use of energy. The range was considered a serious barrier to EV uptake, with almost half of drivers indicating that they require significant trip planning, especially for trips longer than 30km.

The analysis of the driver survey also aimed to refine latent constructs such as *Technology Adoption* and *Environmental Concerns*, leading on to the household survey. With the data from the driver survey, the reliability of the constructs was assessed and items with low value of loadings were revisited. Although *Environmental Concerns* appeared non-significant in the regression models, all clusters exhibited pro-environmental behaviour. Another supporting argument for an environmental concern construct is that "*Zero-tail pipe emissions*" is ranked as the most desirable feature of EVs by the drivers in the trial.

The next chapter (5) explores EV drivers' battery charging behaviour through stated choice experiments: hypothetical scenarios were designed to investigate drivers' preference for charging duration, place where they would prefer to charge (work/home/public), and cost of battery charging. Scenarios presented to drivers were hypothetical, because most drivers used home-charging or work-charging, being part of the WA EV trial. The vehicles were parked and plugged-in for charging at the organisation, and at the time this survey was conducted limited public charging stations were available; hence drivers were given a set of assumptions prior to presenting them with the set of experiments. Findings indicate that drivers had a preference for low charging cost and short charging durations.

CHAPTER 5

5 ELECTRIC VEHICLE BATTERY CHARGING BEHAVIOUR: FINDINGS FROM A DRIVER SURVEY

5.1 INTRODUCTION

Chapter 4 explored the drivers' perceived behaviour towards EV adoption, and the findings indicated that the perceived Benefits of EV, the Environmental Concerns construct, and the Excitement to Learn New Technologies were significant predictors for the Willingness to Recommend and Purchase an EV. This chapter explores drivers' EV battery charging behaviour which is relevant to the adoption of EV – especially when EV charging infrastructure is in early stages of development. As mentioned in Chapter 2, battery-charging characteristic makes EVs different from petrol or alternative fuels and requires a shift in re-fuelling behaviour. While exploring behaviour and attitudes about adopting EVs, it is pertinent to look at the EV drivers' charging preferences.

Charging can be done at home (mostly overnight), at public charging stations, or specific bays provided at workplaces. Depending on battery status, energy requirement for a trip, or charging cost, it might be more convenient to charge an EV at work or a public charging station, rather than at home. Charging at work may not be free and usually a limited number of bays with charging facilities are available. Similarly, public charging stations may be located only at certain locations, which require careful trip planning. Nevertheless, the public charging stations provide quick charging and are located in places of wide interest (shopping centres, hotels, transport hubs), possibly offering also the privilege of a reserved or free parking bay.

In this way, there is a trade-off between the generalised cost (including the electricity price and the duration of charging) and the convenience of charging an EV. For example, charging at home might be convenient and cheap (the cost of electricity at home during off-peak hours is much lower than on-peak (evening or a few hours during the morning), but it takes longer. For the purpose of this study, a number of assumptions were made: drivers privately own a new EV, they have a charging facility at home, and also have the possibility to charge at work (with a free parking bay) and at a public charging station, located within their daily itinerary. It is assumed the EV is the main car at home, and its current battery status is 30% full. Finally, the assumption is that drivers are planning their next working day and travel, so they are not pressed to charge at the first station in order to arrive at the destination.

Although currently the charging infrastructure is not well established in Perth, this study aims to determine drivers' preferences for various options for EV battery charging as if they had full access to charging facilities at work, at a public station and at home. Four choice experiments, in which drivers indicated their best and worst choice for charging an EV were used to elicit information about charging preferences (Section 5.3). The findings of this study indicated that: drivers prefer to charge their EV at home or work rather than at public charging stations; drivers having solar panels at home prefer to charge their EV at home; people having travel commitments involving other family members do not like to charge EV at home, but generally prefer to use a public charging station. Members of the Australian Electric Vehicle Association (AEVA), one of the partners in the WA EV trial, preferred to charge at home. Drivers were in general sensitive to cost and showed a strong preference for low cost EV charging.

The next section gives more detailed information about battery charging options, with the duration and cost, including home charging with solar panels. Discussion of previous studies that explored battery charging behaviour is also included here, followed by a discussion about the design of stated choice experiments. Section 5.4 presents the findings about the drivers' battery charging behaviour. Results of this stated preference experiment bring several useful insights as further elaborated in the discussion section.

5.2 ELECTRIC VEHICLE BATTERY CHARGING

Home charging differs from charging at work or at a public charging station both in terms of charging duration and cost. People with solar panels at home can use solar energy for EV charging during the daytime hours. This and other variations in the options for EV charging, were presented to respondents in a set of assumptions before starting the experiment – as presented in the next section

Battery Charging Levels: Time and CostBattery charging cost

depends on the charging station Level (fast and expensive or slow and inexpensive), the time of the day, and the place. Level II and Level III are fast charging stations, while Level I represents a slow charging station. Accordingly, a Level I charging station is much cheaper (little over $1,000) than the Level II ($2,300 - $6,000), and Level III charging stations ($50,000 to $100,000)[3]. A Level I charging unit (usually installed at home) recharges a battery from empty to full in 6-8 hours. Level I is ideal for home use as it uses 120V circuits providing power to the vehicle (National Research Council, 2013). A Level II charging station provides faster charging by

[3] http://reneweconomy.com.au/2014/pulling-back-veil-ev-charging-station-cost-39804

using 240V AC power, reducing charging time to 2-4 hours. Level III is also called a DC charging station because it converts AC voltage power to DC (National Research Council, 2013) and charges the EV battery at a speed of 10-30 min for a full recharge. The DC charging station is ideal for public charging because of its speed. In 2014, a Level III Combo-CCS fast charging station, costing $30,000 excluding installation and able to charge an EV in 30 minutes from empty to an 80% level,[4] is installed at UWA as part of the renewable electric vehicle (REV) Project. Level III with CHAdeMO technology (CHAdeMO, 2015) is ideal for a public charging station because it can charge to an 80% level in 30 minutes.

The price of electricity is determined by the time of the day; In Perth, the peak rate (morning, late afternoon and evening) is most expensive, while off-peak (usually during the night) has the lowest rate (Table 5.1). The price also differs between home and business (work or public).

There are two power suppliers in WA: Synergy mainly supplies the metropolitan area, while Horizon Power covers the rest. An overview of the on-peak and off-peak rates is given in Table 5.1, as accessed from WA power supplier website (Synergy, 2012a). These values were used when designing the stated choice experiment.

[4] http://www.news.uwa.edu.au/201411127146/business-and-industry/new-fast-charging-station-electric-vehicles-uwa

Table 5.1 Electricity Rate Synergy Home Plan effective from July 2012 (Synergy 2012a)

Time*	Rate
Peak	45.87 cents per kWh
Off-peak	13.97 cents per kWh
Shoulder	24.44 cents per kWh
* *These times vary during summer and winter hours*	

Home Charging with Solar Panels

Solar energy systems allow their owners to generate surplus electricity during the day, thus offering zero cost charging for EVs at home during the day. The photovoltaic power generation systems with benign impact on the environment (Tsoutsos, Frantzeskaki, & Gekas, 2005) can potentially be ideal for EV charging, when compared to conventional energy generation sources. The cost of EV charging at night depends on the type of solar panels and the electricity supplier. Synergy offers a buyback cost of surplus energy during the day at a fixed rate of 8.4 cents/kWh, but during night hours households have to buy at the standard rates (Synergy, 2012b). The buyback rate by Horizon Power varies across rural areas in WA from 10 cents/kWh to 50 cents/kWh (Horizon Power, 2012).

Charging Behaviour: Previous Studies

Yilmaz & Krein (2013) reviewed the current status of battery chargers for plug-in EV and plug-in hybrid vehicles, and found that there are no defined international standards for battery charging infrastructure. A number of studies investigated battery-charging behaviour from different perspectives. For example, Peterson & Michalek (2013) assessed the cost effectiveness of charging infrastructure, and suggested using plug-in hybrid (PIH) electric vehicles to reduce petrol consumption in US. Schroeder & Traber (2012) linked the economic aspect of establishing the charging infrastructure with the adoption of electric vehicles. Through simple valuation methods in Germany, they found that a reasonable return on investment in a Level III charging station depends on demand and the large scale adoption of EV.

Axsen & Kurani (2012) analysed residential access to vehicle charging in order to develop an understanding of demand for plug-in electric vehicles', their use and energy impacts. Their findings from two different experiments were: i) about half of the USA population had Level I home charging access; ii) one third of the population in San Diego County had access to Level II home charging, while 20% of people were willing to pay the costs required for Level II installation. A higher percentage of residents having home charging access desired to have their next vehicle an EV as compared to those who had no access. Their study did not cover all geographic regions in USA; however, they suggested a relationship between EV charging access and EV adoption.

5.3 A STATED PREFERENCE INQUIRY INTO THE CHOICE OF CHARGING LOCATION

The WA EV Trial: Conditions Applying for this Study

As already mentioned in Chapters 3 and 4, a limited number of EVs are being driven in Perth as part of the WA EV trial to monitor the performance, benefits, infrastructure and practical implications of the EV fleet. This trial covers 11 participant organisations, each owning a number of EVs. This survey explores battery charging preferences for the drivers in the WA EV trial (Section 3.1.1) and how EV drivers plan their trip considering the limited range of EVs (A copy of the questionnaire is attached in Appendix C). Because these drivers had experience with EVs owned by their organisations, the drivers were asked to answer the survey as if they possessed "*their own electric car*". The main objective of this assumption was to determine preferences for charging time, charging location, and duration of charging, for EV drivers in Perth.

In addition to the assumption of privately owning a new EV, drivers were asked to consider that they are planning their trip for the next working day, indicated as "*tomorrow*". EV drivers were given the following scenario:

- *"You own a new Electric Vehicle with a charging facility at your home; Level-I charging units are installed at home (Level I charging units are slower as compared to Level II or Level III). The cost of re-charging the EV will be added to your electricity bill, however if you have solar panels at home it will reduce the cost to zero.*
- *Suppose the requirement for your EV battery charging is from Empty (30%) to Full (100%), that is currently your battery status is 30% full.*
- *Your workplace provides free parking space for your car and you can book a bay to recharge your car if needed (Level II and Level III fast charging units are provided). There is however a price for charging at work (you are charged at the rate shown in each combination of options).*
- *A public charging station is available en route between home and work and there is a max 10 mins queuing time. However these public charging bays are located close to attractions (like coffee shop, a mall or a playground). You are charged at the rate shown in each combination, and Level II and Level III fast charging units are provided.*
- *You are planning your activities and travel for tomorrow, which is a working day.*
- *Your new EV is the principal vehicle in your household."*

The Design of the Stated Preference Experiment

The choice tasks in the stated preference (SP) discrete choice experiment for EV charging included three factors identified as relevant to this decision: the time of day, the duration of charging, and the cost of electricity. The attribute levels are shown in Table 5.2.

Table 5.2: Attribute Levels for Experimental Design

Attribute Levels for Work/Public Station Charging	
Attributes	**Attribute levels**
When	8:00 AM; 1:00 PM
How Long	10 mins; 20 mins; 30 mins
Cost/kWh	$0.22; $0.44
Attribute Levels for Home Charging	
When	8:00 AM; 1:00 PM; 9:00 PM
How Long	6 hours; 7hours; 8hours
Cost/kWh	$0.12; $0.30

An orthogonal experimental design was generated using the SPSS statistical software package. Choice combinations deemed infeasible or with dominance were removed. A set of four scenarios was given to each respondent, with each scenario containing three options/alternatives. In designing this experiment, five different sets were generated. These five blocks (A, B, C, D, E) were randomised in that each respondent was randomly given one or more blocks to complete. In this way each respondent provided answers for at least four scenarios.

An example of a scenario with labelled alternatives is given in Figure 5.1.

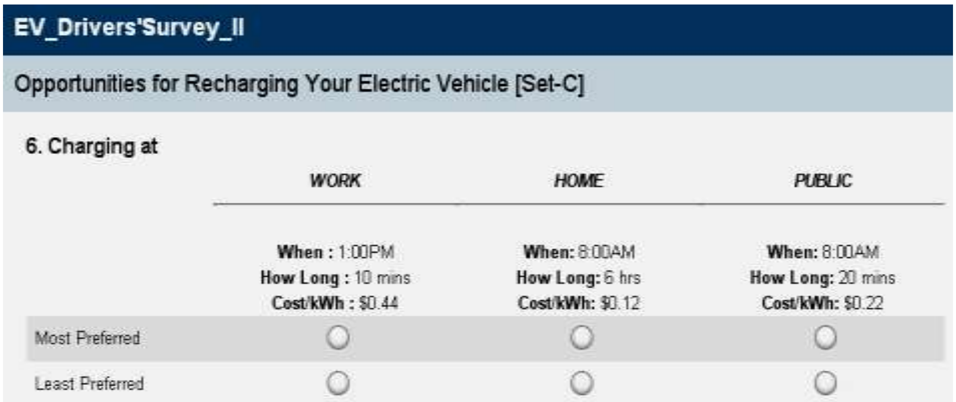


Figure 5.1: An Example of a Choice Scenario

Respondents were asked to indicate the most preferred and the least preferred options. As presented in Section 3.6, there are advantages in allowing the respondent to choose best/worst options, primarily more information being obtained from one scenario (Finn & Louviere, 1992). For example, with a set of three alternatives, a complete ranking of four scenarios provides eight choice situations, even though the respondent looks at only four scenarios.

Information about Respondents

An invitation to participate in the survey was sent out on 24 Sep 2012, to the 11 participant organisations in the WA EV Trial. A large number of respondents in this survey were from AEVA, one of the partner organisations in WA EV Trial (Table 5.3).

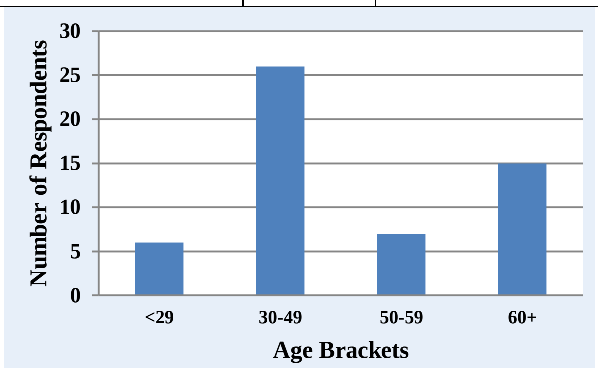
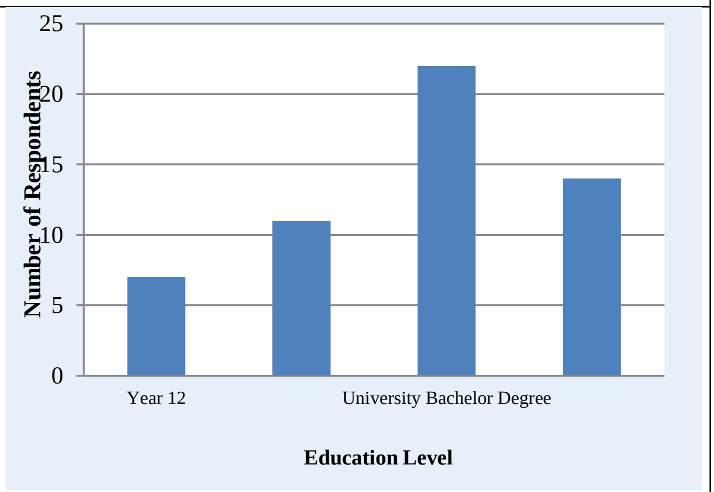
Table 5.3: WA EV Trial Sample

Organisation	Total Respondents = 67	Completed Surveys = 54
AEVA	44	32
Non AEVA	23	22

A total of 67 respondents participated in the survey with 54 complete sets of responses as given in Table 5.3. Many of these drivers had participated in the earlier survey (findings discussed in Chapter 4) of the acceptability of EVs (Jabeen *et al.*, 2012). In addition to the scenarios for EV charging, this second driver survey included five background questions. A summary of the sample socio-demographic characteristics is given in Table 5.4.

The sample was dominated by male respondents (79.6%), reflecting closely the population of EV users in Perth. Approximately half of the respondents (26 out of 54) were in the 30-49 years age group, 15 were above 60 years of age, and only six were young (<29 years). Thirty six (66.6%) of the respondents had university education. In addition to these socio-demographics, respondents were also asked about their travel commitments - involving other family members - and about having solar panels at home. The majority of AEVA members (20 out of 32) had solar panels at home whereas only four of ther 22 non-AEVA members used solar panels.

Table 5.4: Sample Information

Variable	Level	%	Count (Total=54)
Gender	Male	79.6	43
	Female	20.4	11
Age			
What is your highest level of education?			
Do you usually have travel commitments involving other family members (e.g., pick-up/drop-off)?	Yes	44.4	24
	No	55.6	30
Do you have solar panels on your roof?	Yes	44.4	24
	No	55.6	30

5.4 DRIVERS' BATTERY CHARGING BEHAVIOUR

In each choice set, respondents indicated their Best and Worst choices for charging at a particular place, and an exploded choice set was generated. For the purpose of analysis, the Econometric Software NLOGIT 5.0 was used. After data cleaning, a total of 900 valid observations were obtained from the 54 complete sets of responses. There were 18 instances where respondents indicated only their most preferred choice, but did not answer their least preferred option.

Multinomial Logit Model Estimation

The analysis of drivers' preferences for charging EVs at work, home, or in a public place, started with the simplest discrete choice model – the multinomial logit (MNL). This model, already introduced in Chapter 3 (Section 3.2.1), remains the starting point for empirical investigations of data such as preliminary data checks.

MNL Model Specifications: The systematic components of the utility functions tested for this MNL model with the model fit are given below (Equation 5.1 to 5.3) and the parameter estimates obtained from three MNL models are given in Table 5.5. The model was also tested with variables reflecting personal characteristics (age, gender, and education), but they were statistically not significant.

$$V_{home} = \beta_{morning}X_{1,\text{home}} + \beta_{night}X_{2,\text{home}} + \beta_{howlong}X_{3,\text{home}} + \beta_{cost}X_{4,\text{home}} + \beta_{solar}X_5 \quad \textbf{Eq. 5.1}$$

$$V_{work} = \alpha_{work} + \beta_{morning}X_{1,\text{work}} + \beta_{lunch}X_{2,\text{work}} + \beta_{howlong}X_{3,\text{work}} + \beta_{cost}X_{4,\text{work}} + \beta_{AEVA}X_6 \quad \textbf{Eq. 5.2}$$

$$V_{Public} = \alpha_{Public} + \beta_{morning}X_{1,\text{public}} + \beta_{lunch}X_{2,\text{public}} + \beta_{howlong}X_{3,\text{public}} + \beta_{cost}X_{4,\text{public}} + \beta_{fam\_com}X_7 \quad \textbf{Eq. 5.3}$$

Two models were tested: M1 - including only attributes of the alternatives and time of charging as an ordinal variable (linear effects); M2 – which in addition to M1 tested three socio-demographics variables.

Model fit: The log likelihood function of the MNL model with the best fit, model M3 gives log-likelihood (LL) value= -627.811 (Table 5.5) that is improved from LL value for M1 that is LL (M1) = -695.207 (Table 5.5), while LL with constants only = -749.49. Table 5.5 also shows the pseudo-R^2 calculated for each model using relation 5.4.

$$\rho^2 = 1 - \frac{LL_{Estimated\,Model}}{LL_{Base\,Model}} \qquad \textbf{Eq. 5.4}$$

Parameter estimates: The alternative specific constants with a negative sign for work and public places in models M1 and M2 indicate that drivers showed a preference to charge their EV at home or at work instead of public charging stations (Table 5.5). The positive parameters for the *Time of day* variable in both models M1 and M2 indicate that drivers preferred to charge their EV during the night hours.

Drivers are sensitive to the time taken to charge Evs it is consistent with previous studies (Graham-Rowe, Gardner, et al. 2012). Drivers are more sensitive about EV charging cost, as shown by the significant parameter values in all three models (the highest significance in M2, with β= - 4.79, $|t|$= 8.17).

Covariates: Drivers having solar panels at home preferred to charge their EV at home, indicated by significant parameter estimates in M2 (Table 5.5). This preference for charging EVs at home might be due to the savings in cost for charging EV using solar panels, and/or because of the convenience of charging an EV at home. As mentioned above, 20 of the AEVA members who participated in this survey had solar panels at home; thus there was overlap between these two groups, that is, AEVA members showing a strong preference for charging at home and drivers having solar panels at home. AEVA members preferred not to charge their EV at work, with negative coefficients in M2.

Table 5.5: Multinomial Logit Model Estimates

	M 1		M2	
	Beta	**|t|**	**Beta**	**|t|**
Charging at public places	-3.37***	5.24	-3.52***	5.16
Charging at work#	-2.12***	3.33	-1.39**	2.07
Time of Day	0.43***	5.18	0.48***	5.53
Cost ($)	-4.35***	7.76	-4.79***	8.17
How Long (Duration in Mins)	-0.007***	4.75	-0.008***	5.11
Solar Panels At Home			0.97***	5.48
Family Commitments wrt Public Charging			0.32*	1.81
AEVA Members charging at work			-1.06***	5.89
Number of estimated parameters	5		8	
Number of observations	900		900	
Number of individuals	**54**		**54**	
Log likelihood	-695.207		-655.168	
AIC/N	1.55		1.47	
$\boldsymbol{\rho^2}$ **(*Mc Fadden*)**	0.07		0.12	
Log likelihood With constants only	-749.489			
#Home is reference; *****, **, * indicate significance at 1%, 5%, and 10% level respectively.**				

Drivers having travel commitments involving other family members showed a preference for charging their EV at a public charging station during the day (10% significance level).

Charging Price and Duration Elasticities

The results indicate the sensitivity to duration and cost of charging. Choice elasticities (as defined in Section 3.2.1) with respect to charging cost and duration of charging are presented in Table 5.6 and Table 5.7 respectively. The own elasticity for charging at work of -0.57 indicates that a 10% increase in the cost of charging at work results in a 5.7% decrease in the preference for charging at work, all else being equal. The own elasticities for home, and public are -0.40, and -0.52 respectively. As an example of a (*off-diagonal*) cross-elasticity, a 10% increase in the cost of charging at home would result in a 3.8% increase in the preference for charging at public charging stations, *ceteris paribus* (Table 5.6). These values for choice elasticity with respect to charging cost indicate that all three charging alternatives are fairly close substitutes.

Table 5.6: Choice Elasticity with respect to the Charging Cost Attribute

Preference for	Cost at Work	Cost at Home	Cost at Public
Charging at Work	**- 0.569**	0.148	0.208
Charging at Home	0.175	**-0.401**	0.182
Charging at Public	0.464	0.380	**-0.517**

The direct charging duration elasticity of -0.2 for charging at public charging stations indicates that 10% increase in public charging duration will result in 2% decrease in the preference for charging at public charging stations all else being unchanged (Table 5.7). For cross elasticities, a 10% increase in charging duration at public stations results in less than a 1% increase in the preference for charging at home or for charging at work, all else being equal.

Table 5.7: Choice Elasticity for Charging with respect to Charging Duration at Public Charging Stations

Preference for	With respect to charging duration at public stations
Work	0.078
Home	0.073
Public	**- 0.200**

5.5 DISCUSSION

Home-charging remains one of the advantages of EV as drivers had a preference for the convenience of charging overnight or during the day at home. Drivers having solar panels at home preferred to charge at home, this preference being explained by the saving in the cost and also in the convenience. Average daily travel distance requirements of 25-30 km in Australia (BITRE, 2010) are supported by a comment from one of the drivers in this survey: "..... *4 months ago we purchased the all-electric car Nissan LEAF. So far this has nearly always been solar charged at home*........", showing that the current EV range is sufficient for household travel requirements in this part of Australia. An argument for daytime home charging is that the cost of overnight charging EV while having solar panels at home is determined by the buy-back rate provided by the power supplier. As mentioned earlier, Synergy offers 8.4 cents/kWh, while Horizon Power offers 10 cents/kWh to 50 cents/kWh in different rural areas/suburbs of Western Australia (WA). For this reason households may experience various costs for charging at night.

AEVA members preferred not to charge their EV at work, as many had solar panels at home. Another factor is convenience, indicated by drivers' comments, as exemplified here: "*I would insist on charging at home no matter the cost.*"

Drivers having travel commitments involving other family members showed a stronger preference for charging EV at public stations. This could be due to the requirement for their long trip, involving a pickup/drop of a family member or some household chores. One of the respondents who had travel commitments involving other family members made the following comment: "*Public charging facilities, e.g. at shopping centres and in city centre would definitely be useful.*" This substantiates that the opportunity to plug-in EVs at public charging stations installed near places of interest and effectively use the charging time for other activities, is appealing.

Charging at public charging stations is different from charging at home or at work. The convenience of overnight or during the day differentiates home-charging from public charging. For charging at work, the convenient location, less effort and convenient timing makes it different from charging at public stations. The cross elasticities with respect to charging duration in Table 5.6 of about 0.07 indicate that the time to charge at a public station has little impact on the probability of charging at home or work. It is a matter of trip length that leads drivers to charge at public charging stations during the day. In general, drivers were sensitive to charging cost, but convenience was also important, as pointed out by one of the respondents: "*I think if your battery capacity permits, you will charge wherever it is both cheap and convenient. If not one, you will go for the other.*"

The main aim of this experiment was to test WA EV Trial drivers' preferences for EV charging. The study has several limitations, with: i) reduced number of respondents; and ii) lack of a charging infrastructure being the most evident. At the time when this study was conducted, the charging stations in WA were in their infancy, but the drivers in the trial had ample experience of EV charging.

Nevertheless, the insights were relevant for designing the household study that followed. Based on the finding in the second wave of household surveys that drivers having solar panels at home preferred to charge their EV at home, a question about having solar panels at home was added.

5.6 CONCLUSION

This chapter explored the drivers' preferences for charging at work, at home, and at public charging stations. With a limited availability of charging infrastructure, stated choice experiments were used to analyse driver's charging behaviour. Advanced discrete choice models were used to analyse panel data. Main observations from this study are that drivers, in most instances, preferred to charge EVs at home/work, and were sensitive to charging cost and duration. Among the drivers in the WA EV trial, numerous already demonstrated their commitment to use renewable energy, by using solar panels at home. This was also reflected in their preference to charge their EV at home. Yet people having travel commitments with family were prepared for the time required to charge at public charging stations.

The next chapter continues with the main contribution of the research, that is investigating "*attitudes/preferences towards adoption of electric vehicles*", through household surveys. The first household data collection and analysis were conducted in 2012-2013 and the results are presented in Chapter 6.

CHAPTER 6

6 HOUSEHOLD STUDY: DATA COLLECTION AND ANALYSIS

6.1 INTRODUCTION

To this point the inquiry into user acceptance of Electric Vehicle technology has focused on the experiences of the participants in the WA EV trial. In Chapter 4, EV drivers stressed the need for trip planning and they considered the range to be a serious barrier to EV uptake. In addition, EV drivers in this trial emphasised low running cost and low noise level as benefits of the converted EVs in the WA EV trial. The survey administered to the EV drivers also tested the attitudinal constructs drawn from a number of marketing theories (TPB, TAM, PI, WOM) presented in Chapter 2. The constructs that appear significant in the drivers' study include: *Environmental Concern* (KMO=0.701), *Technology Learning* (KMO=0.669)*, and Willingness to Recommend and Purchase an EV* (KMO=0.726). These constructs were used to build the attitudinal questions for the household study. The crucial part of this study addresses the attitudes towards the uptake of EV held by households that are assumed not to have experience of the EV technology; that is the general population in Perth metropolitan area where EV was not readily available. The survey of households aimed to build on the insights obtained from the driver survey, by investigating general population responses to the possibility of adopting EV; this means exploring perceptions about EV benefits and the barriers to the uptake of EV.

Exploring drivers' behaviour and experience in driving EVs, and looking at their attitudes helped in the design of survey instruments for the household study. This chapter elaborates on the method of data collection and sample descriptions of the household sample. Descriptive statistics for the households providing the mail-out sample indicated sample bias. Upon identifying this bias, another sample was collected. The reasons for this second sample collection are also presented in this chapter along with a comparison of the two samples. Later a preliminary choice analysis of household data attempts to determine the most valued vehicle attributes. This helps to answer the main questions of the thesis, as indicated in the objectives (Section 1.6).

The next section outlining the household questionnaire and the choice experiments is followed by a review of sample response rate and a description of the second data collection exercise. Section 6.4 compares the two samples, and Section 6.5 describes the differences in the choice experiments for both samples. Section 6.6 presents a factor analysis of the attitudinal data used to build the attitudinal constructs for the household study. Sections 6.7 and 6.8 provide the preliminary choice modelling analysis of the first sample in this household study. Section 6.9 contains discussion of the initial findings and compares them with previous studies. Section 6.10 concludes the chapter.

6.2 HOUSEHOLD QUESTIONNAIRE

The first stage of the household data collection was carried out by a mail survey. Respondents were given the options of completing either a paper-and-pencil questionnaire or a website questionnaire (https://www.surveymonkey.com/s/EV_households). A printed EV-Brochure (Appendix F) was enclosed with the invitation letter.

Background Information Provided to Respondents

In conducting the household survey it was necessary to provide the respondents with some contextual data (for example, rising petrol prices and the need to reduce emissions on environmental grounds have created pressure to use alternative fuels). Respondents were given information on the features of Plug-in Electric Vehicles (EV) mentioning the limited range but also the environmentally friendly effects, with zero tail-pipe emissions, and low running cost. The adoption of EVs require recharging the battery after 140 to 160km of driving; nevertheless it is suited to a multi-car household. With a limited driving range an EV is useful for short trips, and this information was provided in the EV-Brochure.

Household Data

The survey instrument collected information about household structure, travel patterns, and vehicles in use. A copy of this questionnaire is attached in Appendices G and H. After eliciting information on the suburb and tenancy (whether the household owned or rented their residence), the questionnaire included the following items:

A) Details for each household member (an independent traveller): *gender*, *age, education, number of current jobs*, *driving licences*. To explore the travel patterns, the respondents were asked about *the average distance covered per day, the number of trips longer than 30 km made in a week, and the suburb of their work place/education*.

B) Vehicles owned by the household: *make, year of manufacture, fuel type, engine size, weekly fuel cost, who is paying for fuel (household or company – completely or partially).*

C) Future purchase decisions: The amount of *money* that households are *willing to spend* to purchase their next car and the *likelihood* that this new vehicle would be an EV. Assuming they had an Electric Vehicle, what would be *the chance that they could use it without an additional internal combustion vehicle (ICE).*

D) Attitudinal data: Statements regarding *Environmental Concerns* (11 items), *Perceived Uses or Usefulness of Technology* (6 items), *Technology Awareness/ Excitement about New Technologies* (8 items), and *Social Influence/Norms* (5 items). A list of these items against each construct as presented in this survey instrument is given in Table 6.1.

The Stated Choice Experiment

GA-optimised experimental designs were applied in this household study for analysing the uptake of EV in Australia, drawing on the research by Olaru *et al*. (2011). Pilot surveys were conducted first to obtain the prior parameter values and to fine tune both driver and household questionnaires, particularly the attitudinal and preference questions.

Pilot Study to Test Attributes in Experimental Design

To refine the experimental design, the household survey was pilot tested with the WA EV trial members. In June-July 2012, the trial members were chosen for pilot study due to the fact that they represent the population of EV users in Western Australia. The pilot survey was conducted with 22 respondents, giving 132 observations for the MNL model. Each respondent was given six choice tasks with each choice task having four options. Respondents were asked to select their Best and their Worst option among the given choices.

The sample was male dominated, as only three female respondents participated and there were a higher percentage of educated respondents. Half of the respondents chose to buy a new car in the near future, while the rest preferred to buy a used car. Those respondents who participated in the pilot household survey mostly made decisions based on the price of the vehicle. In addition to their participation, they provided useful qualitative comments about the price of EV in the survey. As the price of EVs was expected to decline by the time the survey was distributed to households, it was suggested that the prices be reduced to bring them close to realistic values. The latent constructs were also tested in this pilot study for their wording and usefulness.

Parameters of the estimated MNL model served as priors for the final experimental design for households (they include: *purchase price, driving range, running cost, charging duration, GHG emissions, battery capacity after 10 years of use, noise, and the availability of charging infrastructure*). As indicated, prior parameters (Appendix I) and comments from the respondents helped not only to change the design but also to change the attribute levels (Table 6.1).

Alternatives, Attributes and Attribute levels in EV Household Study

Alternatives, attributes and the attribute levels were initially chosen from previous studies (Chapter 2) and findings from the drivers' study. The pilot survey then helped to refine these attribute levels in the design. With the main objective of exploring people's propensity to adopt EVs as a new technology or environmentally friendly vehicle, this study focused mainly on Plug-in EV technologies. For this reason, four alternatives identified for the household study are: Electric car, Petrol car, Plug-in

Hybrid (PIH) car, and Diesel car. Attributes identified against each alternative along with their levels are given in Table 6.1.

Experimental Design

The design was D-p optimised using genetic algorithms (Olaru *et al*., 2011), and the prior parameters were obtained from a pilot study with 22 respondents. The pilot study also tested for the optimal number of choice experiments (6, 8, 10 or 12) and their effect on response rate and time. As a result, in the final surveys, each respondent evaluated 6–8 scenarios. The prior parameters used in creating the design are given in Appendix I along with the total of twelve choice situations that were generated (Appendix J). The *D-error* (0.049) was computed by taking the determinant of the AVC matrix and applying a scaling factor to account for the number of parameters.

In the second stage of the household survey a commercial sample was acquired from PureProfile. Experiments were redesigned for the second stage "*PureProfile*" survey and the attribute levels were changed for those marked with an (*) in Table 6.1.

Table 6.1: Attributes and Levels Used in the Experimental Design for the Household Survey

Attribute	Alternative	Number of Levels	Values for Mail-Out Sample
Engine size (L)	Generic	3	1.6; 2.0; 2.4
Range (km)*	EV	3	**100; 120; 140**
	Plug-In Hybrid	3	400; 500; 600 (including 30 minutes of home-charging)
	Petrol	3	**600; 700; 800**
	Diesel	3	**800; 900; 1000**
Running cost ($/100km)	EV	3	1.4; 1.7; 2.0
	Plug-In Hybrid	3	4; 5; 6
	Petrol	3	7.5; 10.0; 12.5
	Diesel	3	6.0; 7.5; 9.0
Purchase price ('000 $)	EV	3	34; 42; 50
	Plug-In Hybrid	3	37; 45; 53
	Petrol	3	28; 36; 44
	Diesel	3	30; 38; 46
Green House Gas emissions (kg/100km)	EV	3	11; 12; 13
	Plug-In Hybrid	3	13; 15; 17
	Petrol	3	21; 26; 31
	Diesel	3	21.0; 23.5; 26.0
Noise*	EV	N/A	**0 (No Noise)**
	Petrol, Diesel, Plug-In Hybrid	3	1; 2; 3 (Low to High)
Charging time (h)**	EV	3	0.2; 1.5; 4.0
	Plug-In Hybrid	N/A	N/A
	Petrol/ Diesel	N/A	N/A
Battery capacity after 10 years*	EV, Plug-In Hybrid	3	**85% ; 90% ; 95%**
	Petrol/ Diesel	N/A	N/A
Number of charging stations*	EV	3	500; 1000; 1500
	Plug-In Hybrid	**N/A**	**Charging at home**
	Petrol/ Diesel	N/A	N/A

** These values were changed for a later version of the survey while the experiments were redesigned for Version II (PureProfile Sample): EV-Range: 80 – 120 – 160; Petrol/Diesel-Range: N/A; and Battery capacity after 10 years: 65% - 80% - 95%; Noise for EV: N/A*
*** For the purpose of analysis these values of charging time were taken in minutes as can be seen in Section 6.8: 12; 90; 240.*

Twelve experiments were generated, with a block of six experiments randomly assigned to each respondent. In each experiment, respondents were asked to select their most preferred and least preferred option among the four choices - an example experiment (where each column is an alternative, and each row is an attribute) shown in Figure 6.1. For the paper-and-pencil survey half of the copies were printed for Set-I and the other half for Set-II as shown in Section C of Appendices G and H. For online responses, a random allocation of the two sets (Set-I or Set-II) was made possible through survey website (Surveymonkey, 2011); however scenario randomisation within a set was not possible over the website.

HOUSEHOLD CHOICE EXPERIMENT – SET I

1. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car	Petrol car	Plug-in hybrid car	Diesel car
Price	\$50,000	\$36,000	\$53,000	\$46,000
Driving range	140km	800km	400km (including 30km electric)	800km
Charging time	Fastest charging available - 1.5h*	n/a	n/a	n/a
No of charging stations	500 public stations available	n/a	Charging at home (30 min)	n/a
Running cost	\$1.4/100km	\$7.5/100km	\$6.0/100km	\$7.5/100km
Engine size	Equiv. 2.4L	2.4L	Equiv. 1.6L	2.0L
Life cycle Emissions	11kg/100km	21kg/100km	17kg/100km	23.5kg/100km
Battery capacity after 10 years	85%	n/a	85%	n/a
Engine noise	No engine noise	Medium engine noise	Medium engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

Figure 6.1: An Example of a Stated Choice Experiment in the Mail-Out Survey

6.3 SAMPLE RESPONSE RATE AND CHARACTERISTICS

In the invitation letter (Appendix E) for the mail-out survey, the two options (website/paper-and-pencil) were offered and the website, contact details, and email were provided, so that respondents could complete the survey online or request a printed copy to be posted to them. In addition the email addresses were kept in the system for a draw of prizes as mentioned in Appendix E. In Perth, most households have internet access (83% according to ABS, 2011b), and the rate of internet use is high; that is 73% of the population in WA use the internet daily (ABS, 2011b). Kaplowitz, Hadlock, & Levine (2004) found that to survey a population with high internet use, a combination of web/mail delivery of survey is very effective, basing their finding on a study at Michigan State University where students were surveyed. In view of the high internet access in Perth, the same combination was adopted, providing respondents with both web and mail options.

A preliminary low-cost flyer distribution service was used in September 2012. The flyers (Appendix D) invited respondents to participate in the survey on one side and information about EV's (Appendix F) was presented on the other. The flyers, without residential addresses, were dropped to all households in selected streets of Perth. The response was minimal and there were only 40 complete responses through the website link. There were also five paper survey forms sent on request but only two of these were returned, with neither being complete. More than half of all responses were received in the first six days after flyer distribution and there was no response received after day 25 (Figure 6.2).

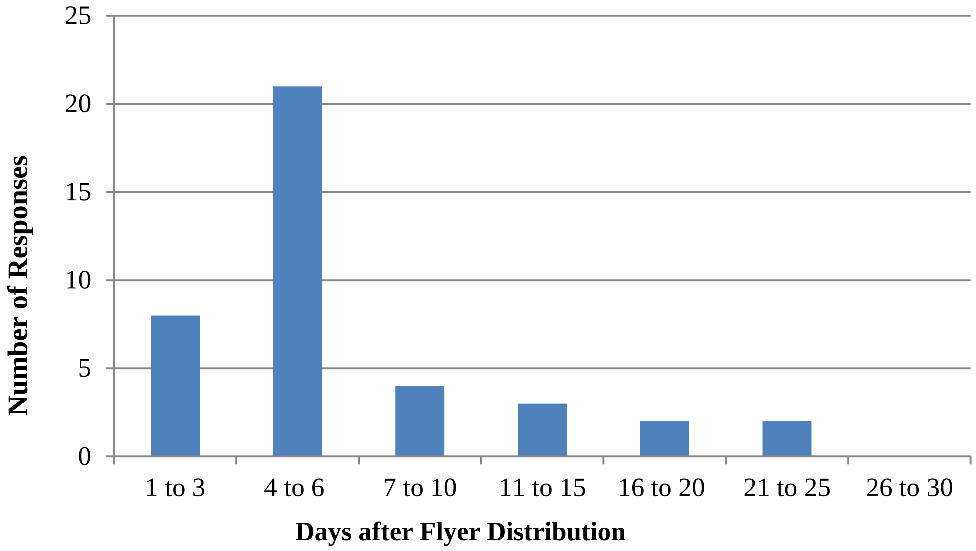


Figure 6.2: Number of Responses Received after Flyer Distribution

A new set of 4,000 survey packs, including invitation letters, information about the study/brochures, questionnaires, and reply-paid envelopes were mailed to individually addressed households in November 2012. Including ready-to-use questionnaires was expected to reduce the time required for those who prefer paper-and-pencil to respond, while still offering the option of online participation. The total response rate was 8.3% with the maximum number of responses (115) received within 20 days after distribution, as shown in Figure 6.3. The number of paper-and-pencil responses was much higher than the online responses, with 84.7% of the total of 333 responses received being on paper. The higher proportion may be due to the printed brochure and survey form attached to the invitation letter. Respondents may have felt impelled to fill in the form in order to avoid wastage. Each respondent made a choice in the six experiments (as in the example provided in Figure 6.1).

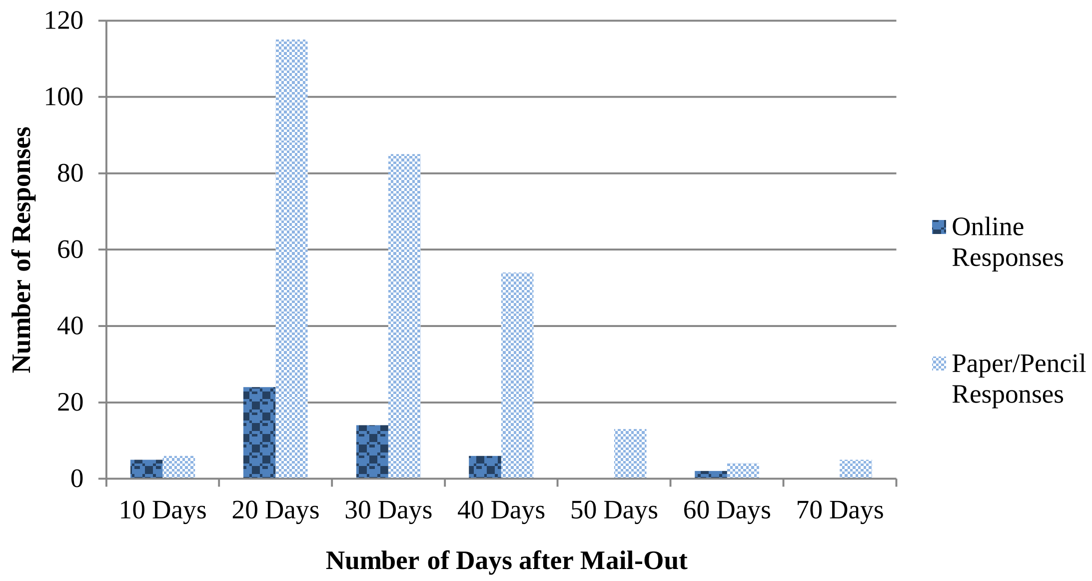


Figure 6.3: Response Pattern Mail-Out November 2012 (4,000 survey packs)

The analysis of the data revealed that most of respondents were from the Southern suburbs of Perth, with a large number of return-to-sender envelopes received, mainly from the Northern suburbs (510 out of the 4,000 survey packs). This was due to clerical errors in the addresses in the sampling framework that was used. It was found that many addresses in the list contained lot numbers instead of street numbers, so that an envelope that was delivered was one where coincidentally the lot number matched a street number.

In order to have a better representation of the population in the sample, a new round of letter distribution was undertaken in February-March 2013 with 500 surveys distributed to underrepresented areas in the Northern suburbs. In this last distribution a much better response rate (14.6%) was achieved, with a higher proportion of paper-and-pencil responses (13 web-based compared to 60 paper-and-pencil completed surveys). From the multiple stages of data collection, a total of 463 responses were received, with 111 being web-based and 352 paper-and-pencil responses. After data cleaning, a total of 450 complete responses were used for further analysis.

Sample Characteristics: Gender, Age, Education, and Income

In the mail-out survey there was a higher representation of male participants (59.7%), compared to the population. Census data from Australian Bureau of statistics (ABS, 2011a) indicates that male population makes 49.6% of Perth, 50.3% of WA, and 49.4% of Australian population (Figure 6.4). This higher percentage of men in the sample can be explained by the higher preference/interest of males in car purchase decisions as compared to women. Consumer behaviour studies (Wolgast, 1958; Davis, 1976; Kirchler, Hoelzl, & Kamleitner, 2008) indicate that decisions related to car buying are more controlled by male partners, while women appear to be more concerned about their preferences for kitchen appliances or number of bedrooms in a house. However, this issue remains debateable, as Belch & Willis (2002) found that female partners are increasingly gaining influence on the decision process regarding vehicle make, model and colour, while male partners have more influence on the initiation of the decision to buy a vehicle in a family.

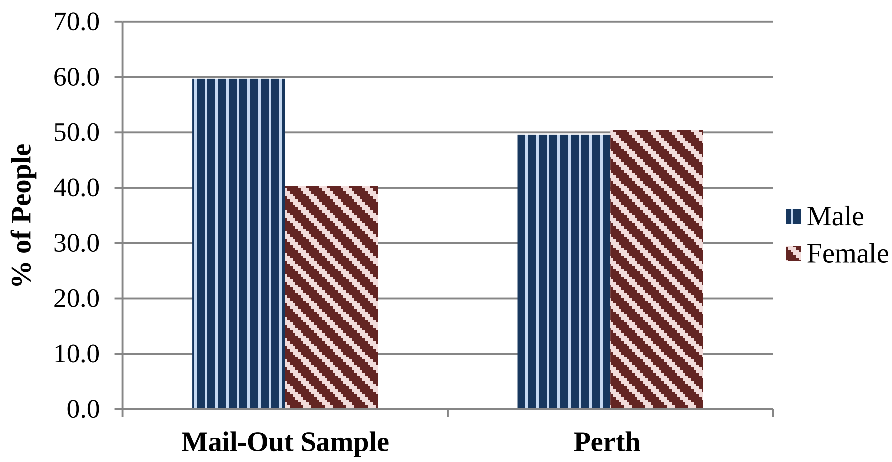


Figure 6.4: Comparison of Gender Proportion (Mail-Out Sample versus Population)

An age comparison (Figure 6.5) reveals some degree of consistency between the 450 respondents (20-71 years) and the population (ABS, 2011a). Only the youngest group is clearly under-represented, whilst the participation rate in the groups above 50 years of age is above the population proportion. The differences may be due to sample self-selection bias: young people below 30 years may not be able to finalise their car purchase decisions due to financial constraints and hence may be less interested in expressing their views on an issue with little relevance to them. Those above 50 years, on the contrary, are expected to have fewer budgetary limitations and thus may be able to invest more money and time into car buying decisions. With almost a quarter of respondents (23.5%) in the age group 50-59, the average age of the respondents in this sample reached 50 years.

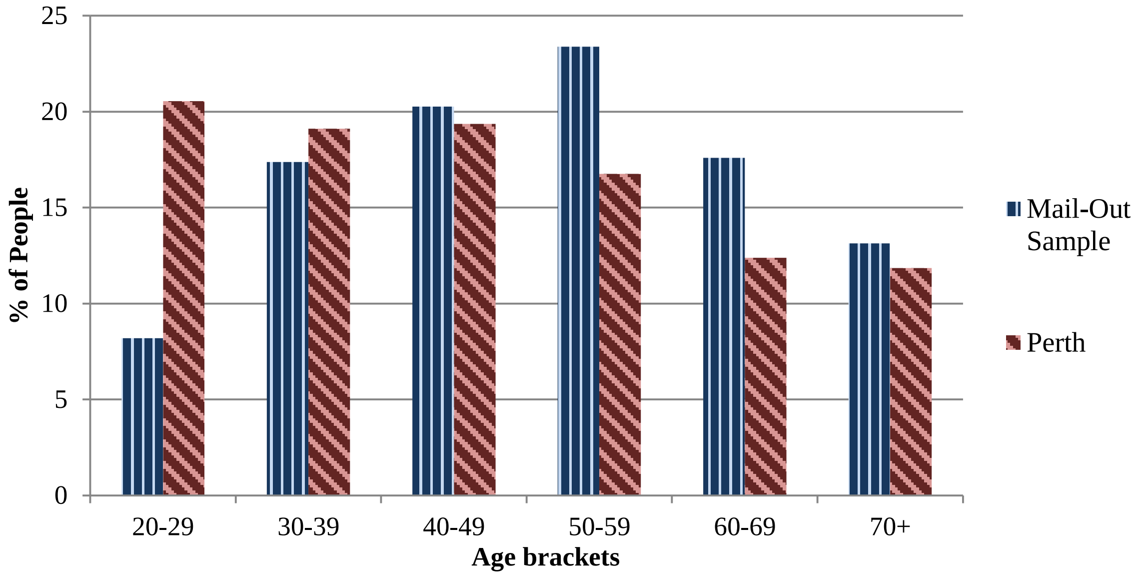


Figure 6.5: Comparison of Age (Mail- Out Sample versus Population)

The higher proportion of people above 50 years might also be the reason that in this sample 72% of the respondents had post-secondary education, and about 22.8% had University degree (Bachelor/Masters). Finally, the average annual household income for the mail-out sample was $112K, with the range between $35K and $250K.

Compared with Perth population, this sample had a low representation of the low-income group and a high representation of high-income groups, as can be seen in Figure 6.6. The differences are pronounced except for income groups above $100,000.

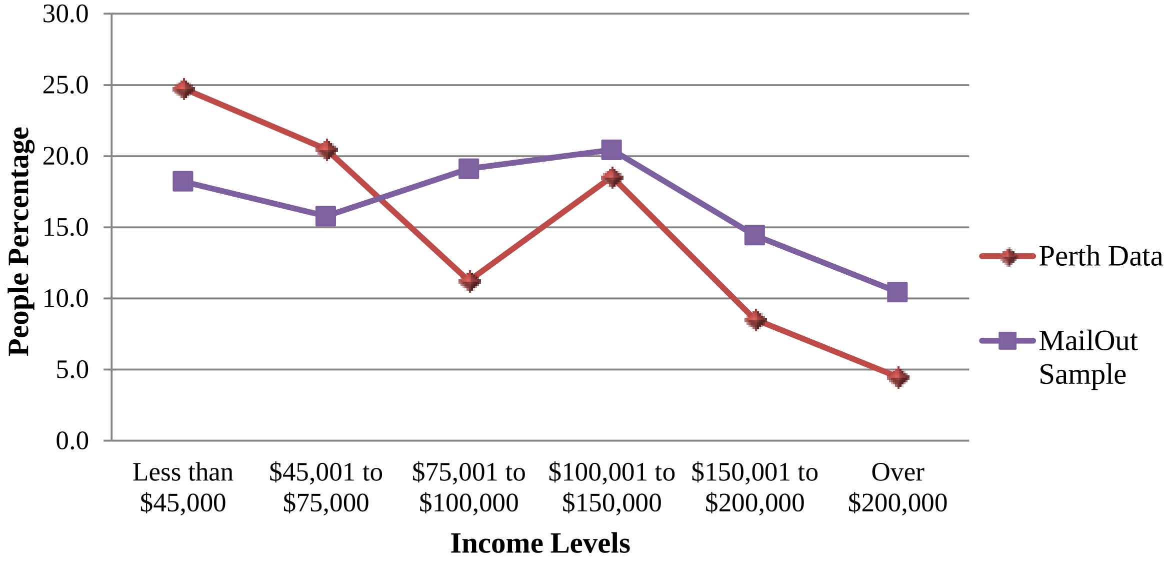


Figure 6.6: Household Annual Income Levels: Mail-Out Sample and Perth Data

The mail-out sample did not appear to be representative of the population due to large differences in sociodemographic profiles, and an initial analysis revealed that 10.9% of respondents selected EVs as their best option in all experiments, regardless of comparing vehicle attributes. The reason for this might be a bias towards EVs or not being able to compare EV characteristics with other vehicle’s attributes. In addition, although this survey used a sampling frame from a utility company in Perth with spatial and socio-demographic strata, the survey returns were more likely to come from southern suburbs with higher incomes and more educated households. This sample bias limited the potential for inference at the population level. Possible sources are: respondent bias or non-trading behaviour which resulted in the negative EV driving range coefficient estimate (Table 6.7) in the choice analysis. These issues are explored in detail in the presentation of the modelling results (Section 6.7). The findings motivated the selection of a second sample, collected using PureProfile (PureProfile, 2013) online panel in October 2013 and delivering 305 sampling responses.

The household survey thus consists of two samples: mail-out/web and PureProfile. The mail-out was conducted by sending an invitation letter for either online or paper-and-pencil participation, while the second sample (PureProfile) comprises web-based respondents achieved/acquired from a commercial service for data collection. This latter sample was analysed separately because the experiment was slightly redesigned to ensure that the meaning of the range attribute was communicated more clearly to the respondents. Before presenting the choice models the PureProfile sample is described (changes in the experimental design are also given below) and then compared to the pencil-and-paper and online household sample that is collectively referred as the "*mail-out*" sample.

PureProfile Survey: Questionnaire Changes

The household questionnaire was also used for PureProfile respondents with changes that are shown in Table 6.1. In relation to items A-E in Section 6.2.2, changes in each section are discussed below:

A) and B) As this survey was implemented by a company that conducts paid surveys and collects panel data through filtering questions, it was ensured by the company that the proportions of age, gender, and education of participants in the survey approximated the population proportions; thus, there were no socio-demographic questions in the survey. Similarly, questions about vehicle make and model were considered unnecessary, but it was important to find the number of vehicles owned by each household, the suburb they live in, and information about their residence (own/rent/paying-off/other). Because the analysis of drivers' charging behaviour indicated preference to recharge the EV at home for those drivers having solar panels, an additional question about having solar panels was included in the household survey deployed in PureProfile.

B) and D) In order to reduce the encumbrance of a long questionnaire, only those questions/items that had strong factor construct loadings in the mail-out survey (Section 6.6) were considered. In this way, items in the attitudinal data were reduced from a total of 30 questions to 18 in the PureProfile study (See Table 6.2). The constructs include statements regarding: *Environmental Concerns* (5 items), *Perceived Usefulness of Technology* (4 items), *Technology Awareness/Excitement for New Technologies* (5 items), *Social Influence/Norms* (4 items), and *Attitudes towards Purchase* (2 items).

C) Changes in Stated Choice experiments are in Section 6.3.3.

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Table 6.2: Attitudinal Items against Each Construct

Construct	Items presented in the survey for Mail-Out Sample	Included for Pure-Profile Sample
Environmental Concerns	Saving the environment requires our immediate efforts.	✓
	Now is high time to worry about the effects of air pollution.	✓
	Climate change is a myth.	✓
	I prefer to walk/cycle in order to reduce pollution.	No
	I might join a group, club, or organisation concerned with ecological issues.	No
	It is acceptable for a modern society to produce a certain degree of pollution.	No
	I am concerned that future generations may not be able to enjoy the world as we know it currently.	✓
	I always recycle products such as: paper, glass, aluminium, etc.	No
	I am willing to pay more for products or services to save the environment.	✓
	Riding public transport helps reduce pollution.	No
	I prefer driving a car with a powerful engine than a car that emits little CO_2.	No
Perceived Usefulness of Technology/ Technology Use	Using new technologies makes life easier.	✓
	Things have become so complicated today that it is hard to understand what is going on in this techno-world.	No
	I use online maps to plan my travel when I need to visit a new place.	✓
	Exploring new technologies enables me to take benefit from latest developments.	✓
	New technologies cause more problems than they solve.	No
	EV Technology would enable me to cut the running costs.	No
	(Not in this construct for mail-out survey) *I love gadgets.*	✓
Technology Awareness/ Excitement for New Technologies	I never travel without a GPS.	No
	I love gadgets.	No
	People often become too dependent on technology to do things for them.	No
	Keeping my knowledge up to date about technology is necessary.	✓
	New technologies enable me to resolve my daily tasks.	✓
	I am excited to learn new technologies.	✓
	I prefer to use the most advanced technology available.	✓
	I enjoy the challenge of figuring out high-tech gadgets.	✓
Social Influence/ Norms	Taking up new technologies makes me trendy.	No
	People who influence my behaviour think I should buy an EV.	✓
	People who are important to me think that I should buy an EV.	✓
	I would buy an EV if many of my friends would use an EV.	✓
	Being fashionable means having up to date knowledge of this techno-world.	✓

Construct	Items presented in the survey for Mail-Out Sample	✓ Included for Pure-Profile Sample
Attitudes towards Purchase	If you were to buy a car within the next five years (independent of you really intend to or not), how likely is it that you would buy an Electric Vehicle?	✓
	Assuming you had an Electric Vehicle available. How likely is it that you would do without an additional car with an internal combustion engine?	✓
	How often would you use your EV?	No

Changes in the Stated Choice Experiments

Stated choice experiments were re-designed for the PureProfile survey instrument. The main change is that the *range* variable was not included for Petrol and Diesel vehicles in this design (Figures 6.7 and 6.8). Given the substantial differences between EV and Petrol and Diesel cars, defining a range value for Petrol or Diesel appeared meaningless, just as the attributes *charging-time*, *battery capacity after 10 years, and number of charging stations* applied only to EVs in the mail-out survey. Figure 6.7 shows a Type 1 experiment similar to the one presented in Figure 6.1, with a choice between the same four vehicle types, but with no range values for Petrol or Diesel. A second change is that, in the Type 2 experiments, an EV was compared with another EV in the same experiment, as shown in Figure 6.8, so that the respondent could compare like with like. This allowed respondents to trade-off between the *range* of the EV, and the *number of available charging stations*, while also considering the other attributes: *running cost*, *purchase price*, *(equivalent) engine size*, *noise and charging time*. However Petrol or Diesel could still be chosen. A summary of the differences in the range and battery capacity values from those in the mail-out survey is shown in Table 6.1 in experiment settings and also in Table 6.4 (Section 6.5). The *D-error* of the experimental design for this sample is lower than the one for the mail-out sample and it equals *0.033* with 2EVs in the same experiment.

HOUSEHOLD CHOICE EXPERIMENT – SET II

1. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car	**Petrol car**	**Plug-in hybrid car**	**Diesel car**
Price	\$50,000	\$28,000	\$45,000	\$30,000
Driving range	80km	n/a	500km	n/a
Charging time	Fastest charging available - 1.5h*	n/a	4 hours	n/a
No of charging stations	500 public stations available	n/a	1500 public stations available	n/a
Running cost	\$1.7/100km	\$12.5/100km	\$5.0/100km	\$6.0/100km
Engine size	Equiv. 2.4L	2.4L	Equiv. 1.6L	2.4L
GHG Emissions	11kg/100km	21kg/100km	13kg/100km	26kg/100km
Battery capacity after 10 years	65%	n/a	65%	n/a
Engine noise	n/a	Low engine noise	Medium engine noise	High engine noise
Most preferred	o	o	o	o
Least preferred	o	o	o	o

Figure 6.7: An Example of a Type 1 Stated Choice Experiment in the PureProfile Survey

In order to implement these changes, a total of eight choice experiments were presented in the PureProfile survey, instead of the six in the mail-out survey. Out of these eight, the two Type 1 choice experiments had Electric, Petrol, Plug-in Hybrid and Diesel as alternatives (Figure 6.7). These Type 1 experiments are similar to the experiments in the mail-out sample except that the values of range variable for Petrol and Diesel vehicles were set to 'not applicable' ('*n/a*') allowing respondents to compare driving range variable only for range-restricted vehicles that is EV, and PIH. Similarly the value of engine noise/noise variable was set to *'n/a'* for the

Electric car. The other six choice experiments had two EVs in each (Figure 6.8); therefore this set of experiments allowed respondent to make a decision by comparing like with like, that is comparing EV attributes.

4. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car 1	Petrol car	Electric car 2	Diesel car
Price	$34,000	$28,000	$42,000	$38,000
Driving range	160km	n/a	80km	n/a
Charging time	Fastest charging available - 0.2h*	n/a	4 hours	n/a
No of charging stations	1000 public stations available	n/a	500 public stations available	n/a
Running cost	$2.0/100km	$7.5/100km	$2.0/100km	$9.0/100km
Engine size	Equiv. 1.6L	1.6L	Equiv. 2.4L	1.6L
GHG Emissions	13kg/100km	31kg/100km	11kg/100km	23.5kg/100km
Battery capacity after 10 years	65%	n/a	95%	n/a
Engine noise	n/a	High engine noise	n/a	Medium engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

Figure 6.8: An Example of a Type 2 Stated Choice Experiment in the PureProfile Survey

6.4 COMPARISON OF THE SAMPLES WITH THE POPULATION

The household survey provided a total of 450 complete responses through "*mail-out*" questionnaire, and 305 respondents through *"PureProfile"* panel data.

In terms of vehicle use, the mail-out sample showed an average of 1.85 vehicles per household, similar to an average of 1.8 vehicles per household for Perth residents (ABS, 2011a). A comparison of number of vehicles owned by mail-out and PureProfile samples was performed by using a goodness-of-fit test for the five categories shown in Figure 6.9 ($\chi_{4d.f.}=5.4;\ p=0.25$), which indicates that in this respect the two samples are not significantly different: approximately 60% of respondents had at least two or more cars in both the mail-out and PureProfile samples. The two sample vehicle counts are plotted against Perth population values in Figure 6.9.

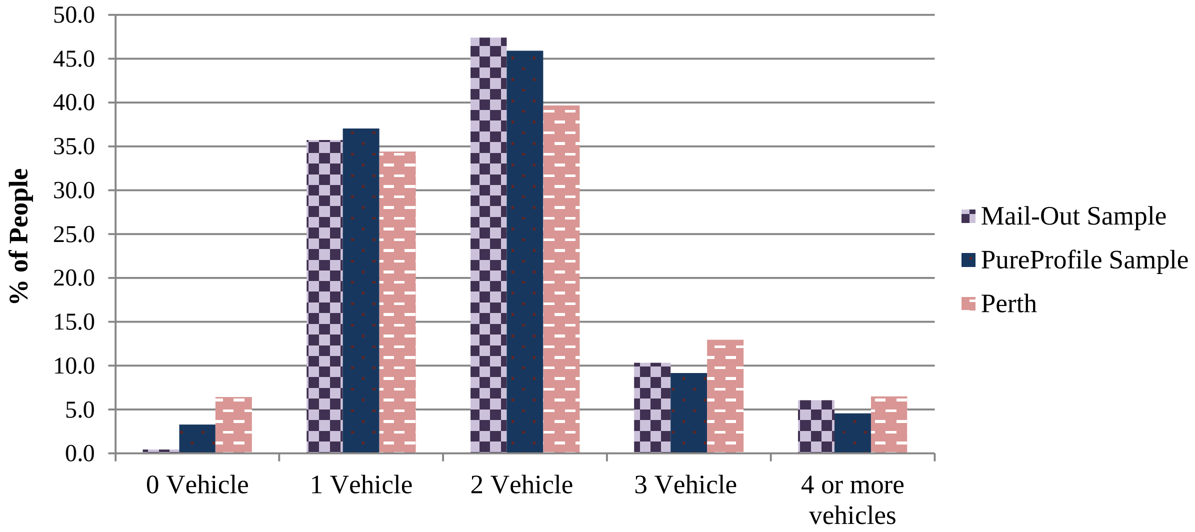
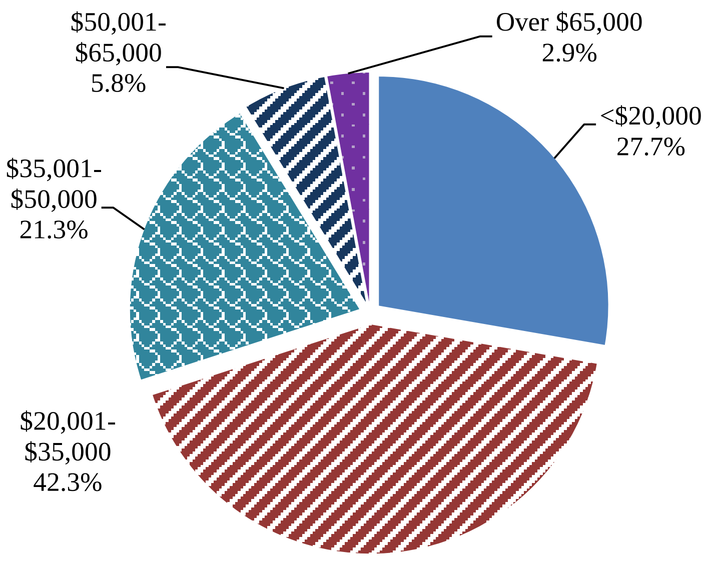


Figure 6.9: Comparison of Number of Vehicles Owned (Sample versus Population in Perth)

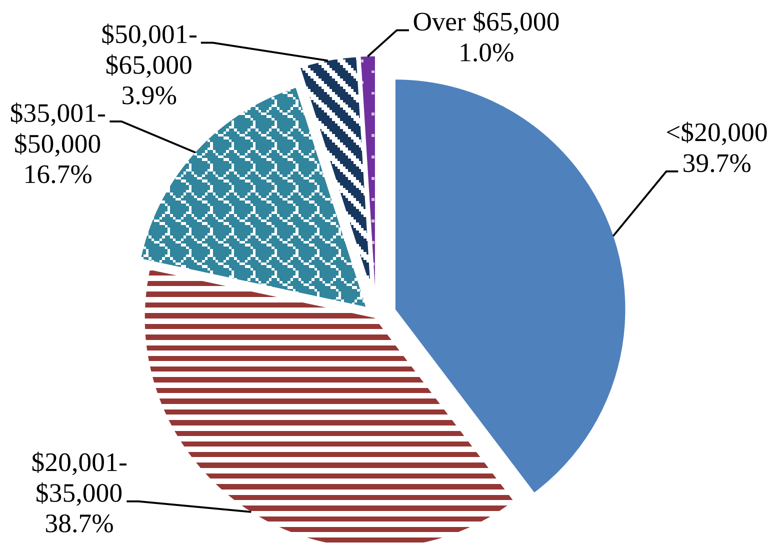
While a substantial proportion of respondents (23.6%) were either retired or had no job, 10.3% of the sample reported two or more jobs and 66.1% one job. On average there were approximately 3.57 persons in a household, which again is much higher than the Perth average (2.6 persons per household, ABS, 2011a). Almost all respondents (98.9%) had a driving licence and there were 1.97 licences per household.

In the mail-out survey responses there was a large variety of car brands, however the most common was Toyota (18%), followed by Holden (11%), which is comparable to the population of Australia, where Toyota and Holden remained the top registered vehicles in 2012 (ABS, 2013). A small proportion (4%) of vehicles had an Engine size greater than 4 Litres, and in 91% of the cases the households paid the vehicle costs. Another observation is that 33% of respondents indicated that it is somewhat likely or likely that they will purchase an EV in the next five years. While looking at the fuels already used by households, Petrol remains the most common: 84% of vehicles were Petrol, 12% were Diesel, while 1% had EV/Hybrid vehicles. Comparing this with the Australia-wide data, Petrol powered vehicle registrations make 79.9% of the total vehicle fleet, while Diesel powered vehicle registration (including heavy vehicles) make 17.2%, and the rest are LPG, dual fuel and EVs (ABS, 2013).

More than half of the respondents in both the mail-out and PureProfile samples expected to buy a new car in the next 3 years. When requested to indicate the amount that they were willing to spend to purchase their next car, 8.7% of the mail-out sample reported above $50K, 21.3% between $35K and $50K, 42.3% between $20K and $35K, with the remainder (27.7%) willing to spend less than $20K, as given in Figure 6.10A. The proportions in the PureProfile sample differed considerably; a larger part (39.7%) of the sample were willing to spend less than $20K, with 38.7% between $20K and $35K, 16.7% between $35K and $50K, and approximately 5% of sample reported above $50K as the amount they are willing to spend for their next vehicle (Figure 6.10B).



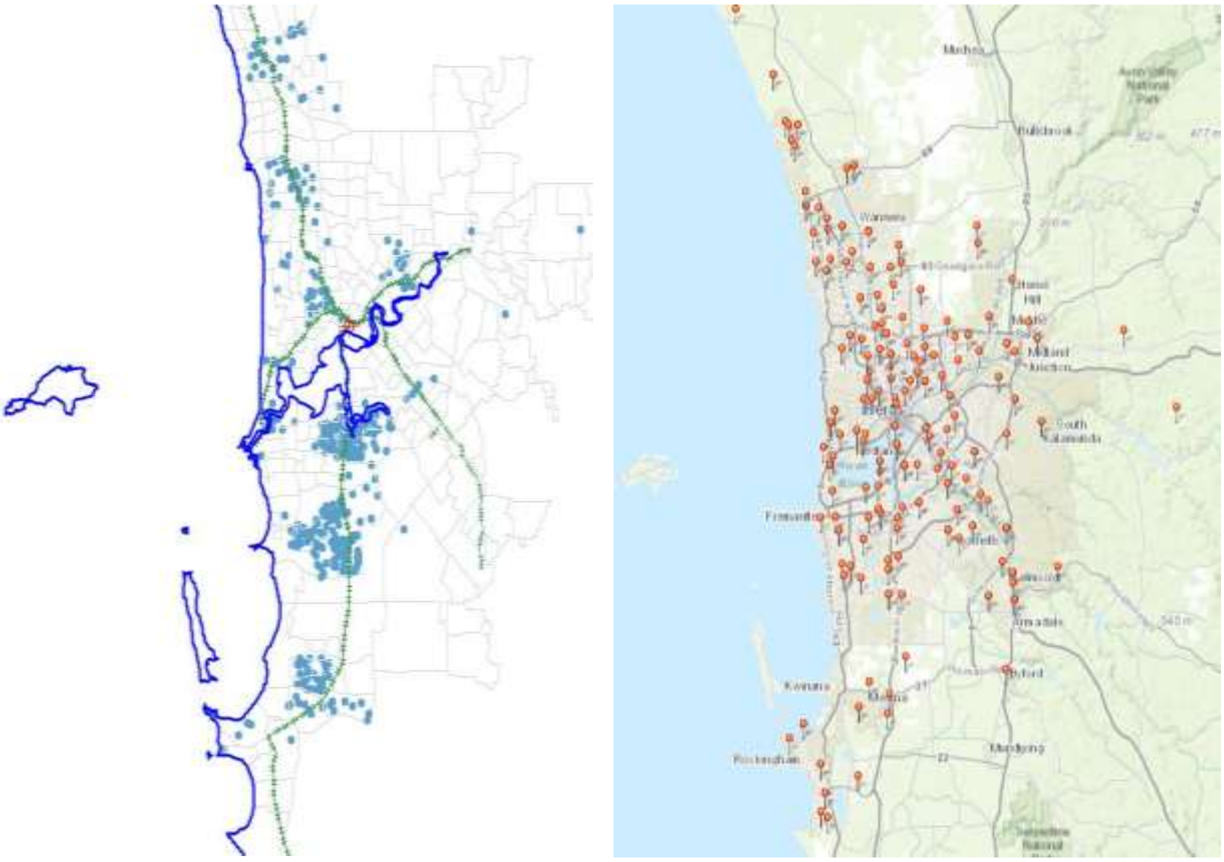
A) Mail-Out Sample



B) PureProfile Sample

Figure 6.10: Amount Households are Willing to Spend to Purchase their Next Car

In terms of spatial coverage, the mail-out sample is not representing all suburbs of Perth. In addition, there were more respondents in the Southern part of the city and they were more clustered along the main railway line, as compared to the North of the city (see Figure 6.11A).



A) Mail-Out Sample **B) PureProfile Sample**

Figure 6.11: Sample Households in Survey from Perth WA

The online PureProfile sample uniformly covers metropolitan areas of Perth with almost an equal spread of respondents across the North and South of Swan River, as shown in Figure 6.11B. A summary comparison of the two samples is given later, as part of Table 6.4. Additional questions to the PureProfile respondents revealed that 30% have Solar Panels at home and 72% were living in a detached or semi-detached house, and either owned or were paying-off the house.

Non-Trading Behaviour

Non-trading behaviour is where respondents choose one alternative as best case in all given choice sets (Hess, Rose, & Polak, 2010) and is relevant to labelled choice experiments. With a total of 450 mail-out responses for the choice data set up, it was found that 58 respondents were EV *Non-Traders (B)*. This means that they selected an EV as their most preferred/best alternative in each experiment,. Ten out of these 58 EV *Non-Traders (B)* were removed from any further analysis as they were not willing to spend more than $35K for their next vehicle purchase, which was considered inconsistent with their choice of EV. In addition to non-traders, three respondents only indicated their least preferred/worst alternative or did not complete a sufficient number of choice tasks, thus they were removed from the analysis set. In the initial choice analysis a total of 437 valid responses remained available: 48 respondents chose EVs as their best choice in all experiments, 13 chose Petrol, 13 chose PIH, and 10 were Diesel non-traders.

In contrast to the mail-out sample, the non-trading was low in the PureProfile sample, with only two respondents out of 305 choosing EVs in all choice tasks. This non-trading behaviour is discussed in detail in the next chapter (Section 7.2).

6.5 CHOICE EXPERIMENTS SETUP FOR PUREPROFILE AND MAIL-OUT

In both samples, respondents indicated their most preferred and least preferred alternatives. Changes in the experimental design were mentioned in Section 6.3.3, and further highlighted in Table 6.1.

Table 6.3: Attributes of Alternative Vehicles and Values Used in Experiments

Attribute	CODE
Engine size (L)	ENGINESIZE
Range (km)	RANGE EV: 100; 120; 140 (Mail-Out) PIH: 400; 500; 600 (Mail-Out and PureProfile) Petrol: 600; 700; 800 (Mail-Out) Diesel: 800; 900; 1000 (Mail-Out) EV: **80; 120; 160 (PureProfile)** Petrol/Diesel: **n/a (PureProfile)**
Running cost ($/100km)	RUNCOST
Purchase price ('000 $)	PRICEK
GHG emissions (kg/100km)	EMISSIONS
Noise	NOISE **n/a (PureProfile)**
Charging time (min)	CHTIME
Battery capacity after 10 years	BATLIFE 0.85; 0.90; 0.95 (Mail-Out) **0.65; 0.80; 0.95 (PureProfile)**
Number of charging stations	CSTATS

With the main difference being the number of EV options in each experiment, the values of attributes for both samples were the same except *range*, and battery *capacity after 10 years* (Table 6.1, Table 6.3, & Table 6.4). These values were changed to provide different choices to respondents. For example, in the Type 2 design with two EV options a respondent could select: an expensive EV with maximum range or an EV with an excellent battery, short charging duration and limited range, or an EV with low running cost, but a medium range. Having two EVs in the same experiment, along with these attributes, allowed a trade-off particularly based on EV attributes. Table 6.4 compares the two samples, mail-out and PureProfile, in terms of their administration and elicited responses. The data collection period for the PureProfile commercial survey was short when compared to the mail-out and the cost per respondent was higher, but it gave a more even distribution of respondents from Perth, covering northern and southern suburbs equally. The changes in experimental design have already been discussed. Values of attribute levels were changed for two variables (*range* and *battery capacity after 10 years*).

Table 6.4: Sample Comparison

	Mail-Out Sample	**PureProfile Sample**
Data collection period	7.5 months [Sep-2012 to Mar-2013]	2 weeks [7-Oct-2013 to 21-Oct-2013]
Sample size	437	305
Representation of the population	Covers most of Perth metro areas with greater participation in southern suburbs	Covers a balanced response from Perth metro suburbs
Number of stated choice experiments	6 scenarios per respondent (>6 or <6)	8 scenarios per respondent
Experiment sets	2 sets of experiments	6 sets of experiments
Alternative Levels	RANGE (100; 120; 140) BATTERY LIFE: (0.85; 0.90; 0.95)	RANGE (**80; 120; 160)** BATTERY LIFE: **(0.65; 0.80; 0.95)**
Alternatives	EV, Petrol, PIH, and Diesel	EV, Petrol, PIH, and Diesel, EV1, EV2
Order of presentation	Fixed order of alternatives in 6 choice tasks	Randomised alternatives, *2 out of 8* experiments consist of (EV, Petrol, PIH, and Diesel) *6 out of 8* experiments with two EVs that is: 2*(EV1, Petrol, EV2, Diesel) 2*(EV1, PIH, EV2, Diesel) 2*(EV1, Petrol, EV2, PIH)
Attitudinal data	30 Items	18 Items
Non Trading Behaviour	58 EV *Non-Traders (B)*	2 EV *Non-Traders (B)*

The order of presentation of experiments was different for the two samples, for PureProfile sample EV was compared with its own counterpart, so that six out of the eight choice experiments had two EVs in the same choice task. Initial results from choice analysis of mail-out sample are presented in this Chapter, and detailed choice analysis of mail-out and PureProfile sample findings are presented in Chapter 7.

6.6 ATTITUDINAL DATA: LATENT CONSTRUCTS

Attitudinal constructs were defined and developed using confirmatory factor analysis (CFA) in AMOS. CFA tested four constructs related to respondents' attitudes towards green sources of energy and new technologies, as well as perceived usefulness of a new technology and the perceived ease of adopting the new technology. As mentioned in Chapter 4, attitudinal constructs were based on the results from the first survey of WA EV drivers. A few items were removed if they had a weak representation in the constructs for the drivers' study, while a few were added to increase the reliability of the constructs. Table 6.4 shows the set of items included for each construct, and the results of CFA for multi-group analysis. Items in italic had already been tested in the drivers' survey, while items in different colours were reworded (as indicated in Chapter 4).

The three constructs estimated in Chapter 4 were: *Environmental Concerns, Technology Learning,* and *Willingness to Recommend and Purchase an EV*. Factor loadings for items in Environmental Concerns have improved for the mail-out study as achieved through a multi-group confirmatory factor analysis given in Table 6.5. For "*Saving the environment requires our immediate efforts*", it has improved from 0.746 (Table 4.2) to 0.862 (Table 6.5, Free Model).; similarly for "*Now is high time to worry about the effects of air pollution*", it has improved from 0.804 (Table 4.2) to 0.933 (Table 6.5, Free Model).

The household data showed some changes in the confirmatory factor analysis. The *Technology Learning* construct was divided into two new constructs: *Perceived Usefulness of Technology* (PU) and *Excitement for New Technologies* (ENT). A new dimension, *Social Norms* (SN) was also added to the survey instrument. Items in these constructs for the two samples are listed in Tables 6.2 and 6.5.

Table 6.5: Construct Items from Multi-group Confirmatory Factor Analysis: Mail-Out Sample (n=450), PureProfile Sample (n=305)

Constructs	Items	Mail-Out Sample					PureProfile Sample				
		Free Model		Constrained Model		% Variance	Free Model		Constrained Model		% Variance
		Loadings	Error Variance	Loadings	Error Variance		Loadings	Error Variance	Loadings	Error Variance	
Environmental Concerns (EC)	Saving the environment requires our immediate efforts.	0.862	0.117	0.883	0.148	46%	0.919	0.16	0.904	0.064	59%
	I am concerned that future generations may not be able to enjoy the world as we know it currently.	0.592	0.699	0.602	0.693		0.690	0.541	0.685	0.545	
	I am willing to pay more for products or services to save the environment.	0.454	0.919	0.436	0.922		0.461	0.923	0.470	0.933	
	Now is high time to worry about the effects of air pollution.	0.933	0.213	0.913	0.187		0.954	0.086	0.967	0.182	
Perceived Usefulness of Technology (PU)	*I love gadgets.*	0.483	1.234	0.541	1.217	35%	0.714	0.557	0.678	0.532	48%
	Using new technologies makes life easier.	0.562	0.187	0.571	0.235		0.615	0.524	0.608	0.146	
	I use online maps to plan my travel when I need to visit a new place.	0.534	1.118	0.537	1.081		0.599	0.943	0.604	0.584	
	Exploring new technologies enables me to take benefit from latest developments.	0.886	0.590	0.851	0.581		0.890	0.17	0.908	0.948	
Social Norms (SN)	People who are important to me think that I should buy an EV.	0.944	0.122	0.938	0.134	53%	0.958	0.085	0.983	0.036	64%
	I would buy an EV if many of my friends would use an EV.	0.910	0.204	0.916	0.193		0.984	0.032	0.757	0.463	
	Being fashionable means having up to date knowledge of this techno-world.	0.689	1.096	0.695	1.098		0.762	0.934	0.469	0.935	
	People who influence my behaviour think I should buy an EV.	0.465	0.674	0.443	0.672		0.438	0.463	0.960	0.082	
Fashion/ Excitement for New Technologies (ENT)	*Keeping my knowledge up to date about technology is necessary.*	0.679	0.445	0.707	0.436	53%	0.714	0.408	0.747	0.418	67%
	I enjoy the challenge of figuring out high-tech gadgets.	0.841	0.501	0.833	0.485		0.858	0.334	0.854	0.339	
	I prefer to use the most advanced technology available.	0.828	0.404	0.811	0.423		0.839	0.275	0.855	0.262	
	I am excited to learn new technologies.	0.783	0.659	0.790	0.640		0.846	0.254	0.854	0.347	
	New technologies enable me to resolve my daily tasks.	0.703	0.321	0.715	0.332		0.778	0.319	0.699	0.245	

All of the EC items tested have strong loadings and explain 46% of the variance of the EC construct; these four items are taken from the drivers' survey (Table 4.2). For PU, two items come from the drivers' survey and two were added to define the Perceived Usefulness of Technology; the added item "*Exploring new technologies enables me to take benefit from latest developments*." has a strong loading (0.886). Two items in ENT were reworded: "*I enjoy the challenge of figuring out high-tech gadgets*.", and "*New technologies enable me to resolve my daily tasks.*" Both have factor loadings greater than 0.6, as given in Table 6.5. The item "*I prefer to use the most advanced technology available.*" is added into ENT in the two household samples and factor loading greater than 0.8 is achieved (Table 6.5). The *"Willingness to Accept EV"* could not be built into a construct because of its low reliability.

The confirmatory factor analysis, for the PureProfile data set (305 records) revealed the same structure but with improved loadings for each construct (Table 6.5). As items in both data sets were the same, a constrained model, with weights for PureProfile and mail-out data made equal, was tested. The better model fit (Table 6.6), showing a considerable level of measurement invariance between the samples (parallel model), enabled pooling of the two samples into a combined model. Pooled together, the aggregated sample became more representative of the population in terms of household size, income, number of owned vehicles, and covered the whole metro area.

Given the level of measurement invariance, factor scores from the pooled data set were taken further for the discrete choice analysis. The percentage variance values are higher for the PureProfile data set, the highest being 67% for *Fashion/Excitement for New Technologies* and the lowest 48% for *Technology Use*.

Table 6.6: Multigroup Confirmatory Factor Analysis: Model Fit for Free and Constrained

Constructs	Items	Model Fit: Free Model	Model Fit: Constrained Model
Environmental Concerns (EC)	Saving the environment requires our immediate efforts.	GFI=0.994 RMR=0.012 χ^2 (2)=9.023; p=0.011	GFI=0.992 RMR=0.023 χ^2 (5)=12.81; p= 0.025; Probability compare (PC) =0.285
	I am concerned that future generations may not be able to enjoy the world as we know it currently.		
	I am willing to pay more for products or services to save the environment.		
	Now is high time to worry about the effects of air pollution.		
Perceived Usefulness of Technology (PU)	I love gadgets.	GFI=0.995 RMR=0.028 χ^2 (7)=11.915; p=0.013	GFI=0.992 RMR=0.037 χ^2 (4)=8.001; p=0.092; PC=0.271
	Using new technologies makes life easier.		
	I use online maps to plan my travel when I need to visit a new place.		
	Exploring new technologies enables me to take benefit from latest developments.		
Social Norms (SN)	People who are important to me think that I should buy an EV.	GFI=0.999 RMR=0.004 χ^2 (2)=1.647; p=0.439	GFI=0.998 RMR=0.025 χ^2 (5)=3.752; p=0.586; PC= 0.551
	I would buy an EV if many of my friends would use an EV.		
	Being fashionable means having up to date knowledge of this techno-world.		
	People who influence my behaviour think I should buy an EV.		
Fashion/ Excitement for New Technologies (ENT)	Keeping my knowledge up to date about technology is necessary.	GFI=0.997 RMR=0.009 χ^2 (4)=5.63; p=0.229	GFI=0.994 RMR=0.028 χ^2 (8)=11.303; p=0.185; PC=0.225
	I enjoy the challenge of figuring out high-tech gadgets.		
	I prefer to use the most advanced technology available.		
	I am excited to learn new technologies.		
	New technologies enable me to resolve my daily tasks.		

6.7 CHOICE ANALYSIS: MAIL-OUT DATA (BEST ONLY)

Discrete choice experiments (DCE) were used to estimate the relative importance given to EV attributes by residents of Perth, Western Australia, with the aim to uncover: "*Which vehicle attributes households would value most in their future vehicle purchase decision?*", and also "*What are the household attitudes towards more sustainable vehicle technologies?*". Nine attributes as presented in Table 6.3, and also the attitudinal constructs identified above in Section 6.6, were analysed for the mail-out sample. Multinomial Logit Model (MNL) was considered suitable for preliminary data checks (See Chapter 3, Section 3.2.1). The systematic utility functions for the experiments used in the mail-out sample (with four alternatives) are defined below in Equations 6.1 to 6.4:

$$V_{EV} = ASC_{EV} + \beta_1 PRICEK + \beta_2 EMISSIONS + \beta_3 NOISE + \beta_4 RUNCOST + \beta_{EV} CHTIME_{EV} + \beta_{EV} BATLIFE_{EV} + \beta_{EV} ChargSTATS_{EV} + \beta_{EV} RANGE_{EV} + \beta_{EV} \mathrm{EC} + \beta_{EV} PU + \beta_{EV} SN + \beta_{EV} ENT$$

Eq. 6.1

$$V_{Petrol} = ASC_{Petrol} + \beta_1 PRICEK + \beta_2 EMISSIONS + \beta_3 NOISE + \beta_4 RUNCOST + \beta_5 ENGINESIZE + \beta_6 RANGE$$ **Eq. 6.2**

$$V_{PIH} = \beta_1 PRICEK + \beta_2 EMISSIONS + \beta_3 NOISE + \beta_4 RUNCOST + \beta_6 RANGE + \beta_{PIH} EC + \beta_{PIH} PU + \beta_{PIH} SN + \beta_{PIH} ENT$$ **Eq. 6.3**

$$V_{Diesel} = ASC_{Diesel} + \beta_1 PRICEK + \beta_2 EMISSIONS + \beta_3 NOISE + \beta_4 RUNCOST + \beta_5 ENGINESIZE + \beta_6 RANGE$$ [5]

Eq. 6.4

In the utility functions given above, generic parameters are estimated for the purchase price, emissions, running costs, and noise levels. The parameter associated with engine size was limited to Petrol and Diesel vehicles only. The EV specific parameters are charging times, the number of charging stations, and the battery life. An alternative specific parameter is estimated on the driving range for EV, but a common parameter is estimated for the Petrol, Diesel, and PIH alternatives. These utilities were tested in MNL and only those that are statistically significant are presented in the findings (Table 6.7). The model is run for the mail-out sample only in order to motivate the coming chapters whereby a second sample (Pureprofile) is used to examine the respondent bias, the high degree of non-trading and the presence of an unexpected sign on the parameter for electric vehicle driving range.

Estimation results are shown in Table 6.7 for 437 respondents with the Best only data (number of observations=2,694). Given that 13 respondents answered both sets of experiments on the website, the number of observations indicates that, on average, a respondent provided more than six choice responses, despite three respondents not completing all choice tasks.

Vehicle Attributes Households Valued Most

The aim of the choice estimation presented here was to obtain a preliminary answer to: "*Which vehicle attributes households would value most in their future vehicle*

[5] Note: Notations presented in Table 6.2.

purchase decision?". In addition to vehicle attributes, households' attitudinal data was also incorporated into choice models to determine "*What are the household attitudes towards more sustainable vehicle technologies?*" (Section 1.6). The findings from an initial choice analysis answer these questions discussed below:

Purchase Price and Running Cost of Vehicles

Findings from MNL parameter estimates from 437 mail-out respondents (Table 6.7) indicate a strong responses to purchase price (β=-0.0375; *t=7.01*) for all vehicles. Findings from this study also indicate a strong response to running cost (β=-0.166; *t=7.61*).

Electric cars have a high purchase price in the current market, although this price is expected to decrease in future (The Motor Report, 2013). High purchase price of EV also presents a challenge for early adopters due to high price depreciation; one of the automotive valuations in UK found that an EV retains only 20.2% of its purchase price after 3 years from purchase (The Telegraph Green Motoring, 2013); another report in the USA indicated that Nissan Leaf is projected to have a residual value of 15% for the 2013 model, while similar Nissan Sentral SL compact model would retain 36% (USA Today, 2013).

Table 6.7: Parameter Estimates for MNL: Mail-Out Best Only Choice Analysis

Attributes$_{(Alternatives)}$	**Mail-Out Best Only MNL (N=437)**	
***ASC*$_{(Alternatives)}$**	**Beta**	**|t|**
ASC_{EV}	-1.61***	3.1
ASC_{Diesel}	0.821*	1.77
ASC_{Petrol} [a]	0.997**	2.14
Attributes$_{Alternatives}$	**Beta**	**|t|**
PRICEK: Purchase Price$_{Generic}$	-0.0375***	7.01
RUNCOST: Running Cost$_{Generic}$	-0.166***	7.61
CHTIME: Charging Time$_{EV}$	-0.0023***	4.29
RANGE: Range$_{EV}$	**-0.00695*****	**2.82**
ENGINESIZE: EngineSize$_{Petrol, Diesel}$	0.919***	6.02
NOISE: Noise$_{Generic}$	-0.289***	7.19
Covariates$_{Alternatives}$	**Beta**	**|t|**
EC: Preference for Environment$_{EV}$	0.735***	7.55
SN: Social Norms$_{EV}$	0.244***	6.32
Rely on Single Car$_{EV}$	0.309***	9.22
Often use EV$_{EV}$	0.283***	7.08
EC: Preference for Environment$_{PIH}$	0.645***	6.05
SN: Social Norms$_{PIH}$	0.0864**	1.99
PU: Perceived Uses of Technology$_{PIH}$	0.0890	1.45
Rely on Single Car$_{PIH}$	0.149***	4.11
Number of estimated parameters	17	
Number of observations	2,694	
Number of individuals	**437**	
Log likelihood	-3,238.79	
AIC/N	2.41	
Log likelihood Base	-3,734.68	
ρ^2 (Pseudo-R^2)[b]	**0.133**	

[a:] ***Plug-in Hybrid is the reference vehicle category;***
[b:] **McFadden Pseudo R^2.**
*****, **, * indicate significance at 1%, 5%, and 10% level respectively;**
Battery life, charging stations, emissions, range, PU and ENT for EV not significant in this model.

Propfe, Kreyenberg, Wind & Schmid (2013) conducted a market penetration analysis of Electric Vehicles for the passenger car market in Germany and found three factors that could affect EV market success: *purchase price incentives, rising oil prices, and low energy costs of electricity.* Purchase price thus remains an important factor that can have an impact on EV uptake and government incentives remain one of the solutions to improve EV penetration in this market. Given that low EV running cost would allow a considerable saving over a year's time, there exists a trade-off between running cost and purchase price of vehicles.

EV Charging Time, Quiet Vehicles Engine Size for Petrol and Diesel Vehicles

The parameter estimates for charging time and noise being negative and significant at 1% indicate a strong preference for fast charging options (β=-0.0023; *t=4.29*), and for quiet (β=-0.289; *t=7.19*) vehicles. Preference for reductions in charging time suggests development of fast charging infrastructures that is consistent with the findings in previous studies (Dagsvik *et al*., 2002; Hidrue *et al.*, 2011; Hackbarth & Madlener, 2016). Drivers' in the WA EV trial also highlighted the importance of battery '*recharging infrastructure'* and they suggested '*low level of noise'* as a desirable feature of EV (Chapter 4, Section 4.4).

Large engine sizes are preferred for Petrol and Diesel vehicles (β=0.919; *t=6.02*) as shown in Table 6.7.

Driving Range

The parameter estimate for electric car driving range (β=-0.00695; *t=2.82*) is unexpectedly negative (Table 6.7). In previous studies (Hess *et al.*, 2006; Bolduc *et al.*, 2008; Lieven *et al.*, 2011; Hidrue *et al.*, 2011; Ziegler, 2012; Hackbarth & Madlener, 2016) the driving range had been identified as the most important positive parameter, but with this sample of 437 responses, that finding was not confirmed, which requires finding the possible cause(s) of the sign reversal for this range parameter estimate. Given non-trading behaviour in the mail-out sample, respondents who chose EVs in each experiment did not decide on attributes in the experiment, but rather made a decision about choosing one of the alternatives and ignoring the characteristics of vehicles. In addition to this, people who had strong preference for environmental concerns and social norms chose EV/PIH, which further confirms that they participated in the study to show their support for sustainable vehicles (further discussed in Chapter 7, Section 7.3). This could be resolved by analysing the trading only responses separately, to ascertain whether non-trading is the cause of this sign reversal. Another reason could be the bias in the mail-out sample.

The negative sign for the range parameter is critical for policy making. As shown by the recent success of Tesla's EV models (The Conversation, 2016), the "*stylistic maturity*" of EVs but also their technological advancement in tackling the *range anxiety* (an important barrier in the uptake of electric vehicles) are key for EV adoption.

Household Attitudes towards Sustainable Vehicle Technologies

It is interesting to note that people who chose EVs were concerned about the environment (β=0.735; *t=7.55*), and were influenced by fashion and friends (β=0.244; *t=6.32*). Similarly, people who chose PIH had a strong preference for environment (β=0.645; *t=6.05*) and were more responsive to Social Norms (β=0.0864; *t=1.99*). However responses showed no preference for the Perceived Uses of Technology or the Excitement for New Technologies.

Two additional items: RELY ON SINGLE CAR (*"Assuming you had an electric vehicle available, how likely is it that you would do without an additional car with an internal combustion engine?"*) and OFTEN USE EV ("*How often would you use your EV?"*) were incorporated into the model. Findings from the MNL model do not provide strong evidence that the EV or the PIH would be used as a second vehicle. In fact respondents who indicated that they would be able to satisfy their mobility needs without a conventional vehicle were more likely to select EVs (β=0.309; *t=9.22*) than PIH (β=0.149; *t=4.11*). Respondents who indicated an intention to use an EV for most of their trips were more likely to select EVs (β=0.283; *t=7.08*).

The Negative Coefficient on Driving Range

Providing incentives to respondents might help in increasing response rate (Laguilles, Williams & Saunders, 2011), however they might also result in getting non-trading behaviour (Hess *et al.*, 2010). Prior scholarly work questioned the quality of responses obtained with financial enticements for participation (Hansen, 1980). For the mail-out sample, respondents were offered incentives through a draw where chances of getting the prize were not clearly mentioned.

It is harder to understand this sign reversal for a key attribute of EVs. The possible causes of this sign reversal as identified in Section 6.7.1 require to answer following:

- "*Is the non-trading behaviour of respondents a sign of social desirability*?"
- *"Is it the sample bias?"*

In Chapter 7, non-trading behaviour is approached by separately analysing the behaviour of trading only responses; that is removing the non-traders from this sample. Sample bias in the mail-out sample is also investigated in Chapter 7 by analysing the PureProfile sample with only two experiments that have similar settings to the mail-out sample; that is having one EV in each experiment. To determine whether it is the sample that caused this sign reversal, findings from the mail-out sample were compared with the PureProfile sample, but restricted to only two observations (one-EV experiments). Findings from attitudinal data for the mail-out sample also supplement the causes of non-trading and sample bias because people who chose EV/PIH were pro-environmental, with strong influence from social norms. Having this strong preference for environment, EV non-traders might have chosen EV because they wanted to support a sustainable vehicle study.

Axsen, Goldberg, and Bailey (2016) have recently presented findings from an analysis of samples from a Canadian Plug-in EV Study (CPEVS). The first sample was from British Columbia and the second sample from other regions in Canada. In their first sample there were a total of 157 "*Pioneers*" who owned an EV, and 538 *"Mainstream"* people who owned conventional vehicles, but had an interest in EVs. It is interesting to note that socio-demographics, and attitudinal data of the "*Pioneers*" group of respondents in Axsen *et al.* (2016) are comparable to mail-out responses with a higher proportion of males (59.7% male in mail-out sample, 65% in the *Pioneers* group), a lower proportion of young (8.2% less than 30 years of age in mail-out, 11% less than 35 years of age in the *Pioneers* group), high household income (34% less than $75K per annum in mail-out, 24% less than $90K per annum in *Pioneers* group), more educated (72% had post-secondary education in mail-out, 80% had diploma or some university qualification in *Pioneers* group), having at least 2 or more vehicles (63.8% had at least two vehicles in the mail-out sample, 86% had 2 or more vehicles in the *Pioneers* group), and both showed pro-environmental behaviour (the goodness of fit index is 0.994 for environmental concern construct through CFA (Table 6.6) for mail-out sample, 17 average scores significant at 99% confidence level for *Pioneers* group). In this study only eight out of 437 mail-out respondents owned EV/PIH as either their first or second household vehicle, and it is interesting to note that socio-demographics and attitudinal data of these eight individuals also depicted similarity with the *Pioneers* group in Axsen *et al.* (2016).

This further confirms that participation of mail-out respondents indicates an interest or preference towards sustainable technologies, and these respondents wanted to depict themselves as *environmentally friendly EV Supporters*.

6.8 CONCLUSION

This Chapter discussed the data collection phase of the study. There were several problems at different stages of data collection: starting with the first sample "*mail-out*" incorrect addresses from the sampling frame, low response rates, having substantial response bias, later identified non-trading behaviour, and a negative estimate for driving range. To solve these problems a second sample was collected from the PureProfile online panel, resolving the sample bias problem. The attitudinal constructs, built from the drivers' study and previous studies were used in an initial analysis of the mail-out sample. The insights from this analysis indicated households' preference for low running cost, decrease in purchase price, quiet vehicles with big engine sizes and fast charging for EVs. In the mail-out household study people who chose EV/PIH had a strong preference for the environment and were influenced by social norms.

Reasons for negative driving range estimates are investigated in the next chapter. To identify the cause of the negative sign firstly it is considered pertinent to separately analyse mail-out sample trading responses to determine if it was the non-trading behaviour that has led to the negative estimate. Secondly, from the PureProfile sample, only two experiments with one EV in each experiment are analysed separately, where the purpose of analysing one-EV experiments from the second sample is to determine whether it is the sample bias that caused this sign reversal in the mail-out sample. The next chapter presents findings from the analysis using advanced choice analysis from the traders in the mail-out sample, only one-EV experiments in the PureProfile samples, and also looks at merging the two samples to make a pooled sample by combining mail-out traders with the one-EV experiments in the PureProfile sample.

CHAPTER 7

7 HOUSEHOLD STUDY: EXPLORING BEHAVIOUR USING CHOICE MODELS

7.1 INTRODUCTION

The problems encountered in the collection of the household data were mainly sample bias; that is sociodemographic differences from the population were high in the mail-out sample as discussed in Chapter 6. There was a biased representation of age (low representation of young respondents), education (72% of respondents with post-secondary education), gender (59.7% male), household income (less representation of low income groups), and geographic locations (more concentrated South of the river) in the mail-out sample, as compared to the Perth population (Section 6.3 elaborated this in detail). Consequently, due to sample bias further data was collected for the verification of findings. This meant that a modified version of the survey was administered to a second sample. As indicated, an online panel – PureProfile – was chosen to balance the samples. An initial analysis of the mail-out sample using a closed form choice model provided interesting insights into which vehicle attributes are valued most by households and also about the attitudinal data. Consequently, due to sample bias further data was collected for the verification of findings. This meant that a modified version of the survey was administered to a second sample. As indicated, an online panel – PureProfile – was chosen to balance the samples. An initial analysis of the mail-out sample using a closed form choice model provided interesting insights into which vehicle attributes are valued most by households and also about the attitudinal data. Whilst a number of parameter estimates were as expected and consistent with previous studies: among vehicle attributes respondents showed a high preference for low running costs, lower purchase price, and quiet vehicles followed by a preference for fast charging time but driving range did not have a significant positive sign. With this exception, the findings were consistent with previous research studies: the biggest concerns about EVs as identified by Egbue & Long (2012) include driving range, purchase price, and lack of charging infrastructure. Hidrue *et al.* (2011) also found driving range, charging time, and fuel cost savings as important for respondents by conducting choice experiments. Similarly Jensen *et al.* (2013) also found high estimates for purchase price and fuel costs along with fast charging, battery life and an increase in driving range. The quietness of EV's is also appreciated by respondents to previous studies (Skippon, & Garwood, 2011, Bühler *et al.,* 2014).

The negative coefficient on the driving range is inconsistent with the a priori expectations and also did not match findings from the drivers' study in Chapters 4. There could be two reasons for the sign reversal on the range variable. The first may be the high proportion of non-trading respondents, and the second is sample bias. In the mail-out sample 10.9% chose EVs in each experiment - disregarding other attributes of vehicles. In this case, removing these respondents from the sample might account for the bias in the estimation result. Related to the first reason the high degree of EV non-trading may be a symptom of pro-environmental bias whereby the respondents were mainly drawn from a sub population of EV enthusiasts, indicated by their pro-environmental views (β=0.735; *t=7.55*) and being highly influenced by social norms (β=0.244; *t=6.32*), as indicated by the attitudinal data in Table 6.7.

This chapter further investigates these two reasons. Firstly the mail-out sample is analysed by removing those people who chose the same vehicle in each experiment as most preferred/least preferred to determine whether the sign reversal is caused by these non-trading responses. Secondly, the PureProfile sample is analysed with two experiments having one EV to answer whether it is sample bias that led to sign reversal. Finally, the mail-out data set is combined with these two EV experiments from PureProfile to find whether data from two samples could be pooled together or not.

The next section defines non-trading responses in the mail-out sample followed by findings from the choice analysis of trading and non-trading responses. Best only choice analysis of the mail-out sample is given in Section 7.4. A discussion about Best-Worst choice data settings is presented in Section 7.5, followed by Section 7.6 where findings from B-W choice analysis of mail-out, PureProfile, and pooled samples are presented. Section 7.7 concludes this chapter.

7.2 NON-TRADING AND LEXICOGRAPHIC BEHAVIOUR

Many observations in the mail-out household survey data indicated either non-trading or lexicographic choices by the respondents (as shown in Table 6.4). Lexicographic behaviour (Blume, Brandenburger, & Dekel, 1989) denotes situations where a respondent chooses in all experiments an alternative based on a single attribute. A small proportion of respondents were ‘price lexicographic’ in the mail-out sample. Several respondents showed non-trading behaviour, not only for EV alternatives but also for PIH/Diesel/Petrol; that is choosing one of these alternatives as their Best choice in all experiments. This non-trading behaviour occurred not only in the most preferred option, rather some respondents did not trade in their least preferred option, and a few did not trade in both most and least preferred options. From a total of 437 valid responses, groups of non-traders for Best and Worst alternatives were separated as shown in Figure 7.1. Respondents selecting one alternative as their Best in all choice experiments were categorised as *Non-Traders*

(B), while the respondents who chose a single alternative as Worst in all choice experiments were categorised as *Non-Traders (W)*. Respondents who overlapped in Figure 7.1 are *Non-Traders (B and W)*.

For this mail-out sample: 48 out of 437 respondents chose EVs in all choice tasks; 13 respondents selected Petrol, 13 chose PIH, and 10 indicated Diesel as their most preferred choice in all given choice tasks. Only four respondents, that is 0.9%, decided on low-price vehicle as their best choice in all given scenarios. With these the total number of *Non-Traders (B)* equals 88 (44+44) (Figure 7.1); out of these 88 *Non-Traders (B)* half of them did not trade on the Worst choice, that is 44 respondents overlapped as *Non-Traders (B and W)*. For example, out of 44 *non-traders (B)* – six chose Petrol as their Worst choice in all given experiments, two were PIH *Non-Traders (W)*, and 10 were Diesel *Non-Traders (W)*. There were total of 59 *Non-Traders (W)* along with 44 that overlapped with *Non-Traders (B)*. Out of 59 *Non-Traders (W)*: 13 respondents chose EVs as their least preferred option in all choice tasks; 15 respondents selected Petrol, 12 selected PIH, and 19 indicated Diesel as their least preferred choice in all given choice tasks. As shown in the Venn Diagram in Figure 7.1, 290 respondents were traders, while 147 were *Non-Traders (B)*, *(W)*, or both *(B and W)*. \

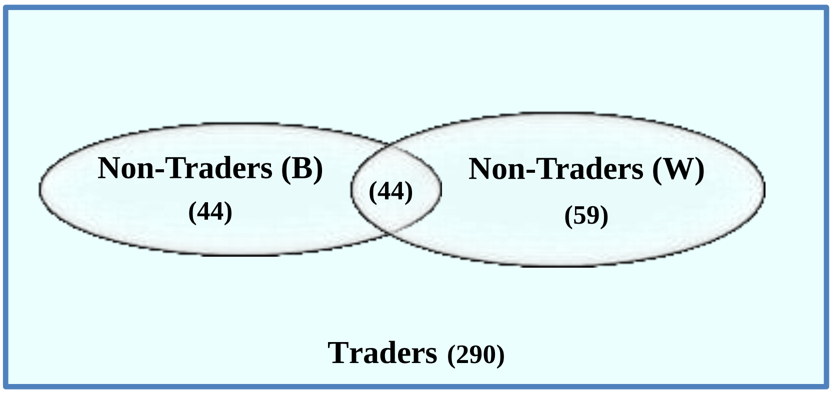


Figure 7.1: Venn Diagram Mail-out Sample (Total=437)

In relation to non-trading behaviour, Hess *et al*. (2010) identified three different reasons for it: *utility maximising agents* (indicates strong preference for an alternative as compared to other alternatives), *heuristics (and/or misunderstanding/boredom), and policy-response bias*. For the last two reasons it is recommended that non-trading respondents be removed from the analysis, but for utility maximising behaviour, that is when a respondent holds a strong preference for a particular alternative, the data should be kept in the model. It is however, not possible to determine the real cause of the respondent's behaviour without a follow-up interview. As this was not achievable in the study, in order to avoid errors in the valuation of attributes, data analysis was also carried out without non-trading observations; that is traders and non-traders were analysed separately and compared. It has already been noted that one of the possible reasons for this non-trading behaviour in the mail-out sample is social desirability, that is respondents' tendency to report more favourably certain attitudes and behaviours when they may feel an underlying incentive (Bonsall, 2009; Leroy, 2011). In addition, mail-out respondents were given an overview on EV characteristics in the form of an EV-Brochure. This information pack, as well as the choice scenarios may have heightened their interest in EVs and the respondents' choice of EVs may indicate their social desirability to the surveyor. These non-traders seem to have neglected vehicle attributes in the experimental setting, and rather focused on an EV alternative as their most preferred choice in all experiments, either to show their pro-environmental attitude or the influence of social norms.

In the mail-out sample, the non-trading and low-price lexicographic behaviour represented 88 *Non-Traders (B)* and 103 *Non-Traders (W)* (as given in Figure 7.1).

Although non-traders/lexicographic responses appear to conflict with economic rationality, (Lancsar & Louviere, 2006), they represent genuine preferences. For this reason, non-traders were not completely neglected in further analysis; but in order to avoid *irrational* responses that can alter the findings for the whole sample, 88 *Non-Traders (B)* responses were analysed separately.

For discrete choice analysis, data was set up considering the Best-Worst choice responses (see Section 3.2.5). For Best only analysis, the 290 traders and 59 *Non-Traders (W)* from the mail-out sample were grouped together (290+59=349), acknowledging that the *Non-Traders (W)* responses were not *irrational* in their decision for the Best/most preferred vehicle. Similarly, for Worst only choice analysis, 290 traders and 44 *Non-Traders (B)* were grouped together (290+44=334) as *Non-Traders (B)* were not *irrational* in their choice decision for the least preferred vehicle (Worst decision). On the other hand, for Best-Worst choice analysis 290 traders were grouped with 44 *Non-Traders (B)*, and 59 *Non-Traders (W)* to get a total 393 (290+59+44) responses, without including the overlapping 44 *B and W* Non-Traders (irrational in choosing both their Best and Worst vehicle).

Appendix K presents findings from 437 responses compared with 349 (290+59) traders in their Best vehicle choice (that is removing 88 *Non-Traders (B)*).

Attitudinal constructs were statistically significant for the 88 non-traders, which means that their elimination from the sample reduced the significance of associations of attitudinal data. However, the parameter estimate for driving range with traders only sample remained negative and significant (β=-0.0119; *t=-3.58,* Appendix K). This required further investigations into the mail-out sample with traders only responses to determine its potential causes.

7.3 MIXED LOGIT MODEL: BEST ONLY

The mail-out sample data including 349 trading responses was then analysed using the panel ML with the random parameters. The model specifications are presented first, followed by the findings from ML.

Selecting Random Parameters (RPs): Considering their relevance and impact on analysis, attributes of vehicles that were significant in MNL model (Table 6.7), were tested as random. They included: Purchase price, running cost, driving range, and charging time (Table 7.1).

Selecting the distribution of Random Parameters: Initially, all RPs were chosen to be normally distributed; however, when standard deviations are substantial, this can result in a change in the sign of the parameter for single draws of the full range of possibilities (Hensher *et al.*, 2005). The parameters for purchase price and running costs had significant standard deviation estimates around their means. The standard deviations for Charging time and range parameters were insignificant. However, the all parameters are retained their random settings for the purpose of model comparisons in subsequent model specifications when the estimating data is based on the Pureprofile sample.

Table 7.1: T-statistics of Random Parameters, and St.Dev. of RP

Random Parameters (RP) in Utility Functions $ASC_{\text{Alternative}}$	Beta	|t|
PRICEK: Purchase Price$_{\text{Generic}}$	-0.04572***	3.76
RUNCOST: Running Cost$_{\text{Generic}}$	-0.23490***	8.27
CHTIME: Charging Time$_{\text{EV}}$	-0.00381***	5.36
RANGE: Range$_{\text{EV}}$	-0.01379***	4.05
St. Dev. of Random Effects RP/Range of triangular distributions RP	**Beta**	**|t|**
PRICEK: Purchase Price$_{\text{Generic}}$	0.09509***	10.55
RUNCOST: Running Cost$_{\text{Generic}}$	0.06156***	3.72
CHTIME: Charging Time$_{\text{EV}}$	0.00039	0.39
RANGE: Range$_{\text{EV}}$	0.00014	0.14

To avoid the potential of sign reversal over the draws a triangular distribution with a limited range will be usied in the specification of subsequent models. Triangular distribution describes the random parameter as:

$RP = \beta + \sigma * \nu$

where: ν: triangular [-1, 0, 1] with the standard deviation σ set to be a proportion of β.

It means that the minimum and maximum of the distribution are $k*\beta$ above and below the mean, where k is a constant (for example if k=0.5, the resulting triangular distribution would be $\nu = [-½\beta, 0, ½\beta]$).

Note: by constraining the estimate of the standard deviations (S.D) to be a fraction of the mean parameter estimate the standard errors for S.D estimates are not meaningful.

Selecting the number of points for the simulations: In general, it is suggested that the number of draws increases with the complexity of model (number of RPs, treatment of preference heterogeneity around the mean, correlation of attributes, and alternatives) (Hensher *et al.*, 2005). In this study, for all experiments, the number of points for the simulation is set to 700. This number of draws helped to refine the mean estimates of random and non-random parameter estimates in the utility expression, as suggested by Louviere *et al.* (2000), p. 205. Halton sequence draws were used for estimation (Chapter 3, Section 3.2.3).

Error components: In this sample, an error covariance was chosen for EV and PIH.

Willingness-to-pay Measure: WTP measures were computed through the mixed logit model by taking the ratio of the variable of interest and the purchase price of vehicle. Simulation draws were used to derive the distribution of WTP measure for each individual.

Findings from Mail-Out Dataset

From 349 respondents a total of 2,154 observations were obtained. Results from a panel-ML with error components are shown in Table 7.2 (LL=-2,444.11, AIC/N= 2.29).

The alternative specific constants were also considered random. The mean of the constant on EV is significantly different from zero (β=-2.18; *t=2.49*; PIH being the base). The means of the constants for Petrol and Diesel did not differ significantly from zero. However, the standard deviations were significant for all three vehicle types, indicating the presence of a component of the unobserved utility characteristic to the fuel and vehicle technology. It was also noted that the preference for Petrol and Diesel were related to respondents' preference for larger engine sizes (β=1.44; *t=7.24*); but at the same time, a strong preference for quieter vehicles was noted (β=-0.368; *t=6.7*), as shown in Table 7.2.

As expected, the parameter estimates for purchase price (β=-0.047; *t=4.82*) and running cost (β=-0.244; *t=8.01*) are negative and significant. Recall that the standard deviation estimates are constrained to one half the mean parameter estimates and the standard errors are not to be interpreted. The attractiveness of lower running cost afforded by EVs was reflected in previous studies (e.g., Potoglou & Kanaroglou 2007). In addition, respondents with a price cap of $30k on their next vehicle were more responsive to price; the interaction between purchase price and the stated price cap was negative and significant (β=-0.0281; *t=2.92*).

Table 7.1: Parameter Estimates for Panel-ML Base model with random effects and Error Components: Best Only Mail-Out data — 1 EV Experiments

	Mail-Out Traders Best Only Panel-ML with random effects and Error Components	
Random Parameters (RP) in Utility Functions *ASC*$_{Alternative}$	**Beta**	**|t|**
ASC_{EV}	-2.18**	2.49
ASC_{Diesel}	-0.375	0.45
ASC_{Petrol} [a]	-0.0554	0.06
PRICEK: Purchase Price$_{Generic}$	**-0.0470*** **	**4.82**
RUNCOST: Running Cost$_{Generic}$	**-0.244*** **	**8.01**
CHTIME: Charging Time$_{EV}$	**-0.00413*** **	**5.71**
RANGE: Range$_{EV}$	**-0.0123*** **	**3.50**
Attributes$_{Alternative}$ in Utility Funtions	**Beta**	**|t|**
NOISE: Noise$_{Generic}$	-0.368***	6.70
ENGINESIZE: EngineSize$_{Petrol, Diesel}$	1.44***	7.24
St. Dev. of Random Effects RP/Range of triangular distributions RP	**Beta**	**|t|**
ASC_{EV}	1.35***	8.15
ASC_{Diesel}	1.22***	6.64
ASC_{Petrol} [a]	0.963***	4.28
PRICEK: Purchase Price$_{Generic}$	**0.0235*** **	**4.82**
RUNCOST: Running Cost$_{Generic}$	**0.122*** **	**8.01**
CHTIME: Charging Time$_{EV}$	**0.00206*** **	**5.71**
RANGE: Range$_{EV}$	**0.00615**	**3.50**
Interaction$_{Alternative}$	**Beta**	**|t|**
CheapCar_buyers X PRICEK$_{Generic}$	-0.0281***	2.92
Covariates$_{Alternatives}$	**Beta**	**|t|**
EC: Preference for Environment$_{EV}$	1.052***	3.49
SN: Social Norms$_{EV}$	0.215*	1.74
PU: Perceived Uses of Technology$_{EV}$	-0.0093	0.05
Rely on Single Car$_{EV}$	0.363***	3.74
Often use EV$_{EV}$	0.231**	2.3
EC: Preference for Environment$_{PIH}$	0.754***	3.55
SN: Social Norms$_{PIH}$	0.0589	0.66
PU: Perceived Uses of Technology$_{PIH}$	0.0497	0.37
Rely on Single Car$_{PIH}$	0.183***	2.79
Error Component	**Beta**	**|t|**
EV and PIH	1.062***	6.42
Number of estimated parameters	24	
Number of observations	2,154	
Number of individuals	**349**	
Log likelihood	-2,444.11	
AIC/N	2.29	
ρ^2 (Pseudo-R^2)[b]	0.181	

[a:] ***Plug-in-Hybrid PIH is the reference fuel and vehicle technology;***
[b:] **McFadden Pseudo *R^2*;**
******, **, * indicate significance at 1%, 5%, and 10% level respectively.***

Kurani *et al.* (1996) also found that consumers were sensitive to vehicle performance in terms of refuelling time and driving range. Whilst the respondents to the mail-out survey preferred faster charging times (β=-0.00413; *t=5.71*), the parameter estimate for range variable still revealed a preference towards shorter driving ranges (β=-0.0123; *t=3.50*). This finding is in contrast to previous empirical studies (Potoglou & Kanaroglou, 2007; Bolduc *et al*., 2008; Ziegler, 2012). Even by analysing data using advanced ML model also confirmed the driving range parameter estimate sign reversal it was thus essential to collect another wave of data as already indicated in Chapter 6. The issue appears to be more involved than model estimation and suggests that respondent bias be examined more thoroughly (Section 7.5) or that experimental design was revisited (Chapter 8). In either case a second sample was needed to test each of these possibilities.

The latent constructs entered the models by way of an interaction with the ASC's for EV and PIH. Heightened environmental concern (β=1.052; *t=3.49*) and greater compliance to social norms (β=0.215; *t=1.74*) were associated with a higher likelihood of selecting the EV alternative in the SP experiment. Respondents who chose PIH were also concerned about environment (β=0.754; *t=3.55*) and this finding is consistent with previous studies (e.g., Noppers *et al.*, 2014). Respondents who indicated that they would to be able to satisfy their mobility needs without a conventional vehicle were more likely to select EVs (β=0.363; *t=3.74*) than PIH (β=0.183; *t=2.79*). Respondents who indicated an intention to use an EV for most of their trips were more likely to select EVs (β=0.231; *t=2.30*).

WTP measures for this data set are presented in Section 7.8 where they are compared with the computed WTP measures for Best then Worst Choice analysis, for the second sample.

7.4 SETTING UP THE DATA –BEST-WORST CHOICE DATA

A best-worst (BW) choice task allows the respondents to indicate their most preferred and least preferred alternative. Given that there are four alternatives in this study, the BW selections do not reveal a complete ranking. However, the choice data provides the analyst with a partial ranking, which means more detail than the traditional choice data. In Section 3.2.6 a number of random utility models, consistent with best-worst observations, were outlined. This section details the way in which the choice data needs to be set up in order to run the corresponding choice models. There are two ways in which the partial ranking is transformed into choice data: (1) Best then Worst (B-W) choice data; and (2) Exploded logit choice data. These two choice data setups were done for both samples and are therefore explained here for both samples.

Best then Worst (B-W) Data Setup

This Section describes the data set up for B-W choices. Whilst a max-difference choice model (Section 3.2.6) may also be valid, that requires a full combinatorial set of Best-Worst pairs. In the case of four alternatives the choice set for each observation would be the 24 possible Best and Worst combinations.

In the B-W mirror image setup, data enrichment is achieved by exploding the data into these two blocks or '*frames*'; the first frame containing the Best choice, while the second frame omits the Best choice. However the important difference between B-W mirror image and Exploded logit is the coding, with the attributes of the Worst set being a mirror image of the first block and having a negative sign for all attribute values (Rose, 2013). Application to attribute levels is achieved by multiplying each value by -1:

$$\beta_{k|W} x_{nsjk|W} \quad = \quad \beta_{k|W}\left(-\, x_{nsjk|B}\right) = -\, \beta_{k|W} x_{nsjk|B}$$

Eq.7.2

where: W and B represent the Worst and Best case respectively; s is the choice set; k the attribute; and j the fuel and vehicle alternative.

Representing the B-W choice is shown in Figure 7.2 for the two samples, where data are presented in seven rows (4+3). Each observation is represented by two choices. The first block of data consists of four alternatives with the Best choice and the second block with three alternatives without the Best choice, but negative sign. Figure 7.2A presents an example corresponding to the mail-out sample with two choice blocks. Firstly, the four rows at the top of the table indicate Diesel as the Best choice (Diesel > EV, PIH, Petrol). Secondly, the Worst alternative is selected from the three remaining alternatives, after the Best is removed. The utilities are multiplied by -1 to reflect that the choice indicator (value 1) corresponds to the alternative with the lowest utility. This allows construction of 42 rows (6*7) for each respondent, provided that each respondent answered six experiments.

ALT	CHOICE INDICATOR	WORST	CHOICE SET-SIZE	NUMBER OF CHOICE SETS	NUMBER OF ROWS	Purchase Price ('000 $)	Range (km)	Running Cost ($/100km)	Engine Size (L)	Emissions or GHG (kg/100km)	Noise	Battery Capacity after 10 years	Charging Time (min)	Number of Charging Stations
EV	0	0	4	12	42	50	140	1.4	2.4	11		0.85	90	500
Petrol	0	0	4	12	42	36	800	7.5	2.4	21	2			
PIH	0	1	4	12	42	53	400	6	1.6	17	2	0.85		
Diesel	1	0	4	12	42	46	800	7.5	2	23.5	3			
EV	0	0	3	12	42	-50	-140	-1.4	-2.4	-11		-0.85	-90	-500
Petrol	0	0	3	12	42	-36	-800	-7.5	-2.4	-21	-2			
PIH	1	1	3	12	42	-53	-400	-6	-1.6	-17	-2	-0.85		

Figure 7.2 A) B-W Choice Analysis: Mail-Out Sample Data (Negative sign in the second frame of B-W data is a computational device)

ALT	CHOICE INDICATOR	WORST	CHOICE SET-SIZE	NUMBER OF CHOICE SETS	NUMBER OF ROWS	Purchase Price ('000 $)	Range (km)	Running Cost ($/100km)	Engine Size (L)	Emissions or GHG (kg/100km)	Noise	Battery Capacity after 10 years	Charging Time (min)	Number of Charging Stations
EV1	0	0	4	12	42	50	160	2	2.4	11		0.95	12	500
PIH	0	1	4	12	42	37	600	6	2.4	13	2	0.65		
EV2	0	0	4	12	42	42	80	2	2.4	13		0.95	12	1000
Diesel	1	0	4	12	42	30		6	1.6	26	1			
EV1	0	0	3	12	42	-50	-160	-2	-2.4	-11		-0.95	-12	-500
PIH	1	1	3	12	42	-37	-600	-6	-2.4	-13	-2	-0.65		
EV2	0	0	3	12	42	-42	-80	-2	-2.4	-13		-0.95	-12	-1000

Figure 7.2 B) B-W Choice Analysis: PureProfile Sample Data (Negative sign in the second frame of B-W data is a computational device)

Figure 7. 2: B-W Mirror Image Data Setup

In the PureProfile experiments, with two EVs in the same experiment example, in the B-W mirror image choice data setup (Figure 7.2B) there are two choice situations: first for the Best (Diesel > EV1, PIH, EV2) and the second one is the B-W mirror image of the first after removing the Best. Again for 2EV experiments in this sample there are 42 rows for each respondent, while for a 1EV experiment in this sample there are (2*7) 14 rows for each respondent. The *Vehicle_Code* variable (not shown in Figure 7.2B) in this sample data indicates the type of vehicle tested in the particular experiment.

Exploded Logit Data Setup

Taking the same examples as for the B-W mirror image data, in the Exploded logit data setup, there are three comparisons bringing about three blocks (Figure 7.3), and eight rows (4+2+2) for each experiment. The first block is the same as in the B-W data setup, that is it has four alternatives; the second block compares the Worst choice with one of the two alternatives not chosen as Best or Worst; and the third block compares the Worst choice with the next alternative not chosen as Best or Worst.

In the mail-out sample, the first block of Exploded logit data (Figure 7.3A) is the same as in the B-W mirror image data (Figure 7.3A); the second block compares the Worst alternative with the first not chosen alternative (EV>PIH); the third block compares the Worst alternative with the second not chosen alternative (Petrol>PIH). Six experiments for each respondent in the mail-out sample, and eight rows for each experiment in this data setup, results in 48 rows against each respondent.

ALT	CHOICE BEST	WORST	CHOICE SET-SIZE	NUMBER OF CHOICE SETS	NUMBER OF ROWS	Purchase Price ('000 $)	Range (km)	Running Cost ($/100km)	Engine Size (L)	Emissions or GHG (kg/100km)	Noise	Battery Capacity after 10 years	Charging Time (min)	Number of Charging Stations
EV	0	0	4	18	48	50	140	1.4	2.4	11		0.85	90	500
Petrol	0	0	4	18	48	36	800	7.5	2.4	21	2			
PIH	0	1	4	18	48	53	400	6	1.6	17	2	0.85		
Diesel	1	0	4	18	48	46	800	7.5	2	23.5	3			
EV	1	0	2	18	48	50	140	1.4	2.4	11		0.85	90	500
PIH	0	1	2	18	48	53	400	6	1.6	17	2	0.85		
Petrol	1	0	2	18	48	36	800	7.5	2.4	21	2			
PIH	0	1	2	18	48	53	400	6	1.6	17	2	0.85		

Figure 7.3 A) Exploded logit Choice Analysis: Mail-Out Sample Data*

ALT	CHOICE BEST	WORST	CHOICE SET-SIZE	NUMBER OF CHOICE SETS	NUMBER OF ROWS	Purchase Price ('000 $)	Range (km)	Running Cost ($/100km)	Engine Size (L)	Emissions or GHG (kg/100km)	Noise	Battery Capacity after 10 years	Charging Time (min)	Number of Charging Stations
EV1	0	0	4	18	48	50	160	2	2.4	11		0.95	12	500
PIH	0	1	4	18	48	37	600	6	2.4	13	2	0.65		
EV2	0	0	4	18	48	42	80	2	2.4	13		0.95	12	1000
Diesel	1	0	4	18	48	30		6	1.6	26	1			
EV1	1	0	2	18	48	50	160	2	2.4	11		0.95	12	500
PIH	0	1	2	18	48	37	600	6	2.4	13	2	0.65		
EV2	1	0	2	18	48	42	80	2	2.4	13		0.95	12	1000
PIH	0	1	2	18	48	37	600	6	2.4	13	2	0.65		

Figure 7.3 B)Exploded logit Choice Analysis: PureProfile Sample Data*

Figure 7. 3: Exploded Logit Data Setup

* Negative sign in the second frame of B-W Mirror Image data is a computational device

In the PureProfile sample, the first block of Exploded logit data (Figure 7.3B) is the same as in the B-W mirror image data (Figure 7.3B); the second block compares the Worst alternative with the first not chosen alternative (EV1 > PIH); and third block compares the Worst alternative with the second not chosen alternative (EV2 > PIH). For PureProfile 2EV experiments there is a total of six experiments thus, 48 rows for each respondent, whereas for 1EV experiments there are only 16 rows for each respondent.

7.5 IS IT SAMPLE BIAS: FINDINGS FROM 1EV EXPERIMENTS POOLED SAMPLES

Findings from Pure Profile Sample

There were two experiments in PureProfile where 1EV was presented to respondents. Four vehicle options being similar in both samples allowed for the posibility of systematically assessing the differences between the PureProfile and mail-out samples, and to determine if sample bias is the reason of the sign reversal in mail-out data. Another aim of analysing these two experiments separately in the PureProfile sample is to determine if these could be combined with the mail-out data to get a pooled sample. In contrast to the mail-out sample, the non-trading and lexicographic behaviour was low for the PureProfile sample, with only two respondents out of 305 choosing EVs in all choice tasks, and four respondents considering a low-price vehicle as their best option in all given experiments. These six responses (two EV *Non-Traders (B)* and four purchase price lexicographic) were removed, thus leaving 299 responses for choice analysis.

The same attributes as in the mail-out sample were selected as random (purchase price, driving range, running cost, and charging time) for consistency. To jointly model B-W data, a scale parameter was estimated by way of a preliminary nested logit. The scaling factor was applied to the best data to rescale the attribute levels. The value of the scale parameter in this sample was $\lambda B=0.6636$, and the scaled data provided a good model fit (LL=-1,263.25; AIC/N=2.17; Pseudo R2 =0.492). The alternative specific constants for Best and Worst data were estimated as shown in Table 7.3.

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Table 7.2: Best-Worst Panel-ML with Error Components: Mail-Out Sample Traders, PureProfile – 1 EV Experiments

	Mail-out Traders B-W – Scaled		PureProfile 1EV B-W – Scaled	
Random Parameters in Utility Functions *ASC*$_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	-4.10***	3.86	-3.56**	2.45
ASC_{Diesel}	1.14	1.52	4.41***	3.49
ASC_{Petrol} [a]	1.40*	1.83	5.72***	4.39
ASC_{EVW}	-0.0444	0.09	1.43	1.53
$ASC_{DieselW}$	0.0554	0.17	-4.17***	4.28
$ASC_{PetrolW}$	-0.0327	0.1	-4.49***	4.86
PRICEK: Purchase Price$_{Generic}$	**-0.0199*** **	**6.01**	**-0.059*** **	**7.17**
RUNCOST: Running Cost$_{Generic}$	**-0.1001*** **	**9.29**	**-0.168*** **	**4.05**
CHTIME: Charging Time$_{EV}$	**-0.0017*** **	**6.50**	**-0.000049**	**0.05**
RANGE: Range$_{EV}$	**-0.0029***	**1.69**	**0.00226**	**0.92**
Attributes$_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
NOISE: Noise$_{Generic}$	-0.148***	7.46		
ENGINESIZE: EngineSize$_{Petrol, Diesel}$	0.523***	7.89	-0.0789	0.39
CSTATS: Number of Charging Stations$_{EV}$	0.00012*	1.66	0.000091	0.37
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	1.97***	12.79	1.71***	3.68
ASC_{Diesel}	1.14***	7.23	2.06***	3.41
ASC_{Petrol}	1.12***	5.59	2.06***	3.61
ASC_{EVW}	3.07***	10.43	1.43	1.53
$ASC_{DieselW}$	0.849***	4.69	-4.17***	4.28
$ASC_{PetrolW}$	1.25***	8.12	-4.49***	4.86
PRICEK: Purchase Price$_{Generic}$	**0.00997*** **	**6.01**	**0.0297*** **	**7.17**
RUNCOST: Running Cost$_{Generic}$	**0.05004*** **	**9.29**	**0.0840*** **	**4.05**
CHTIME: Charging Time$_{EV}$	**0.00084*** **	**6.5**	**0.000025**	**0.05**
RANGE: Range$_{EV}$	**0.00026**	**0.22**	**0.00434**	**0.92**
Interaction $_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
HaveSolarPanels X RUNCOST$_{Generic}$			0.0664**	2.09
ET X Noise$_{PIH,Diesel,Petrol}$			-0.096***	5.73
CheapCarbuyers X PRICEK$_{Generic}$	-0.0116***	3.46		
Covariates$_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
EC: Environmental Concerns$_{EV}$	0.689***	6.49	0.463*	1.7
SN: Social Norms$_{EV}$	0.114***	2.96	0.249**	2.04
PU: Perceived Uses of Technology$_{EV}$	-0.0925	1.04	0.621**	2.39
ENT: Excitement for New Technology$_{EV}$	0.0779	1.11	-0.521**	2.55
Rely on Single Car$_{EV}$	0.162***	4.55	0.776***	6.35
Often use EV$_{EV}$	0.0997**	2.35		
EC: Environmental Concerns$_{PIH}$	0.485***	7.32	0.751***	3.49
SN: Social Norms$_{PIH}$	0.0582**	2.08	0.342***	3.64
PU: Perceived Uses of Technology$_{PIH}$	-0.0229	0.51	-0.030	0.23

Rely on Single Car$_{PIH}$	0.0845***	3.88	0.49***	4.98
Error Components	**Beta**	**|t|**	**Beta**	**|t|**
EV and PIH	1.39***	9.8	2.18***	4.51
EV$_W$ and PIH$_W$	1.46***	9.75	0.138	0.07
Number of estimated parameters	33		32	
Number of observations	4,844		1,196	
Number of individuals	**393**		**299**	
Scale Parameter (λ)	0.3771		0.6636	
Log likelihood	-4,745.47		-1,263.25	
AIC/N	1.97		2.17	
ρ^2 (Pseudo-R^2)[b]	0.529		0.492	

[a:] ***Plug-in Hybrid is the reference fuel and vehicle technology;***
[b:] **McFadden Pseudo R^2;**
*****, **, * indicate Significance at 1%, 5%, and 10% level respectively.**

Unlike the mail-out traders' sample findings, for this small part of the PureProfile sample, with only 1EV experiments, people are only concerned about purchase price (β=-0.0594; *t=-7.17*), and running cost (β= -0.168; *t=-4.05*). Driving range is still negative (mail out) or not-significantly different from zero (Pureprofile). This suggests that including worst data may have a small contribution to correcting the sign of the range parameter but the evidence is not strong. The estimates charging time and number of charging stations were also not significant here. The weak estimates on these variables that are specific to EVs suggest that by only having one-EV in the choice tasks the experimental design does not reveal preferences for EV characteristics.

Comparing the latent constructs added as covariates in the random parameters logit model for PureProfile, the 1EV experiment reveals that people who chose EVs in this group were comparatively less concerned about environment (β=0.463; *t=1.7*), as compared to mail-out trader responses (β=0.689; *t=6.49*). This group is influenced by social norms (β=0.249; *t=2.04*). The group is different from the mail-out sample such that: i) people who chose EVs believe in perceived usefulness of technologies (β=0.621; *t=2.39*); ii) people who are excited about new technologies did not prefer to choose EV (β=-0.521; *t=2.55*), however further investigations revealed that these people were more concerned about operating characteristics of vehicles - that is they preferred low noise vehicles (β=-0.0963; *t=5.73*), while in the mail-out sample these attitudes were not depicted. An extra question added in this sample, that is 'Having solar panels at home', suggests as expected that people having solar panels at home were not concerned about the increase in running cost, as tested by the interaction between these two variables (β=0.0664; *t=2.09*). The next step is to test whether the PureProfile sample could be combined with mail-out traders to get a pooled sample.

Is it possible to Pool Samples: 1EV Experiments and Mail-Out Sample Best AND Worst Traders?

The PureProfile sample covered primarily geographic areas of the city where the mail-out survey had produced insufficient answers and from socio-economic groups with lower income or owning fewer vehicles; these were under-represented in the mail-out sample. However, the two sources of data together are expected to produce more reliable parameter estimates and to cover the population characteristics better. Yet, it was not possible to assign population weights as the PureProfile sample's sociodemographic details were not accessible (respondents in this sample were recruited on quota by a commercial organisation).

Pooling Data with Weights: Choice data from the two samples were merged together to create a pooled sample. Two experiments (1EV) from the PureProfile sample were merged with six experiments (1EV) from the mail-out sample by assigning weights to the first so that they are equal in number to the mail-out sample, otherwise the pooled dataset and the findings from it would be dominated by the mail-out sample.

The scale parameters for the mail-out sample (λ_1) and PureProfile (λ_2) were computed through their best and worst choices separately (Table 7.4), and the scaled data merged in one sample. Still, to account for the differences in the mail-out and PureProfile samples, the data was scaled again using a two-step process. In the first step, a Nested Logit model was estimated, then scaled variables were created for the mail-out sample by multiplication with the scale parameter (λ_3=1.79). A total of 692 pooled (393 mail-out + 299 PureProfile) respondents yield 6,040 observations. Findings from the B-W ML choice analysis from this scaled pooled dataset with error components and random effects are given in Table 7.4.

To determine if data can be pooled from two samples a log-likelihood ratio (LL Ratio) was conducted[7].

The random parameters were kept same as in the two separate samples, that is: purchase price, running cost, charging time, and driving range random (Table 7.5). The results indicated that it is not possible to pool these two samples. Nevertheless, the parameter for driving range becomes positive and marginally significant (at α=0.1). The significance of the standard deviation parameter cannot be tested as it a fixed parameter being half the mean of the triangular distribution.

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[7] Because two experiments from PureProfile were combined with the six experiments from mail-out data adding LL of two separate models and comparing it with the pooled model LL is unfitting. For this reason a pooled model with all free parameters for mail-out sample and PureProfile sample was estimated and compared with the pooled and partially constraint model. The free/unconstraint model with free variables for two samples had a model fit (LL= -10,339.64; AIC/N=3.44; K=64). In this pooled model with the free parameters, some of the variables (such as vehicle attributes and attitudes) were constrained and rest set free, as shown in the partially constraint model (LL=-10,360.90; AIC/N=3.45; K=58)

Table 7.3: Best-Worst Panel-ML with Error Components: Pooled Sample – 1 EV Experiments

	POOLED B-W – Scaled Partially Free			
	Estimates for Mail-out Sample		Estimates for PureProfile Sample	
Random Parameters (RP) in Utility Functions *ASC*$_{\textbf{Alternative}}$	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	-5.55***	6.54	-3.21***	4.95
ASC_{Diesel}	0.999	1.45	4.89***	8.42
ASC_{Petrol} [a]	1.06	1.51	6.07***	10.18
ASC_{EVW}	0.394	0.83	1.35***	3.28
$ASC_{DieselW}$	-0.0414	0.14	-4.33***	10.53
$ASC_{PetrolW}$	-0.166	0.57	-4.74***	11.15
RP in Utility Functions RP$_{\textbf{Alternative}}$ Constraint	**Beta**		**|t|**	
PRICEK: Purchase Price$_{\textbf{Generic}}$	**-0.0502*** **		**16.15**	
RUNCOST: Running Cost$_{\textbf{Generic}}$	**-0.170*** **		**12.7**	
CHTIME: Charging Time$_{\textbf{EV}}$	**-0.00159*** **		**5.2**	
RANGE: Range$_{\textbf{EV}}$	**0.00184***		**1.81**	
Attributes$_{\textbf{Alternative}}$ in Utility Funtions	**Beta**	**|t|**	**Beta**	**|t|**
CSTATS: Number of Charging Stations$_{EV}$	0.00037***	3.79	0.000041	0.38
NOISE: Noise$_{GenericM}$	-0.251***	7.47		
ENGINESIZE: EngineSize$_{Petrol, Diesel}$	0.954***	7.89	-0.145	1.49
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	1.91***	12.76	1.87***	9.57
ASC_{Diesel}	0.913***	5.27	1.66***	6.01
ASC_{Petrol} [a]	1.26***	6.19	1.85***	7.23
ASC_{EVW}	3.14***	10.22	2.38***	11.41
$ASC_{DieselW}$	0.863***	5.45	2.69***	11.81
$ASC_{PetrolW}$	1.29***	8.67	1.23***	5.75
St. Dev. of random effects RP/limits of triangles of random effects Constraint RP	**Beta**		**|t|**	
PRICEK: Purchase Price$_{\textbf{Generic}}$	**0.0251*** **		**16.15**	
RUNCOST: Running Cost$_{\textbf{Generic}}$	**0.08516*** **		**12.7**	
CHTIME: Charging Time$_{\textbf{EV}}$	**0.0008*** **		**5.2**	
RANGE: Range$_{\textbf{EV}}$	**0.00033**		**0.19**	
Interaction$_{\textbf{Alternative}}$	**Beta**	**|t|**	**Beta**	**|t|**
HaveSolarPanels X RUNCOST$_{GenericP}$			0.0706***	4.82
ET X Noise$_{PIH,Diesel,Petrol}$			-0.0751***	12.26
CheapCarbuyers X PRICEK$_{Generic}$	-0.00331	0.68		

Covariates$_{\text{Alternatives}}$	**Beta**	**|t|**	**Beta**	**|t|**
EC: Environmental Concerns$_{EV}$	1.11***	5.59	0.483***	3.71
PU: Perceived Uses of Technology$_{EV}$	*-0.172*	*1.1*	*0.621****	*5.44*
ENT: Excitement for New Technology$_{EV}$	0.182	1.44	-0.511***	5.4
Rely on Single Car$_{EV}$	0.321***	4.73	*0.803****	*13.79*
Often use EV$_{EV}$	*0.162***	*2.07*		
EC: Environmental Concerns$_{PIH}$	0.837***	6.46	0.759***	7.58
SN: Social Norms$_{PIH}$	0.130***	2.7	0.326***	7.93
Rely on Single Car$_{PIH}$	0.150***	3.7	0.508***	10.93
Constraint Covariates$_{\text{Alternatives}}$	**Beta**		**|t|**	
SN: Social Norms$_{EV}$	0.221***		4.76	
PU: Perceived Uses of Technology$_{PIH}$	-0.0325		0.66	
Error Components	**Beta**	**|t|**	**Beta**	**|t|**
EV, PIH	1.41***	9.45	2.33***	10.47
EV$_W$, PIH$_W$	1.45***	9.33	0.242	0.58
Number of estimated parameters	58			
Number of observations	6040			
Number of individuals	692			
Scale Parameter (λ)	**λ_1= 0.3771 (Mail-out BW Scale)**			
	λ_2= 0.66356 (Pure-Web Based BW Scale)			
	λ_3= 1.79 (Mail-Out Sample Scale)			
Log likelihood	-10,360.90			
AIC/N	3.45			
ρ^2 (Pseudo-R^2)[b]	0.63			

[a]: ***Plug-in Hybrid is the reference fuel and vehicle technology;***
[b]: **McFadden Pseudo R^2;**
*****, **, * indicate Significance at 1%, 5%, and 10% level respectively.**

The results suggest that the mail out sample showed a favourable bias toward the adoption of EV's and this affected non-trading behaviour as well as some parameter estimates.

These mail-out sample respondents displayed similarities to the respondents in the first drivers' study, presented in Chapter 4. Socio-demographics common to both samples are a higher proportion of male responses (59.7% male in in mail-out sample; 68% male drivers), a higher proportion of educated responses (University/bachelor degree - 72% had post-secondary education in mail-out, 68%

went to a University with post-secondary education in drivers sample), a low proportion of young responses (8.2% less than 30 years of age in mail-out, 24.3% less than 30 years of age in the drivers' sample), a higher proportion of responses own at least 2 vehicles (63.8% had at least 2 or more vehicles in mail-out sample, 70.7% of the drivers had at least 2 or more vehicles). Commonalities between the two samples were also evident in the attitudinal data: both groups are pro-environmental (significant CFA goodness of fit index for EC construct is 0.994 (Table 6.6) for mail-out sample, while two of the three groups identified in the drivers' study (*Supporter-EV* and *Technology promoters-Env*) had the factor scores above 4.5/6.0 for the environmental concerns). In addition the *Supporter-EV* cluster profile in drivers' study had high factor scores in their willingness to recommend and purchase an EV (4.0/6.0). Considering the similarities between drivers and the mail-out sample, these two samples reflect their 'Pioneer' characteristics as indicated by Axsen *et al.* (2016) and discussed in Chapter 6 (Section 6.7.3).

7.6 WILLINGNESS-TO-PAY MEASURES: ONE EV EXPERIMENT SAMPLES

WTP measures for running cost and charging time were computed for the mail-out sample Best only, B-W traders data, PureProfile 1EV experiments, and pooled samples. These two variables, running cost and charging time, were significant in all samples (except charging time that was not significant in PureProfile 1EV experiments).

WTP Measure for Running Cost

The WTP obtained for running cost was quite high in the 1EV experimental settings. Respondents were willing to pay $2,956 more in the purchase price of vehicle for $1/100km decrease in the running cost. This WTP measure was even higher for the mail-out sample where the amount was $5,861.25 for mail-out traders.

WTP Measure for Charging Time

The WTP measure for EV charging time was highest in mail-out traders' sample, with a value of $97.3 for a minute decrease in the EV charging time and decreased in the pooled sample to $33.35 per minute (Table 7.5). For mail-out sample Best only choice model, this variable indicates that on average people were willing-to-pay $919.7 per 10 min reduction in EV charging time. Given that on average motor vehicles registered in Australia travelled =13,800km in 12 months (ABS, 2015) and life expectancy of EV battery is eight years, which means a total number of 112,000 kilometres driven in EV life, if an EV battery is recharged every 140kms, it will require total of 800 times to recharge an EV, equivalent to 133 hours (800*10min/60min). WTP in dollars per hour would be $6.9/hr (91.97*10/133).

Considering that no charging infrastructure exists yet in Western Australia, this WTP for reduction in charging time also suggests a preference for fast charging stations (as discussed in Section 5.2.1).

Table 7.4: WTP Measures for Mail-out and PureProfile Samples

Variable	Statistic	Mail-out Best Only n=349	Mail-out Traders n=393	PureProfile 1EV n=299	Pooled Sample n=692
RUNCOST	**Average**	$5,444.88	$5,861.25	$2,955.99	$3,565.96
Generic	**Std.Dev.**	255.07	436.8	165.28	254.59
$\mathbf{CHTIME_{EV}}$	**Average**	$91.97	$97.53		$33.35
	Std.Dev.	3.73	7.64		1.96

7.7 CONCLUSION

This chapter presents findings from the mail-out sample and investigates the reasons for the negative parameter estimates for driving range. Two reasons were mainly investigated: 1) non-trading responses; and 2) sample bias. By analysing the mail-out sample with and without non-trading responses, it was found that non-traders were not the cause of sign reversal. Data from the PureProfile sample having 1EV in each experiment was then analysed to determine if it was sample bias that caused sign reversal. Given the inconclusive results, further exploration is required. The results presented in Section 7.5 suggest that respondents could not make a decision about the EV characteristics when only one EV was included in the experiment. That is, respondents were unable to compare EV characteristics (mainly range and charging) with Petrol, Diesel, and PIH features, given their considerable differences. It was thus concluded that juxtaposing the ranges of Petrol and Diesel vehicles with the range of an EV in the choice experiments (Figure 6.1) was either confusing or irrelevant as far as the respondents were concerned. Whereas an EV buyer will pay great attention to range, a Petrol or Diesel car buyer will scarcely give it a thought. This is explored next by analysing the experiments where two EVs are presented in one experiment, allowing respondent to compare EV features side by side. It is hypothesised that having two electric vehicles in the same experiment would allow the respondent to make a decision about EV features. An analysis of these 2EV experiments for the PureProfile sample is presented in the next chapter.

With respect to data pooling, it was concluded that pooling is not justified due to the differences between the samples (such as their locations, sample bias in the mail-out sample, differences in attitudes). The differences in attitudinal data indicate that people who chose an EV in the mail-out sample were more concerned about the environment, as compared to the ones in the PureProfile sample. The sign for driving range parameter estimate goes in right direction in pooled data.

CHAPTER 8

8 HOUSEHOLD STUDY: EXPLORING BEHAVIOUR USING ADVANCED CHOICE ANALYSIS

8.1 INTRODUCTION

The previous Chapter investigated the causes of sign reversal for EV driving range parameter estimate for mail-out sample and PureProfile 1EV experiments. Many of the respondents in the mail-out sample and the driver respondents in Chapter 4 represent *EV enthusiasts* who are *conscious about saving the environment*. In Chapter 7, data was analysed using Panel ML with Error Component, looking first at the non-trading behaviour. The *Non-trader (B)* respondents were removed from Best only data and, similarly, *Non-trader (B and W)* were removed from the analysis of B-W data. As the range estimate remains negative in both cases another potential reason for the sign reversal was investigated. Sample bias was explored by comparing results from the mail-out sample with a sub-sample of experiments in PureProfile. Two out of the eight experiments shown to PureProfile respondents included the same four alternatives as in the mail-out sample (i.e., 1EV in each experiment). These 1EV experiments were analysed separately and combined with the mail-out data and the results did not display meaningful estimates (Table 7.4) due to differnces in samples. This suggested that the experimental design (1EV), rather than the sample bias, may explain the unexpected result. With only one EV, it was difficult for respondents to trade-off EV characteristics such as driving range, charging time and number of charging stations against traditional ICE alternatives and thus they could not decide on the EV attributes (Table 7.5). Consequently, data from 2EV experiments was analysed, hypothesising that 2EVs in the same scenario would allow respondents to make a decision about their future vehicle choice by trading-off the EV characteristics of the 2EV options. This chapter presents findings from the 2EV experiments data in the PureProfile sample.

The next section presents findings from the Panel Mixed Logit models with Error Components in Best only, Worst only, and B-W Choice analysis. Section 8.3 compares B-W with Exploded Logit choice analysis and Section 8.4 provides the WTP measures. Section 8.5 discusses the importance of having two electric vehicles in the same experiment and how it affects the estimation. Conclusions from this chapter are provided in the last section.

8.2 RESULTS FROM PUREPROFILE SAMPLE TWO EV EXPERIMENTS: B-W CHOICE ANALYSIS

In PureProfile, the sample set of six experiments having 2EVs in each experiment was analysed separately. In each choice situation, the 2EVs were compared against two ICE options, including Petrol, Diesel, and PIH. Given 299 respondents in this sample, a total of 1,794 observations were achieved in Best Only choice data, while 3,588 observation were achieved in Best-Worst choice Data.

Selecting Random Parameters (RPs): The random parameters were tested first through MNL considering their impact on the analysis, and most of them were the same as in the 1EV experiments. The four RPs, common to 1EV and 2EV experiments included: purchase price, running cost, charging time, and EV driving range. Additionally, the number of charging stations was also considered random, thus a total of five RPs in this data-set.

Selecting the distribution of Random Parameters: All random parameters were assumed to follow triangular distributions, with standard deviation constrained to 0.5, to ensure comparability with the 1EV experimental data. Results are given below for Best only and Best-Worst Choice data (Table 8.1).

Selecting the number of points for the simulations: Number of points for the simulation was set to 700, the same as for 1EV experiments in Chapter 7.

Error components: In this sample, having two EVs in the same experiment, an error covariance was chosen for EV1, EV2 and PIH for Best and Worst.

Findings from PureProfile Two EV Experiments: Best Only vs. Worst Only Choice Analysis

Results for Panel-ML with Error Components for Best only and Worst only data are given in Table 8.1. Worst only data shows a better model fit (LL=-1,627.47; AIC/N=1.84, Pseudo R^2 = 0.44) compared to Best only data (LL=-1,847.70; AIC/N=2.09, and Pseudo R^2 = 0.36), although findings are similar.

Estimates from Best Only Data

The ASC for Petrol and Diesel were positive and significant at 1% level and the ASC for EV negative, similar to the results with PureProfile 1EV data in Section 7.5 (Table 7.4). Similar to the findings from 1EV experiments, people had a strong preference for low purchase price (β=-0.0624; *t=5.98*) and running cost (β=-0.189; *t=3.61*).

Notably, with this data, the parameter estimate for EV driving range is positive and significant at 0.01 level, showing strong positive preference for an increase in EV driving range (β=0.0084; *t=6.55*). This evidently supports the hypothesis made in Chapter 7 (Section 7.7) that having two EVs in the same experiment allows respondent to compare EV attributes in a more meaningful way. The absence of driving range values in Petrol, and Diesel vehicles might have also allowed respondents to make a decision about this attribute as it applies to EV/PIH vehicles only. The finding that people prefer an increase in EV driving range is similar to the previous studies (Potoglou & Kanaroglou, 2007; Bolduc *et al*., 2008; Ziegler, 2012). People also had a strong preference for increase in the number of charging stations (β=0.00036; *t=4.02*), although the charging time was not significant in the Best only setting (Table 8.1).

Three interaction were tested for this sample: i) People having solar panels (Have Solar Panel) interacted with running cost reveals that people having solar panels for electricity at home are least bothered by an increase in running cost (β=0.133; *t=2.16*) given that they could use free energy during bright days; ii) Cheap car buyers when interacted with purchase price of vehicles indicate their strong preference for low priced vehicles (β=-0.0376; *t=3.43*); iii) The technology savvy people when interacted with the noise variable for Petrol, PIH, and Diesel vehicles are sensitive to noisy vehicles (β=-0.106; *t=5.71*), that is individuals excited about new technologies prefer quiet vehicles (Table 8.1).

It was found that people who chose EV believed in perceived usefulness of technology (β=0.949; *t=2.24*), and could rely on EV as the only vehicle in the household (β=1.18; *t=5.21*). People who chose PIH had a higher preference for the environment (β=0.995; *t=2.21*), comparable to the base model (β=1.09; *t=3.44*); they are influenced by social norms (β=0.332; *t=2.06*), and could RELY ON SINGLE CAR (β=0.563; *t=3.11*).

Estimates from Worst Only Data in Contrast to Best Only

When using the Worst choice data, it was found that respondents prefer low purchase price vehicles (β=-0.0467; *t=4.4*), and increased EV driving ranges (β=0.0066; *t=4.11*), but the estimates were not as strong as for Best only data (Table 8.1).

Still, the analysis of Worst choice data offered additional insights: for example, there is a preference for reduction in charging time (β=-0.00104; *t=2.01*), an aspect that was not clear in the Best choice data. Also, people having an excitement for new technologies ENT preferred quiet vehicles (β=-0.111, *t=6.84*) and the estimate for this interaction is stronger than for Best choice data. While the estimate for interaction between purchase price and cheap car buyers is less significant (β=-0.0194, *t=1.76*) in Worst choice data as compared to the Best choice data.

Perhaps the most remarkable differences are in attitudes to the purchase decision: Worst choice data shows that people who choose EV were highly concerned about environment, EC (β=1.11, *t=3.26*) and influenced by social norms, SN (β=0.312, *t=2.25*). As with Best choice data, people indicated that they could rely on a single car either choosing EV (β= 0.670; *t*=5.16), or choosing PIH (β=0.481; *t*=3.16). In Worst choice data people who chose PIH were concerned about environment, EC (β=0.744; *t*=2.12), but were not significantly influenced by social norms, SN.

Table 8.1: Best-Worst Choice Models for Panel-ML and Error Components:

PureProfile – 2 EV Experiments

Variables	PureProfile Best Only		PureProfile Worst Only	
Random Parameters in Utility Functions *ASC*$_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
ASC$_{EVB}$	-4.83***	3.69		
ASC$_{DieselB}$	4.63***	3.52		
ASC$_{PetrolB}$ [a]	6.01***	4.34		
ASC$_{EVW}$			2.04**	2.52
ASC$_{DieselW}$			-2.54**	2.52
ASC$_{PetrolW}$			-3.21***	3.09
PRICEK: Purchase Price$_{Generic}$	-0.0624***	5.98	-0.0467***	4.4
RUNCOST: Running Cost$_{Generic}$	-0.189***	3.61	-0.0148	0.33
CHTIME: Charging Time$_{EV}$	-0.00061	1.62	-0.00104**	2.01
RANGE: Range$_{EV}$	0.0084***	6.55	0.0066***	4.11
CSTATS: Number of Charging Stations$_{EV}$	0.00036***	4.02	0.00012	1.17
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	**|t|**	**Beta**	**|t|**
ASC$_{EVB}$	2.68***	11.07		
ASC$_{DieselB}$	1.57***	4.08		
ASC$_{PetrolB}$ [a]	2.23***	7.13		
ASC$_{EVW}$			1.3501***	8.17
ASC$_{DieselW}$			0.960***	2.65
ASC$_{PetrolW}$			2.13***	7.37
PRICEK: Purchase Price$_{Generic}$	0.0312***	5.98	0.0233***	4.4
RUNCOST: Running Cost$_{Generic}$	0.0946***	3.61	0.00739	0.33
CHTIME: Charging Time$_{EV}$	0.00031	1.62	0.00052**	2.01
RANGE: Range$_{EV}$	0.0042***	6.55	0.0033***	4.11
CSTATS: Number of Charging Stations$_{EV}$	0.00018***	4.02	0.00006	1.17
Interaction $_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
HaveSolarPanels X RUNCOST$_{Generic}$	0.133**	2.16	-0.00248	0.06
ENT X Noise$_{PIH,Diesel,Petrol}$	-0.106***	5.71	-0.111***	6.84
CheapCarbuyers X PRICEK$_{Generic}$	-0.0376***	3.43	-0.0194*	1.76
Covariates$_{Alternatives}$	**Beta**	**|t|**	**Beta**	**|t|**
EC: Environmental Concerns$_{EV}$	0.785	1.55	1.11***	3.26
SN: Social Norms$_{EV}$	0.350	1.65	0.312**	2.25
PU: Perceived Uses of Technology$_{EV}$	0.949**	2.24	0.0937	0.33
ENT: Excitement for new Technology$_{EV}$	-0.245	0.70	-0.370	1.55
Rely on Single Car$_{EV}$	1.18***	5.21	0.670***	5.16
EC: Environmental Concerns$_{PIH}$	0.995**	2.21	0.744**	2.12
SN: Social Norms$_{PIH}$	0.332**	2.06	0.181	1.18

PU: Perceived Uses of Technology$_{PIH}$	0.464	1.54	-0.0406	0.18
Rely on Single Car$_{PIH}$	**0.563*** **	**3.11**	**0.481*** **	**3.16**
Error Component	**Beta**	**|t|**	**Beta**	**|t|**
EV and PIH (EV1$_B$, EV2$_B$, PIH$_B$)	**2.46*** **	**8.71**		
EV$_W$ and PIH$_W$ (EV1$_W$, EV2$_W$, PIH$_W$)			**1.56*** **	**6.64**
Number of estimated parameters	24		24	
Number of observations	1,794		1,794	
Number of individuals	**299**		**299**	
Log Likelihood at constants	-2887.03		-2887.03	
Log likelihood	-1,847.70		-1,627.47	
AIC/N	2.09		1.84	
ρ^2 (Pseudo-R^2)[b]	0.36		0.436	
[a:] ***Plug-in Hybrid is the reference fuel and vehicle technology;*** [b:] **McFadden Pseudo R^2;** ****, **, * indicate Significance at 1%, 5%, and 10% level respectively.**				

As illustrated by the results in Table 8.1, the analysis of Best versus Worst only choice data for the PureProfile sample with 2EV experiments reveals interesting findings, particularly for EV attributes. Having 2EVs in the same experiment has triggered trading behaviour and resulted in positive estimates for driving range (Table 8.1). B-W choice analysis, combining Best and Worst data, is presented next.

Findings from PureProfile Two EV Experiments: B-W Choice Analysis

With the objective of determining which EV vehicle attributes are important to the respondents in the purchase decision, the 2EV experiments were analysed in the B-W data setting. A similar approach to the one described in Section 7.5. was adopted for data preparation, with Best data being multiplied by the estimated scale parameter (λ) of 0.5718. The model fit (LL=-3,482.17; AIC/N=1.95) and parameter estimates for B-W scaled choice model are given in Table 8.2.

Findings reveal stronger and more significant parameter estimates than by using only one response (Best or Worst): as expected, people prefer lower purchase prices (β=-

0.0442; *t=9.97*) and running costs (β=-0.0780; *t=3.59*); they are also concerned about charging time (β=-0.00052; *t=2.51*) and prefer more opportunities for charging/more charging stations (β=0.00018; *t=3.92*); more importantly, an increase in the driving range for electric vehicle is likely to increase the probability for choosing an EV, hence the EV uptake in the market (β=0.00518; *t=7.64*). This clearly supports the argument that by having 2EVs in the same experiment enabled respondents to compare the EV characteristics to the traditional ICE in a more meaningful manner.

HAVE SOLAR PANELS interacted with running cost (Table 8.1) indicates that using solar panels for generating electricity at home provides green and free energy and hence the respondents are least concerned by an increase in running cost (β=0.0477; *t=2.02*). Cheap car buyers, when interacted with vehicles' purchase price, indicate these respondents' strong preference for low cost vehicles (β=-0.0150; *t=3.15*).

People who chose EV in this data-set were concerned about the environment, EC (β=0.927; *t=5.42*), were influenced by social norms, SN (β=0.178; *t=2.51*), believed in the perceived usefulness of technologies, PUT (β=0.308; *t=2.17*), and could rely on EV as the single household vehicle (β=0.699; *t= 9.69*). Yet, people excited about new technologies, ENT (β=-0.235; *t=1.81*) were less likely to choose EV. This group appears concerned about the operating characteristics of vehicles because the interaction between being technology savvy, ENT and the noise variable for Petrol, PIH, and Diesel vehicles was negative (β=-0.0758; *t=8.37*), that is individuals excited about new technologies prefer advanced features, including low noise vehicles (Table 8.2).

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Table 8.2: Best-Worst Choice Models for Panel-ML with/without Error Components: Pure-Web Based – 2 EV Experiments

	PureProfile BW-Scaled	
Random Parameters in Utility Functions $ASC_{Alternatives}$	**Beta**	**|t|**
ASC_{EVB}	-5.01***	6.04
$ASC_{DieselB}$	4.18***	4.95
$ASC_{PetrolB}$[a]	5.53***	6.03
ASC_{EVW}	2.16***	4.62
$ASC_{DieselW}$	-2.99***	5.44
$ASC_{PetrolW}$	-3.67***	6.4
PRICEK: Purchase Price$_{Generic}$	**-0.0442*** **	**9.97**
RUNCOST: Running Cost$_{Generic}$	**-0.0780*** **	**3.59**
CHTIME: Charging Time$_{EV}$	**-0.00052** **	**2.51**
RANGE: Range$_{EV}$	**0.00518*** **	**7.64**
CSTATS: Number of Charging Stations$_{EV}$	**0.00018*** **	**3.92**
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	**|t|**
ASC_{EVB}	2.75***	11.22
$ASC_{DieselB}$	1.78***	4.84
$ASC_{PetrolB}$[a]	2.35***	7.96
ASC_{EVW}	1.29***	7.78
$ASC_{DieselW}$	0.924***	2.9
$ASC_{PetrolW}$	2.021***	7.19
PRICEK: Purchase Price$_{Generic}$	**0.0221*** **	**9.97**
RUNCOST: Running Cost$_{Generic}$	**0.0399*** **	**3.59**
CHTIME: Charging Time$_{EV}$	**0.00026** **	**2.51**
RANGE: Range$_{EV}$	**0.0026*** **	**7.64**
CSTATS: Number of Charging Stations$_{EV}$	**0.000091*** **	**3.92**
Interaction $_{Alternatives}$	**Beta**	**|t|**
HaveSolarPanels X RUNCOST$_{Generic}$	**0.0477** **	**2.02**
ET X Noise$_{PIH,Diesel,Petrol}$	**-0.0758*** **	**8.37**
CheapCarbuyers X PRICEK$_{Generic}$	**-0.0150*** **	**3.15**
Covariates$_{Alternatives}$	**Beta**	**|t|**
EC: Environmental Concerns$_{EV}$	**0.927*** **	**5.42**
SN: Social Norms$_{EV}$	**0.178** **	**2.51**
PU: Perceived Uses of Technology$_{EV}$	**0.308** **	**2.17**
ENT: Excitement for New Technology$_{EV}$	**-0.235***	**1.81**
Rely on Single Car$_{EV}$	**0.699*** **	**9.69**
EC: Environmental Concerns$_{PIH}$	**0.692*** **	**4.22**
SN: Social Norms$_{PIH}$	**0.138** **	**2.13**
PU: Perceived Uses of Technology$_{PIH}$	*0.128*	*1.15*
Rely on Single Car$_{PIH}$	**0.419*** **	**5.86**

Error Component	Beta	|t|
EV and PIH ($EV1_B$, $EV2_B$, PIH_B)	**2.35*** **	**9.53**
EV_W and PIH_W ($EV1_W$, $EV2_W$, PIH_W)	**1.48*** **	**6.84**
Number of estimated parameters	31	
Number of observations	3,588	
Number of individuals	**299**	
Scale Parameter (λ)	**0.5718**	
Log likelihood	-3,482.17	
AIC/N	1.95	
ρ^2 (Pseudo-R^2)[b]	0.578	

[a:] ***Plug-in Hybrid is the reference fuel and vehicle technology;***
[b:] **McFadden Pseudo R^2;***, **, * indicate Significance at 1%, 5%, and 10% level respectively.**

Consistently with the findings for EV, individuals who chose PIH in this data-set were also concerned about environment (β=0.692; *t=4.22*), were influenced by social norms (β=0.138; *t=2.13*), and could rely on EV as single car (β=0.419; *t=5.86*). But these attitudes were less strong as compared to people who chose EV (Table 8.2).

In the next section findings from the Exploded Logit settings for the 2EV experiments are compared to the findings obtained with the B-W data.

8.3 COMPARING FINDINGS FROM 2EV EXPERIMENTS: EXPLODED LOGIT VS B-W CHOICE ANALYSIS

While analysing data for PureProfile and mail-out samples (Section 7.5) with Best only and Worst only options, it was found that no major differences arise between the B-W and Exploded Logit settings. Also, results from Section 8.2 showed that B-W data generated more significant findings by combining Best and Worst answers. In this section, B-W and Exploded Logit data are compared, to assess whether there is any data setting effect on the reliability of parameter estimates (Table 8.3).

Exploded Logit data (Section 7.5.2) triples the number of observations (three comparisons in experiments with four alternatives) as compared to the Best only data, which doubles the number of observations. This means that the number of observations used in Exploded Logit was 5,382, while for B-W it was 3,588 (1,794 for the Best only data).

As with the B-W data, the scale effect is accounted for by first estimating a Nested logit model and then multiplying Best only data with the scale parameter λ=0.7202. In this setting, for PureProfile 2EV experiments, λ for Exploded Logit was larger than the λ=0.5718 for B-W data (Table 8.3).

The Exploded Logit model presented a better goodness-of-fit measures (LL=-3,694.90; AIC/N=1.38; Pseudo-R^2 = 0.702), while the B-W choice settings fit measures were (LL=-3,482.17; AIC/N=1.95; Pseudo-R^2 = 0.578). However, not too much should be read in to this as the exploded logit effectively provides one-third more choice tasks.

Findings from the Exploded Logit choice analysis are consistent (no sign reversals) to the results presented in Table 8.2 for B-W data. However, most of the parameter estimates (discussed below) have smaller standard errors, hence are deemed more reliable in the Exploded Logit choice analysis.

As shown in Table 8.3, significant estimates are in boldface, and stronger estimates are also in italics. All five random parameters were significant in both data settings, with four of them being more significant in the Exploded Logit and one being more significant in the B-W choice setting. Purchase price (β=-0.0591; *t=13.35*), driving range (β=0.0067; *t=9.37*), running cost (β=-0.0907; *t=3.9*), and fast charging (β=0.00072; *t=3.11*) were more significant for Exploded Logit choice analysis, while number of charging stations (β=0.00018; *t=3.92*) was marginally more significant in the B-W choice analysis.

Table 8.3: Best-Worst Choice Models for Panel-ML with Error Components: PureProfile – 2 EV Experiments

Variables	**PureProfile BW-Scaled**[#]		**PureProfile Exploded Logit Scaled**	
Random Parameters in Utility Functions *ASC*$_{\text{Alternatives}}$	**Beta**	**|t|**	**Beta**	**|t|**
ASC$_{EVB}$	-5.01***	6.04	-4.74***	5.75
ASC$_{DieselB}$	4.18***	4.95	3.74***	4.51
ASC$_{PetrolB}$[a]	5.53***	6.03	5.23***	6.03
ASC$_{EVW}$	2.16***	4.62	-2.55***	4.29
ASC$_{DieselW}$	-2.99***	5.44	3.44***	5.53
ASC$_{PetrolW}$	-3.67***	6.4	4.24***	6.44
PRICEK: Purchase Price$_{Generic}$	**-0.0442*** **	**9.97**	***-0.0591**** ***	***13.35***
RUNCOST: Running Cost$_{Generic}$	**-0.0780*** **	**3.59**	***-0.0907**** ***	***3.90***
CHTIME: Charging Time$_{EV}$	**-0.00052** **	**2.51**	***-0.00072**** ***	***3.11***
RANGE: Range$_{EV}$	**0.00518*** **	**7.64**	***0.0067**** ***	***9.37***
CSTATS: Number of Charging Stations$_{EV}$	***0.00018**** ***	***3.92***	**0.00020*** **	**3.86**
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	|t|	**Beta**	|t|
ASC$_{EVB}$	2.75***	11.22	2.77***	12.33
ASC$_{DieselB}$	1.78***	4.84	1.84***	5.27
ASC$_{PetrolB}$[a]	2.35***	7.96	2.08***	7.14
ASC$_{EVW}$	1.29***	7.78	1.90***	11.63
ASC$_{DieselW}$	0.924***	2.9	0.0871	0.21
ASC$_{PetrolW}$	2.021***	7.19	2.76***	10.55
PRICEK: Purchase Price$_{Generic}$	**0.0221*** **	**9.97**	***0.0295**** ***	***13.35***
RUNCOST: Running Cost$_{Generic}$	**0.0399*** **	**3.59**	***0.0454**** ***	***3.90***
CHTIME: Charging Time$_{EV}$	**0.00026** **	**2.51**	***0.00036**** ***	***3.11***
RANGE: Range$_{EV}$	**0.0026*** **	**7.64**	***0.0033**** ***	***9.37***
CSTATS: Number of Charging Stations$_{EV}$	***0.000091 **** ***	***3.92***	**0.000097*** **	**3.86**
Interaction $_{\text{Alternatives}}$	**Beta**	**|t|**	**Beta**	**|t|**
HaveSolarPanels X RUNCOST$_{Generic}$	**0.0477** **	**2.02**	***0.0557**** **	***2.05***
ET X Noise$_{PIH,Diesel,Petrol}$	**-0.0758*** **	**8.37**	***-0.0960**** ***	***10.12***
CheapCarbuyers X PRICEK$_{Generic}$	***-0.0150**** ***	***3.15***	**-0.0146*** **	**3.04**
Covariates$_{\text{Alternatives}}$	**Beta**	**|t|**	**Beta**	|t|
EC: Environmental Concerns$_{EV}$	***0.927**** ***	***5.42***	**0.783*** **	**3.94**
SN: Social Norms$_{EV}$	**0.178** **	**2.51**	***0.338**** ***	***3.97***
PU: Perceived Uses of Technology$_{EV}$	**0.308** **	**2.17**	***0.565**** ***	***3.18***
ENT: Excitement for New Technology$_{EV}$	**-0.235* **	**1.81**	***-0.348**** **	***2.31***
Rely on Single Car$_{EV}$	***0.699**** ***	***9.69***	**0.793*** **	**9.57**
EC: Environmental Concerns$_{PIH}$	***0.692**** ***	***4.22***	**0.711*** **	**3.97**
SN: Social Norms$_{PIH}$	**0.138** **	**2.13**	***0.210**** ***	***2.66***
PU: Perceived Uses of Technology$_{PIH}$	*0.128*	*1.15*	*0.215*	*1.63*
Rely on Single Car$_{PIH}$	**0.419*** **	**5.86**	**0.466*** **	**5.56**

Error Component	Beta	|t|	Beta	|t|
EV and PIH ($EV1_B$, $EV2_B$, PIH_B)	2.35***	9.53	2.31***	8.91
EV_W and PIH_W ($EV1_W$, $EV2_W$, PIH_W)	1.48***	6.84	2.32***	12.17
Number of estimated parameters	31		31	
Number of observations	3,588		5,382	
Number of individuals	**299**		**299**	
Scale Parameter (λ)	**0.5718**		**0.7202**	
Log likelihood	-3,482.17		-3,694.90	
AIC/N	1.95		1.38	
ρ^2 **(Pseudo-R^2)**[b]	0.578		0.702	

[a:] ***Plug-in Hybrid is the reference fuel and vehicle technology;***
[b:] **McFadden Pseudo R^2;**
*****, **, * indicate Significance at 1%, 5%, and 10% level respectively.**
[#:] **These results are reproduced from Table 8.2 to compare with the Exploded Logit Scaled Model.**

The interactions tested in this sample: Have Solar Panels at home with the running cost (β=0.0557; *t=2.05*), and technology savvy people, ENT, with the noise variable for Petrol, PIH, and Diesel vehicles (β=-0.0960; *t=10.12*) were more significant in Exploded Logit. The interaction of cheap car buyers with purchase price (β=-0.0146; *t=3.04*) in Exploded Logit was slightly less significant than in the B-W choice data.

For people who chose EV, the *t* values of social norms, SN (β=0.338; *t=3.97*), perceived usefulness of technologies, PUT (β=0.565; *t=3.18*), and excitement for new technologies, ENT (β=-0.348; *t=2.31*) were more significant in Exploded Logit choice data, while the estimates for environmental concerns, EC (β=0.783; *t= 3.94*), and relying on a single car (β=0.793; *t= 9.57*) were less significant than with the B-W data.

For people who chose PIH, the *t* values of social norms, SN (β=0.210; *t=2.66*) in Exploded Logit choice were greater than the B-W choice settings. Again, the estimates for environmental concerns, EC (β=0.711; *t=3.97*), and relying on single car (β=0.466; *t= 5.56*) were significant, but had marginally higher standard errors than the Best-Worst choice settings; unsurprisingly, these parameters were less sharp as compared to EV choices.

To assess the effect of data setting on findings, further comparisons are made using the WTP measures computed for the same dataset using Exploded, B-W, and Best only choice analysis. The next section presents this comparison of WTP measures.

8.4 WTP MEASURES: TWO EV EXPERIMENTS

WTP measures were computed for running cost, charging time, range, and number of charging stations variables using simulation draws in the Panel-ML Error Component model for Best only, B-W, and Exploded Logit choice data with 2EV experiments using the PureProfile sample.

The WTP measures are computed as the ratio of the marginal utility for the variable of interest (running cost, charging time, range, and number of charging stations) and purchase price. As the estimating function is a mixed logit the computation makes use of a simulated draw over the random parameters. The results in table 8.4 will differ from the estimates given in Table 7.5 because the presence of a second EV in the choice tasks refines the estimates for the parameters on charging time, range, and number of charging stations.

ANOVA tests highlight that the WTP values are significantly different at the 0.05 level. The value of WTP measure for the number of charging stations variable computed in B-W choice analysis is relatively higher than with the Exploded Logit data, while the WTP measure for the charging time variable is lower in the B-W data setting (Table 8.4).

WTP Measure for Running Cost

The lowest WTP estimate for running cost is obtained when using the Exploded Logit choice settings, \$1,602.65 increase in the purchase price of the vehicle per \$1/100km reduction in the running cost of vehicle. This value is relatively higher in the B-W data setup and about half of the WTP with Best only data (\$3,171.37 for a \$1/100km decrease in the running cost). When compared to the WTP computed from 1EV experiments, it was found that the WTP was higher in the mail-out sample where traders were willing to pay \$5,444.88, and slightly lower in the PureProfile 1EV experiments (\$2,955.99) as presented in Table 7.5.

Although this WTP measure for the running cost variable is quite high, it is comparable to the running cost in recent studies: Hackbarth and Madlener (2016) fuel cost saver class had a WTP €2,528.52 (AUD 3,683.11) for a €1/100km reduction in the running cost of vehicles.

WTP Measure for Charging Time

The WTP measure for charging time variable (Exploded Logit) indicated that on average people are willing to pay \$127.8 per 10min reduction in EV charging time. Given that motor vehicles registered in Australia travelled an average of 13,800km in 12 months (ABS, 2015) and that life expectancy of an EV battery is eight years, the total number of kilometres driven during an EV life equals 112,000km. If the EV battery is recharged every 140km, this would require 800 recharges, equivalent to 133hours (800*10min/60min). WTP in dollars per hour would be \$0.96/hr (12.78*10/133), which is low when compared to the WTP measure computed for mail-out sample with traders at \$6.9/hr (Section 7.6).

Table 8.3: Pure-Web Based 2EV Experiments WTP Measures

Variable		Best Only	B-W	Exploded Logit
RUNCOST Running Cost$_{Generic}$	**Average**	\$3,171.37	\$1,895.02	\$1,602.65
	SD	166.03	192.03	171.58
CHTIME (1 minute) Charging Time$_{EV}$	**Average**		\$12.34	\$12.78
	SD		1.24	1.42
RANGE Range$_{EV}$	**Average**	\$140.83/km	\$122.57/km	\$117.93/km
	SD	8.45	12.55	14.3
CSTATS Number of Charging Stations$_{EV}$	**Average**	\$5.97/unit	\$4.31/unit	\$3.46/unit
	SD	0. 323	0.385	0.375

The values of willingness-to-pay measure for running cost, charging stations, and EV driving range variables computed in Exploded Logit data settings are lower as compared to the B-W choice analysis and substantially lower than the Best Only data results. Conversely, the value of WTP measure for charging time variable is higher when compared to B-W choice analysis.

Again, when comparing the WTP measures for 1EV experiments as presented in Table 7.5 with the 2EV experiments in Table 8.4, it was found that the WTP measures for running cost and charging time were higher with 1EV experiments, however not significant for driving range and number of charging stations.

WTP Measure for Driving Range

Using Best only data, for a kilometre increase in driving range of EV people were willing to pay an extra \$140.8 in the purchase price of an EV. In Exploded Logit this value was reduced to \$117.93, which is closer to the WTP computed by Hidrue *et al.* (2011) that is \$35 to \$75 for an extra mile of added driving range.

WTP Measure for Number of Charging Stations

For the number of charging stations, on average, respondents were willing to pay extra $5.97 for EV purchase price per unit increase in the number of charging stations (Table 8.2), while in the B-W setting this WTP measure equals $4.31.

Comparing the price of a converted EV five seater, which is $20,000 (EVWORKS, 2013) in Australia, with a similar capacity Petrol car, that is $12,500 (CARSGUIDE, 2012), their difference is comparable to the WTP for low running cost, charging time, and driving range. Hidrue *et al.* (2011) found that for an *EV with desired attributes* people would be willing to pay a premium price of $6,000 to $16,000 over Petrol vehicles.

8.5 SYNTHESIS OF RESULTS: WHY USING TWO EVS IN THE SAME EXPERIMENT IS MORE APPROPRIATE

Designing experiments with two EVs in one choice situation has led to a positive parameter estimate for driving range, as expected, but also resulted in more accurate estimates for charging time, and number of charging stations. These attributes are particularly relevant to EVs.

An interesting finding from the PureProfile – 2EV experiments is that respondents had a strong preference for a large number of charging stations and the parameter estimate is highest in the Exploded Logit setting (β=0.00020; *t=3.86*, as shown in Table 8.3). This reflects a requirement to establish charging infrastructure in Perth, which is consistent with the findings by Robinson, Blythe, Bell, Hübner, & Hill (2013) who explored the EV driver recharging behaviour in the North East of UK. Their findings suggest a requirement for public recharging infrastructure in order to improve the EV market. Robinson *et al.* (2013) recommended the provision of financial incentives for charging at home/work during off-peak hours.

8.6 CONCLUSION

The 2EVs experiments used in the PureProfile sample helped respondents to make a decision about vehicle characteristics, by attending to EV features such as charging time, driving range, and charging stations.

Although, the driving range variable for Petrol and Diesel vehicles were explicitly set to ‘not applicable’ (n/a) in the PureProfile 1EV experiments, this did not result in a clear decision about the range parameter estimate, as presented in the Chapter 7 findings (Section 7.7.1). Responses to choice situations including 2EVs clearly indicated the relevance of increases in driving range (β=0.00518; $t=7.64$), low charging times (β=-0.00052; $t=2.51$), and an increase in the number of charging stations (β=0.00018; $t=3.92$). These estimates are from the B-W data settings (Section 8.2.1).

The parameter estimates were even more improved with Exploded logit data settings.

Finally, the WTP measures for driving range and charging stations are similar to prior scholarly literature, whereas the WTP for running cost was higher.

CHAPTER 9

9 DISCUSSION AND CONCLUSION

9.1 SUMMARY OF THE THESIS

This thesis aimed to provide evidence on the likely uptake of Electric Vehicles in Western Australia, combining several sources of data: qualitative focus groups and quantitative drivers' and household surveys. The thesis started with a review of the previous studies about EV uptake and acceptance (Chapter 2). Chapter 3 presented a review of methodologies and also the structure of the thesis (Diagram 3.4 in Section 3.5). Chapters 4 and 5 focused on the drivers' survey. Findings from the drivers' experiences and attitudes were presented in Chapter 4, and the drivers' battery charging behaviour was explored in Chapter 5. Then, findings from the household study, along with problems encountered in household data collection, were presented in the last three chapters (6, 7, and 8).

Drawing on a number of previous studies which examined electric car characteristics: benefits and disadvantages (as presented in Chapter 2), this research selected the most appealing EV characteristics (running cost, environmental features and low noise) for further investigation. The hurdles for EV adoption however remains the driving range , high purchase price, number of charging stations and long charging times (highlighted in the estimation results – Table 8.3 – and the WTP measures – Table 8.5). Among these attributes purchase price is marked as most sensitive followed by driving range and then charging durations, and number of charging stations (Chapter 8).

It was also considered essential to look at public attitudes; aligned with previous EV uptake studies it is found that having a pro-environmental behaviour, along with being influenced by social norms and being inspired by gadgets/technologies might influence EV purchase decision. These attributes have been examined in detail (Chapter 8).

Given the study location and the fact that the WA state Government supported the EV trial commencing in 2011, this study explored EV driving and purchase behaviour to further determine acceptability of EVs in the metropolitan area of Perth, Western Australia. The perceptions and behaviour of EV drivers in the WA EV trial were analysed and a pilot study was conducted with WA EV drivers (Chapter 4). As drivers in this trial had experience in charging the EV batteries, their battery charging behaviour was also analysed (Chapter 5).

9.2 ACCEPTABILITY OF ELECTRIC VEHICLES – EV DRIVERS

As EV is a new technology in WA, the perspective of existing EV users has been invaluable. Hence, the behaviour of drivers' in the WA EV trial was analysed prior to exploring the household behaviour. Through a focus group conducted in Nov 2011, with 11 EV drivers, it was found that they were generally satisfied with the electric car performance indicated in Chapter 4. The EV benefits as picked up by the drivers in trial (Chapter 4: Section 4.4) that were mentioned include smooth and quiet operation, good torque, resource management, low running cost, and low maintenance ("no need to go for oil checks"). Although a new technology, the EV appears like an ordinary car, it can use clean energy and parking is often free. Among the drawbacks drivers mentioned: limited driving range, need for charging overnight or finding a charging station, and trip planning, which is critical (Chapter 4: Section 4.4). A few technical problems in acceleration were also noticed as well as in the range dashboard indicator. Drivers were concerned about the range of an EV and they clearly indicated in their discussions that they would purchase an EV if either the range is extended, or sufficient fast charging stations become available (Chapter 4: Section 4.4). That is, either increase in range or decrease in charging time for EV could reduce their range anxiety. Finally, the EV drivers highlighted the high purchase price and perhaps low resale value along with limited choice of EV models in the WA market (Chapter 4:Section 4.5).

Following the focus group, a survey was conducted with the EV drivers to understand their driving experiences and attitudes towards EV. In this survey a higher proportion of male respondents' participated, with a small proportion of young respondents. Factor analysis of the attitudinal data revealed that the pro-environmental behaviour of the drivers (*KMO value= 0.701*), and the technology learning constructs (*KMO value= 0.669*) were significant (Chapter 4:Section 4.5). Findings revealed drivers' satisfaction with the use of EV. The analysis showed substantial heterogeneity, with three clusters emerging: *i) Unlikely to recommend and purchase an EV; ii) Supporter EV-Env; iii) Technology promotors-Env* (Chapter 4: Section 4.6). Nevertheless, all three clusters displayed high concern about the environment. Antecedents of EV adoption were identified and then tested through a regression model (Chapter 4: Section 4.8). Overall satisfaction in driving EV appeared to be a mediator between perceived EV benefits, EV technical difficulties, attitudes towards technologies constructs and willingness to recommend and purchase an EV. This was confirmed through a SEM model presented in (Chapter 4: Section 4.9).

9.3 ELECTRIC VEHICLE BATTERY CHARGING BEHAVIOUR – EV DRIVERS

An examination of charging location choice was conducted by way of a stated preference instrument in Chapter 5. Whilst charging at home was popular among EV drivers, they were sensitive to charging time and charging cost. The results indicated drivers' preference for charging at home, and if required during the day (due to travel commitments) a preference for using public charging stations (Chapter 5).

The charging behaviour survey confirmed that home-charging is one of the benefits of EV ownership and use, given its convenience and low cost. The prevalence of solar panels in WA suburban housing is another determinant for home-charging (Chapter 5: Section 5.4).

In regard to charging at public stations (Type II or III), their main appeal is the reduced time. This is critical, considering the limited infrastructure. Respondents also commented that installing stations close to shopping centres, business centres, and recreational facilities would be beneficial for effective use of time (Chapter 5: Section 5.4). Although cost is relevant, convenience and duration of charging were seen as more important.

9.4 PURCHASE BEHAVIOUR

Findings from the drivers' survey helped to further design the household study and explore the purchase attitudes towards EV in the metropolitan area of Perth, WA. The capital city of WA is dispersed over a large area, stretching about 150 km along the Indian Ocean coast. Collecting a sample that is a true representation of population (within budget constraints and limited time frame) is a challenging endeavour, and this study required two samples to address representativeness and some of the biases associated with data collection on a new technology (e.g., desirability bias).

In the mail-out sampling, along with an invitation letter for participation, a printed copy of the survey and a glossy information brochure about EV was included (Appendix F).

The printed survey may have attracted those interested in the topic and keen to express their enthusiams or concerns; many of them chose EV as their most preferred choice in all experiments, perhaps only to indicate their positive thoughts towards EV. A small group also chose EV as their least preferred option in all experiments, clearly communicating their negative attitudes towards EV. These responses indicate a clear bias and do not reflect the views of the population at large. The non-trading behaviour means that these respondents did not make their decisions based on vehicle attributes, rather they selected a vehicle based on their general preference, most of them supporting the idea of having green vehicles.

Non-Trading Responses

Non-traders seem to have neglected the vehicle attributes in the experimental setting, and rather focused on indicating one alternative as their most preferred choice in all experiments. Another aspect to note here is that in these choice experiments the alternatives (EV, Petrol, PIH, and Diesel) were always presented in the same sequence for both the web-based and the paper-and-pencil version; this may have led a respondent to focus on EV. In addition, EV non-traders displayed strong pro-environmental attitudes, again confirming their positive attitude towards EV, high scores for subjective norms, and also highly rated intentions to purchase and use an EV. All these clearly indicate their social desire to present a positive attitude towards EV. In doing so, EV non-traders ignored the vehicle attributes (such as EV's high purchase price), either because EV were almost non-existent in the market at the time when the survey was conducted, or because of the limited driving range barrier.

Change in Experimental Setttings/Design

Having a sample bias in the mail-out sample, and the non-trading responses has led to the second phase of data collection. Experiments were redesigned and set in a different way for the PureProfile sample, including a different order of presentation. For the PureProfile sample, the EV was compared with its own counterpart, so that six out of the eight choice experiments had two EVs in the same choice task. The participants recruited for this second sample covered the whole metropolitan area of Perth. With a sample that was a better representation of the population, and a change in experiments (that is having 2EVs, removing range from Petrol, and Diesel vehicles) more meaningful estimates were obtained.

9.5 CONTRIBUTIONS OF THIS THESIS

The contributions of this thesis can be classified as methodological and practical:

Methodological Contributions

- A combination of data collection methods and modelling techniques were used to understand driver charging behaviour and household purchase behaviour. Findings from drivers' and the households' surveys cross-validate each other (see Chapters 4 and 8).
- Collecting a second sample as a method to offset the potential sample bias from the mail-out survey; for this second sample respondents were recruited using an online panel with a representative pool of participants across Australia; the coverage of metropolitan area of Perth was balanced in terms

of sociodemographic representation (i.e., gender, age group, income) (Chapters 6, 7, and 8).

- Use of attitudes in the sequential hybrid choice models – based on traditional adoption models, constructs relevant to EV as a new technology were included in models, to account for respondents' environmental concerns, perceived use of technology, social norms, and excitement for new technologies (Chapters 6, 7, and 8).
- Changes in the experimental designs, eliminating the range variable for Petrol and Diesel vehicles, and including two EVs in the same choice set, to induce trade-off between electric vehicles (Chapters 6, 7, and 8).
- Use of B-W settings to obtain more information from the stated preference survey, not only by increasing the number of observations but also by sharpening the parameter estimates and obtaining better GOF measures; this was combined with the use of state-of-the-art DCM (Panel-ML Logit with Error Components). B-W and Exploded Logit settings were compared with the latter leding to more significant parameter estimates, and even better model fit (Chapters 7 and 8).
- Combining mail-out and PureProfile samples where experiment settings were matched (Chapter 7).

Practical Contributions

The findings from this research should assist policy making and provide recommendations for EV infrastructure investments:

- Drivers in the WA EV trial prefer EVs because they are quiet vehicles with a smooth ride, have low running cost and no tailpipe emissions; they were satisfied with the overall performance and efficiency of the vehicle, suggesting that experience with EV is likely to fast-track uptake of this vehicle and fuel technology (Chapter 4).

- Drivers are also concerned about technical aspects of EVs, primarily limited driving range, charging infrastructure and charging time. This indicates that increasing driving range and providing ample opportunities for charging may alleviate worries about trip planning, which many drivers hold (Chapter 4).
- Drivers prefer fast charging stations and are sensitive to charging cost. In most instances they prefer to charge at home/work. Drivers having solar panels at home were unlikely to charge their EVs at work (Chapter 5). Considering the positive interest on solar energy in Perth (strong government incentives), EV charging at home may gradually become as common as charging mobile phones or tablets;
- Respondent bias or self selection may lead to incorrect inferences of population estimates. For example, EV enthusiasts responding to the mailout survey had a measure of willingness to pay $5,445 for decreasing the running costs (Table 7.5), more than three times the value for the PureProfile sample respondents ($1,603 – Table 8.5).
- This research has highlighted significant spatial and socio-demographical differences in the market and heterogeneity in preferences for EV technology. Transport and planning professionals should be aware of these differences and of the issues of sample representativeness. Adopting findings from the mail-out survey in feasibility studies may substantially alter cost-benefit ratios, given the WTP values several times higher than for the PureProfile sample. New data collection efforts should acknowledge the presence of bias,

especially for new technologies and consider a combination of samples to reduce this bias.

- This research is the first in WA to provide evidence useful to gauge the uptake of EVs in the light of new prices and WTP for running cost, charging time, range represent the starting point for further policy evaluations.

9.6 FUTURE WORK

This research highlighted the importance of checking for social desirability bias and accounting for attitudes when analysing new vehicle and fuel technologies. Future studies should include additional questions aimed at capturing biases (e.g., social desirability predispositions) and further tease out the attitudes and norms. In addition, this research showed that having experience with EVs enhanced those attitudes and preferences to EV, suggesting that trials before purchase may ease the anxiety of driving an EV.

It is also important to note that this research explored only the domestic sector (through household study). However, looking at vehicle purchase, the decision to buy vehicles is made at different levels in different market segments; the purchase decision can be in the hands of households, fleet managers, rental car companies, and corporate car buyers. Decisions on car purchase by fleet managers can have impacts on subsequent car purchase decisions, as fleet vehicles represent a large proportion of cars in the used vehicle market. Rental car companies represent another important segment of new car buyers, although this group might not be as concerned about reducing the running cost of vehicles as households. However they are concerned about the EV's low maintenance costs (as the *battery, motor, and associated electronics* might require minimal scheduled maintenance, AFDC, 2014). Safety of EVs may be another issue for consideration by corporate fleets and rental companies:

with their lower centre of gravity EVs prove to be safe vehicles avoiding the risk of roll over (AFDC, 2014). Yet, the limiting factor in purchasing EVs by car rental companies is the nature of the travel in rented cars; to the extent that they are used for long drives by families/groups of travellers, large vehicles with a substantial driving range may be more convenient. For these reasons, rental car companies might not be an ideal group to purchase EV. Corporate car buyers represent a group of people that can choose EV for their organisation. An example of such corporate car owners is the group of eleven organisations in the WA EV trial, where this study explored the drivers' experiences (Chapter 4) and charging behaviour (Chapter 5). The propensity of organisations to buy EV could be one of the future extensions of this study.

To conclude, this research brings evidence for EV uptake in Perth, WA. Driving experience is an enabler of adoption and positively affects the attitudes towards EV. Households in Perth are still concerned about driving range and charging conditions, but their environmental concerns and views towards social norms may be the pathway towards a large scale uptake of EVs.

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11 APPENDICES

APPENDIX A: DRIVERS' SURVEY INSTRUMENT

Exit this survey >>

EV_Driver

1. Research Background & Consent

Thank you for agreeing to participate in this survey aiming to understand the perceived benefits and barriers for range-restricted electric vehicles (EV) uptake in Australia, and forecast of EV market share. Particularly, driver behaviour and movement patterns for EVs, as well as the recharging patterns, will be explored.

The survey includes three sections: your experiences with driving an EV, attitudes towards EV, and background information.

All information collected is anonymous.
By filling in the information in this survey you consent to participate in the study. At any stage you may withdraw without justification or providing a reason.
This research has the approval of UWA Human Research Ethics Committee, RA/4/1/5043 from October 2011.

For any further information, please contact Fakhra Jabeen (0411694924, fakhra2005@gmail.com) or Doina Olaru (6488 3908).

Again, thank you for your involvement.
Sincerely yours,
Fakhra Jabeen and Doina Olaru

Next >>

Exit this survey >>

EV_Driver

2. Section 1: About EV Characteristics and Your Experiences

1. What kind of EV do you drive or use?

- ◯ Converted EV
- ◯ Commercially available EV
- ◯ Both

2. Using the scale below, please select the response that best describes your views.

1 = Not at all confident
2 = Not very confident
3 = Somewhat confident
4 = Extremely confident

	1	2	3	4
How confident do you feel driving an EV?	◯	◯	◯	◯
How confident are you in the environmental performance and efficient use of energy of EV?	◯	◯	◯	◯

3. Using the scale below, please select the response that best describes your views or behaviour.

1 = Strongly disagree
2 = Moderately disagree
3 = Neither agree or disagree
4 = Moderately agree
5 = Strongly agree

I believe EV produces less noise during driving.	○	○	○	○	○
I believe EV has problems with acceleration.	○	○	○	○	○
I believe EV goes to a heat-up stage frequently during summer.	○	○	○	○	○
I believe EV is ensuring the proper ambient temperature in winter.	○	○	○	○	○
Battery recharging at home is convenient for my EV.	○	○	○	○	○
Recharging at stations is convenient for my EV.	○	○	○	○	○
EV driving reduces my average travel cost/trip.	○	○	○	○	○
I spent a significant amount of money to fix my EV in the last 3 months.	○	○	○	○	○
I need to do a lot of planning of activities in the day when I drive the EV.	○	○	○	○	○

4. Please select all the technical difficulties that you encountered while driving the EV.

- [ ] No regenerative braking
- [ ] Blown fuses
- [ ] Power storage
- [ ] Power steering failure
- [ ] Power station limitations
- [ ] In vehicle transmission line loss
- [ ] Range indicator errors

Other (please specify)

5. How useful or beneficial do you consider the following features of EV? Rank the answers, using each number once, with 1 meaning the least desirable, and 6 most desirable characteristic.

Low level of noise
Low running cost
Home recharging
Zero tail-pipe emissions
Low maintenance
Reliability

6. How do you rank the following barriers to the uptake of EV? Rank the answers, using each number once, with 1 meaning least serious barrier, and 5 most serious barrier.

Purchase cost
Recharging time
Limited range
Recharging infrastructure
Reliability

*** 7. How far do you drive EV in one trip?**

8. Overall, how satisfied are you driving the EV?

○ Extremely satisfied ○ Satisfied ○ Neutral ○ Unsatisfied ○ Very unsatisfied

<< Prev Next >>

Exit this survey >>

EV_Driver

3. Section 2: Attitudinal Questions

1. Using the scale below, please select the response that best describes your views or preferences.

1 = Strongly disagree
2 = Moderately disagree
3 = Neither agree or disagree
4 = Moderately agree
5 = Strongly agree

	1	2	3	4	5
Saving the environment requires our immediate efforts.	○	○	○	○	○
Now is the real time to worry about the effects of air pollution.	○	○	○	○	○
Climate change is a myth.	○	○	○	○	○
Vehicle emissions can destroy our flora and fauna.	○	○	○	○	○
I am concerned that future generations may not be able to enjoy the world as we know it currently.	○	○	○	○	○
I am willing to spend extra time only to save the environment.	○	○	○	○	○
I always recycle products such as: paper, glass, aluminium, etc.	○	○	○	○	○
I am willing to pay more for products or services only to save the environment.	○	○	○	○	○

2. Using the scale below, please select the response that best describes your views or preferences.

Using new technologies makes our lives easier.	◯	◯	◯	◯	◯
New technologies give more control over our daily life.	◯	◯	◯	◯	◯
Taking up new technologies makes one trendy.	◯	◯	◯	◯	◯
Things have become so complicated today that it is hard to understand what is going on in this techno-world.	◯	◯	◯	◯	◯
I learn new technologies without help from others.	◯	◯	◯	◯	◯
New technologies cause more problems than they solve.	◯	◯	◯	◯	◯
I am excited to learn to use new technologies.	◯	◯	◯	◯	◯
Being fashionable means having up-to-date knowledge of the techno-world.	◯	◯	◯	◯	◯
I love gadgets.	◯	◯	◯	◯	◯
Keeping up with the new knowledge on technologies is necessary.	◯	◯	◯	◯	◯

3. Using the scale below, please select the response that best describes your views or preferences.

1 = Strongly disagree
2 = Moderately disagree
3 = Neither agree or disagree
4 = Moderately agree
5 = Strongly agree

	1	2	3	4	5
I prefer to use EV over any other type of cars.	◯	◯	◯	◯	◯
I would recommend EV to others.	◯	◯	◯	◯	◯
I would buy an EV as my next car.	◯	◯	◯	◯	◯

<< Prev | Next >>

Exit this survey >>

EV_Driver

4. Section 3: Background questions

1. What is your gender?

- Male
- Female

2. What is your age (years)?

- 17-22
- 23-29
- 30-39
- 40-49
- 50-59
- 60+

3. What is your highest level of education?

4. How many vehicle do you have at home?

- None
- 1

Exit this survey >>

EV_Driver

5. Thank you.

Thank you for taking the time to complete this survey, your opinion is important. If you have any further questions or comments, please feel free to contact Ms Fakhra Jabeen on 08-6488 5814 or 0411 694 924.

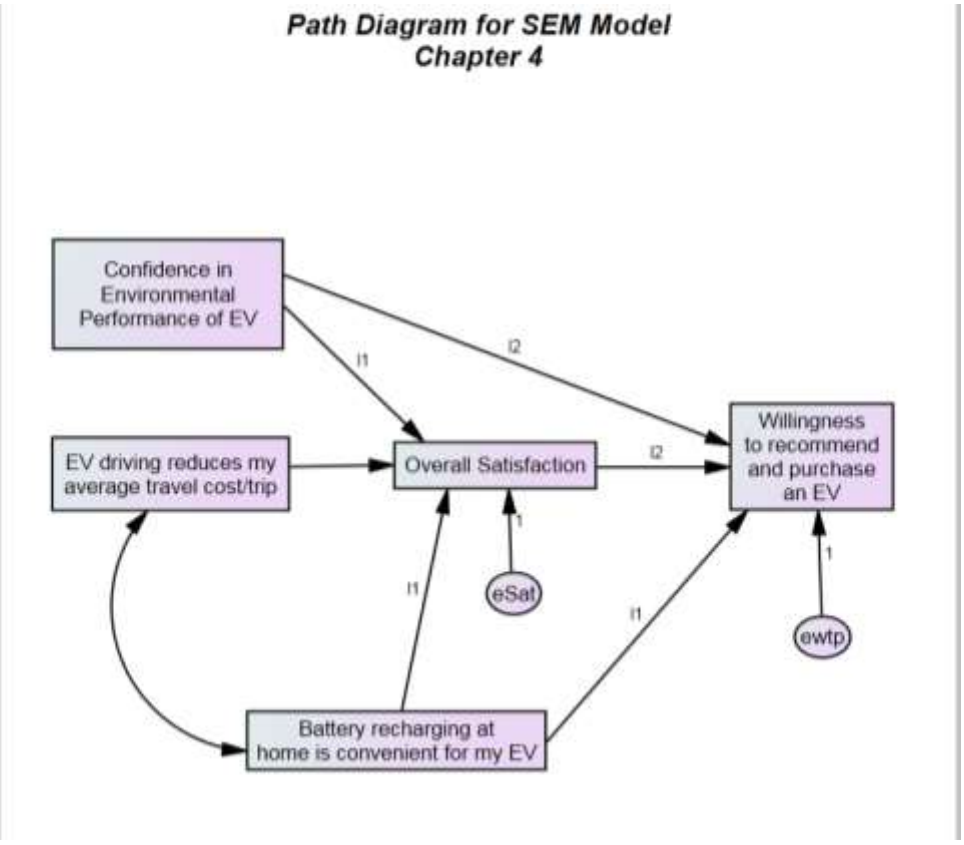
If you want to participate in the random draw please enter your email address below:

1. Email:

Thank you once again.

<< Prev   Done >>

APPENDIX B: PATH DIAGRAM OF STRUCTURAL EQUATION MODEL (SEM)



APPENDIX C: DRIVERS' CHARGING BEHAVIOUR SURVEY INSTRUMENT

EV_Drivers'Survey_II

Electric Vehicle Battery Charging

Battery Charging Levels: Cost and Time

The cost of battery charging depends on the charging station Level, time of the day, and place.

For Level I charging station it can take 6-8 hours for a battery recharge from empty to full usually it is installed as a home charging unit. Level II and Level III charging stations are usually installed at the public places or at the parking bays at work. The charging time can be from 10-30 mins for a full recharge depending on current state of battery.

The cost of electricity is defined based on the time of the day for example on peak rate is the most expensive morning/evening or some part of afternoon hours, while off peak would be least expensive usually during the night. <tb>

Home charging with solar panels at home

With solar energy system, it allows to generate surplus amount during the day thus allows charging EV at home with zero cost during the day. The cost of charging an EV depends on the type of solar panels and the electricity supplier. For example the electricity supplier may purchase surplus energy from household during the day at a fixed rate
($0.07/kWh), and sell it back to household during evenings at on peak rate and during night at an off peak rate.

Having solar energy at home reduces EV Battery Charging cost to zero at HOME.

Prev Next

EV_Drivers'Survey_II

Objectives and Assumptions

Objectives of Study

This study aims to explore the battery charging behaviour of the drivers in the WA EV Trial on the assumption that you privately own a new EV. It will explore drivers' preferences for charging at home, at work, or at a public charging station. When charging an EV there is a trade-off between cost of re-charging and convenience.

Conditions applying for this survey

Assume the following scenario:

- You own a new Electric Vehicle with a charging facility at your home; Level-I charging units are installed at home (Level I charging units are slower as compared to Level II or Level III). The cost of re-charging the EV will be added to your electricity bill, however if you have solar panels at home it will reduce the cost to zero.

- Suppose the requirement for your EV battery charging is from Empty (30%) to Full (100%) , that is currently your battery status is 30% full.

- Your workplace provides free parking space for your car and you can book a bay to recharge your car if needed (Level II and Level III fast charging units are provided). There is however A PRICE for charging at work (you are charged at the rate shown in each combination of options).

- A public charging station is available en route between home and work and there is a max 10 mins queuing time. However these public charging bays are located close to attractions (like coffee shop, a mall or a kid's play area). You are charged at the rate shown in each combination, and Level II and Level III fast charging units are provided.

- You are planning your activities and travel for tomorrow, which is a working day.
- Your new EV is the principal vehicle in your household.

For this survey drivers having solar energy at HOME, please assume to have ZERO COST of charging EV battery at HOME, though it might not show the same in scenarios.

With these assumptions in mind please complete this questionnaire.

Prev Next

EV_Drivers'Survey_II

1. What is your age group?

- ◯ <25
- ◯ 25-29
- ◯ 30-39
- ◯ 40-49
- ◯ 50-59
- ◯ 60+

2. What is your gender?

- ◯ Male
- ◯ Female

3. What is the highest level of education you completed?

- ◯ Year 12 or lower
- ◯ Some college/Professional qualification
- ◯ University Bachelor Degree
- ◯ Masters or PhD

4. Do you usually have travel commitments involving other family members (e.g., pick-up/drop-off)?

- ◯ Yes
- ◯ No

5. Do you have solar panels on your roof top?

- ◯ Yes
- ◯ No

Prev Next

EV_Drivers'Survey_II

Opportunities for Recharging Your Electric Vehicle [Set-D]

6. Charging at

	WORK	*HOME*	*PUBLIC*
	When : </hb> 1:00PM **How Long :** 20 mins **Cost/kWh :** $0.44	**When:** 9:00PM **How Long:** 6 hrs **Cost/kWh:** $0.30	**When:** 1:00PM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred	○	○	○
Least Preferred	○	○	○

7. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 10 mins **Cost/kWh:** $0.22	**When:** 8:00AM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 1:00PM **How Long:** 30 mins **Cost/kWh:** $0.22
Most Preferred	○	○	○
Least Preferred	○	○	○

8. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 30 mins **Cost/kWh:** $0.22	**When:** 1:00PM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred	○	○	○
Least Preferred	○	○	○

9. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 30 mins **Cost/kWh:** $0.44	**When:** 8:00AM **How Long:** 7 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred	○	○	○
Least Preferred	○	○	○

Prev Next

EV_Drivers'Survey_II

Opportunities for Recharging Your Electric Vehicle [Set-C]

10. Charging at

	WORK	*HOME*	*PUBLIC*
	When : </hb> 1:00PM **How Long :** 10 mins **Cost/kWh :** $0.44	**When:** 8:00AM **How Long:** 6 hrs **Cost/kWh:** $0.12	**When:** 8:00AM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred			
Least Preferred			

11. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 30 mins **Cost/kWh:** $0.22	**When:** 1:00PM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred			
Least Preferred			

12. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 10 mins **Cost/kWh:** $0.22	**When:** 8:00AM **How Long:** 6 hrs **Cost/kWh:** $0.12	**When:** 8:00AM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred			
Least Preferred			

13. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 20 mins **Cost/kWh:** $0.44	**When:** 8:00AM **How Long:** 7 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred			
Least Preferred			

Prev Next

EV_Drivers'Survey_II

Opportunities for Recharging Your Electric Vehicle [Set-A]

14. Charging at

	WORK	*HOME*	*PUBLIC*
	When : </hb> 1:00PM **How Long :** 10 mins **Cost/kWh :** $0.44	**When:** 9:00PM **How Long:** 6 hrs **Cost/kWh:** $0.30	**When:** 1:00PM **How Long:** 30 mins **Cost/kWh:** $0.22
Most Preferred	○	○	○
Least Preferred	○	○	○

15. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 10 mins **Cost/kWh:** $0.22	**When:** 1:00PM **How Long:** 7 hrs **Cost/kWh:** $0.12	**When:** 1:00PM **How Long:** 30 mins **Cost/kWh:** $0.22
Most Preferred	○	○	○
Least Preferred	○	○	○

16. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 30 mins **Cost/kWh:** $0.44	**When:** 9:00PM **How Long:** 8 hrs **Cost/kWh:** $0.12	**When:** 1:00PM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred	○	○	○
Least Preferred	○	○	○

17. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 20 mins **Cost/kWh:** $0.44	**When:** 1:00PM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred	○	○	○
Least Preferred	○	○	○

Prev Next

EV_Drivers'Survey_II

Opportunities for Recharging Your Electric Vehicle [Set-B]

18. Charging at

	WORK	*HOME*	*PUBLIC*
	When : 8:00AM **How Long :** 10 mins **Cost/kWh :** $0.44	**When:** 9:00PM **How Long:** 8 hrs **Cost/kWh:** $0.12	**When:** 1:00PM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred			
Least Preferred			

19. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 10 mins **Cost/kWh:** $0.44	**When:** 1:00PM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 8:00AM **How Long:** 20 mins **Cost/kWh:** $0.22
Most Preferred			
Least Preferred			

20. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>1:00PM **How Long:** 20 mins **Cost/kWh:** $0.44	**When:** 9:00PM **How Long:** 6 hrs **Cost/kWh:** $0.30	**When:** 1:00PM **How Long:** 10 mins **Cost/kWh:** $0.44
Most Preferred			
Least Preferred			

21. Charging at:

	WORK	*HOME*	*PUBLIC*
	When: </hb>8:00AM **How Long:** 10 mins **Cost/kWh:** $0.22	**When:** 1:00PM **How Long:** 8 hrs **Cost/kWh:** $0.30	**When:** 1:00PM **How Long:** 30 mins **Cost/kWh:** $0.22
Most Preferred			
Least Preferred			

Prev Next

EV_Drivers'Survey_II

Thank you

Thank you for taking the time to complete this survey, your opinion is important. If you have any further questions or comments, please feel free to contact Ms Fakhra Jabeen (6488 5698).

22. Please feel free to enter feedback or comments. (optional)

Prev Done

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See how easy it is to create a survey.

APPENDIX D: FLYER

THE UNIVERSITY OF WESTERN AUSTRALIA
Achieve International Excellence

The University of Western Australia
35 Stirling Highway, Crawley WA 6009
T +61 8 6488 5698
E 20873104@student.uwa.edu.au
CRICOS Provider Code: 00126G

25th August 2012

Dear Householder,

We are writing to you on behalf of the University of Western Australia (UWA), to request your participation in the **WA Electric Vehicle (EV) Household Survey**. This study is a major step towards an understanding of the potential uptake of range-restricted electric vehicles (EV) in Australia. It primarily explores the acceptability of EV as new technology with zero tailpipe emissions. This research has the approval of the UWA Human Research Ethics Committee, RA/4/1/5043.

All information collected is anonymous, thus information collected from the survey will not include names or other details. All information collected will be kept strictly confidential and will be used for this study only.

The survey is expected to take no more than 15-20 minutes of your time. As a token of our appreciation for your participation in this study, upon receipt of your completed questionnaire we will enter your address into a draw to win prizes (*one iPad and ten $50 gift vouchers for Coles and Woolworths*).

The survey has four parts:
A) Information about your household; B) Attitudes towards Electric Vehicle and technology; C) Household car choices; and D) Additional background information.

There are two options offered to complete the survey:

- Online, at https://www.surveymonkey.com/s/EV_households

OR

- Using a paper version of the survey (In this case please call UWA at 64885698/0411694924 OR email fakhraj01@student.uwa.edu.au, and tell us the address so that we can post the survey to you).

Filling in the information in the survey will indicate your agreement to participate in the study. At any stage you may withdraw without giving a reason. Please turn over for basic information about Electric Vehicles.

For any further information about administration of this survey please contact Fakhra Jabeen (fakhraj01@student.uwa.edu.au or 6488 5698).

Again, thank you for participation.

Sincerely,

E/Prof John H E Taplin
Transport and Logistics
Business School
Crawley, WA 6009, Australia
Phone: +61 8 6488-2081
Fax: +61 8 6488-1004
Email: john.taplin@uwa.edu.au

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APPENDIX E: INVITATION LETTER

THE UNIVERSITY OF
WESTERN AUSTRALIA
Achieve International Excellence

The University of Western Australia
35 Stirling Highway, Crawley WA 6009
T +61 8 6488 5698
E 20873104@student.uwa.edu.au
CRICOS Provider Code: 00126G

7th February 2013

Dear Householder,

We are writing to you on behalf of the University of Western Australia (UWA), to request your participation in the **WA Electric Vehicle (EV) Household Survey**. This study is a major step towards an understanding of the potential uptake of range-restricted electric vehicles (EV) in Australia. It primarily explores the acceptability of EV as new technology with zero tailpipe emissions. This research has the approval of the UWA Human Research Ethics Committee, RA/4/1/5043.

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A) Information about your household; B) Attitudes towards Electric Vehicle and technology; C) Household car choices; and D) Additional background information.

There are two options offered to complete the survey:

- Using a paper version of the survey (In this case please fill in the survey enclosed in this envelope and send it back to us using the reply back envelope). OR
- You can go online at the link: **https://www.surveymonkey.com/s/EV_households**
  (*please ignore the attached paper survey in this case*).

Filling in the information in the survey will indicate your agreement to participate in the study. At any stage you may withdraw without giving a reason. Please turn over for basic information about Electric Vehicles.

For any further information about administration of this survey please contact Fakhra Jabeen (fakhraj01@student.uwa.edu.au or 6488 5698).

Again, thank you for participation.

Sincerely,

E/Prof John H E Taplin
Transport and Logistics
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[redacted]

APPENDIX F: BROCHURE

What are Plug in Electric Vehicles (EVs)?

Plug in Electric Vehicle Characteristics

- Driving Range
- Low running cost
- Zero tailpipe Emissions
- Battery Recharging
- Charging Standards

Driving Range

- EVs are range restricted cars.
- Once fully charged an EV can cover only a certain distance (130 – 150kms), called the EV driving range, then requires to be plugged in for a recharge.
- Driving an EV thus requires trip planning.

Low Running Cost

The travel cost is reduced to around one quarter of the cost of a petrol car. For a small economy car the travel cost is $2.9/100km, as compared to $10/100km for a petrol car.

BATTERY RECHARGING

Electric Vehicles (EVs) are different since they need to be recharged.

Instead of going to a fuel station and using a bowser, an EV is plugged in at home or at a charging station to get the battery charged!

Home Charging

- A charging unit can be installed at home so that the vehicle can be recharged overnight.
- Home charging is an important EV benefit.
- It takes about 6-10 hours to get a full charge at home.

Public Charging Places

- These charging stations are currently being installed at public access points like coffee shops, or parking areas.
- They are 2 types of fast charging stations Level 2 and Level 3. Level 3 stations can recharge an EV battery to 80% full in 25 minutes.

COMBO Charging Standard

The combined charging system integrates one-phase AC-charging, fast three-phase AC-charging, DC-charging at home and ultra-fast DC-charging at public stations into one vehicle inlet.
Audi, BMW, Chrysler, Daimler, Ford, General Motors, Porsche and Volkswagen have agreed to support this harmonised single-port fast charging approach.

Zero Tailpipe Emissions

An EV is a green vehicle, because it has zero tailpipe emissions.

APPENDIX G: HOUSEHOLD SURVEY INSTRUMENT SET I

EV_Households_Aug12

1. Research background & consent

Thank you for agreeing to participate in this survey. We are interested in your thoughts and opinions about the appropriateness/acceptability of range-restricted Electric Vehicles (EV) and their likely uptake in Australia.

By participating in this survey you are eligible to be in a draw to win an iPad.

The survey includes four sections: A) Information about the household; B) Attitudes towards Electric Vehicles and new technologies; C) Household car choices; and D) Background information.

All information collected is anonymous, except that participation in the draw to win an iPad requires email address. By filling in the information in this survey you consent to participate in the study. At any stage you may withdraw without justification or providing a reason.
This research has the approval of UWA Human Research Ethics Committee, RA/4/1/5043 from October 2011.

For any further information, please contact Fakhra Jabeen (6488 5698, fakhrj01@student.uwa.edu.au).

Again, thank you for your involvement.

Sincerely yours,
Fakhra Jabeen

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2. Electric Vehicle (EV) Characteristics and your choices

Electric Vehicle (EV) Characteristics

- ***Driving Range***
- ***Low Running Cost***
- ***Battery Recharging***
- ***Zero Tailpipe Emissions***
- ***Combo Charging Standard***

A Brochure with details about Electric Vehicles is provided here.

DRIVING RANGE

Electric Vehicles are range restricted. Once fully charged an EV can be driven for 130 to 150km – called the Electric Vehicle driving range – and then needs to be plugged in for recharge.

LOW RUNNING COST

By using electric energy instead of petrol, the electric car reduces the travel cost by almost 70%.
Over one year the running cost of an electric car= **$550**
For a similar size the travel cost for a petrol car = **$1,900**
This is a saving of **$1,350** per year.
In addition, EVs do not require frequent service, thus lower maintenance cost.

BATTERY RECHARGING

Electric vehicles can be charged at home or by stopping at a charging station to get the battery recharged.

HOME CHARGING

- A charging unit can be installed at home so that the vehicle can be recharged overnight.
- It takes between 8 to 10 hours to get a full recharge at home.

PUBLIC CHARGING PLACES

- These charging stations are in process of being installed at public access points like shopping centres, recreation parks, or parking areas. There are 2 types of fast charging stations (Level 2 and Level 3)
- Level 3 stations can recharge an empty EV battery in 30 mins, while recharging on Level 2 stations takes between 2 and 4 hours.

ZERO TAILPIPE EMISSIONS

Electric vehicles are greener with zero tailpipe emissions (so they do not pollute). They may have however upstream emissions, depending on the processes used for generating electricity.

COMBO CHARGING STANDARD

The combined charging system integrates one-phase AC-charging, fast three-phase AC-charging, DC-charging at home and ultra-fast DC-charging at public stations into one vehicle inlet.

Audi, BMW, Chrysler, Daimler, Ford, General Motors, Porsche and Volkswagen have agreed to support this harmonized single-port fast charging approach.

For more details please click here.

Your survey begins now.

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3. A. Information about Your household and Vehicles You Use

1. Do you own or rent your property?

- Owned
- Paying-Off
- Rented

Other (please specify)

2. Where do you live?

Suburb

Other (please specify)

3. Please enter the following details for each person in your family over 16 years of age:
(You are considered person 1 in the list below.)

	Gender	Age Group	Education (Completed)	Number of Jobs	Av. Travel Distance/day (km)	No. of Trips >30km per Week	Suburb of Your Workplace/Education	Driving Licence
1								
2								
3								
4								
5								

4. For each vehicle that your household uses, please complete the following information:

	Make	Manufactured	Fuel Type	Engine size (Litres)	Body Type	Weekly Fuel Cost ($)	Fuel Paid By:
1							
2							
3							
4							
5							

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4. Future Purchases and Attitudes towards Electric Cars

1. How much are you willing to spend to purchase your next car?

- ◯ <$20,000
- ◯ $20,001-$35,000
- ◯ $35,001-$50,000
- ◯ $50,001-$65,000
- ◯ Over $65,000

2. Using the scale below, please select the response that best describes your views or preferences.

1 = Unlikely
2 = Somewhat unlikely
3 = Neither likely or nor unlikely
4 = Somewhat likely
5 = Likely

	1	2	3	4	5
If you were to buy a car within the next five years (whether you really intend to or not), how likely is it that you would buy an electric vehicle?	◯	◯	◯	◯	◯
Assuming you had an electric vehicle available. How likely is it that you would do without an additional car with an internal combustion engine?	◯	◯	◯	◯	◯

3. Using the scale below, please select the response that best describes your views or preferences.

1 = Rarely
2 = Occasionally
3 = Frequently
4 = Often
5 = Always

	1	2	3	4	5
How often would you use your EV?	◯	◯	◯	◯	◯

4. Using the scale below, please select the response that best describes your views or preferences.

1 = Strongly disagree
2 = Moderately disagree
3 = Neither agree or disagree
4 = Moderately agree
5 = Strongly agree

	1	2	3	4	5
Saving the environment requires our immediate efforts.	○	○	○	○	○
Now is high time to worry about the effects of air pollution.	○	○	○	○	○
Climate change is a myth.	○	○	○	○	○
I prefer to walk/cycle in order to reduce pollution.	○	○	○	○	○
I might join a group, club, or organisation concerned with ecological issues.	○	○	○	○	○
It is acceptable for a modern society to produce a certain degree of pollution.	○	○	○	○	○
I am concerned that future generations may not be able to enjoy the world as we know it currently.	○	○	○	○	○
I always recycle products such as: paper, glass, aluminium, etc.	○	○	○	○	○
I am willing to pay more for products or services to save the environment.	○	○	○	○	○
Riding public transport helps reduce pollution.	○	○	○	○	○
I prefer driving a car with a powerful engine than a car that emits little CO2.	○	○	○	○	○

5. Using the scale above, please select the item that best describes your views or preferences.

	1	2	3	4	5
Using new technologies makes life easier.	○	○	○	○	○
Things have become so complicated today that it is hard to understand what is going on in this techno-world.	○	○	○	○	○
I use online maps to plan my travel when I need to visit a new place.	○	○	○	○	○
Exploring new technologies enables me to take benefit from latest developments.	○	○	○	○	○
New technologies cause more problems than they solve.	○	○	○	○	○
EV Technology would enable me to cut the running costs.	○	○	○	○	○

6. Using the scale above, please select the response that best describes your views or preferences.

	1	2	3	4	5
Taking up new technologies makes me trendy.	○	○	○	○	○
People who influence my behaviour think I should buy an EV.	○	○	○	○	○
People who are important to me think that I should buy an EV.	○	○	○	○	○
I would buy an EV if many of my friends would use an EV.	○	○	○	○	○
Being fashionable means having up to date knowledge of this techno-world.	○	○	○	○	○

7. Using the scale above, please select the response that best describes your views or preferences.

	1	2	3	4	5
I never travel without a GPS.	○	○	○	○	○
I love gadgets.	○	○	○	○	○
People often become too dependent on technology to do things for them.	○	○	○	○	○
Keeping my knowledge up to date about technology is necessary.	○	○	○	○	○
New technologies enable me to resolve my daily tasks.	○	○	○	○	○

5. Instructions for completing Household Vehicle Choice Experiments

To explore the factors contributing to vehicle purchase we would like to ask your preference for one of the alternatives in the following hypothetical scenarios.

It is fun and easy to complete.

1. You will be shown four cars in each scenario/game. You may treat the values as if true.
2. Indicate your most preferred and least preferred option from the set of given choice.
3. Please answer all questions.

A brief description of the attributes used in the scenarios is given below:

Attribute		***Description***
Driving Range		This value indicates the distance that can be covered with one full recharge/re-fuel. Its value ranges from 100 to 1,000km for different cars, as shown in the choice scenarios.
Charging Electric Car		This value indicates time taken to recharge an Electric Vehicle. It depends on type of charging station, and car size. Level 1 is ideal as a home-charging station and takes 10 hours for a full recharge. As average distance driven is around 40km, a full charging may not be necessary. Forty % recharging takes 4 hours. Level 2 and 3 are much faster charging stations. For small to medium cars, Level 3 takes 30 mins, while Level 2 requires 2-4 hours. The scenarios or choice tasks include the fastest charging available for that case i.e., for example Level 1 is best as if no public charging station available.
Full life-cycle CO_2 Emissions		Greenhouse Gas Emissions (GHG) value tells the amount of CO_2 equivalent produced from "well-to-wheel" (extraction to combustion).
Engine Size or power		In choice tasks, mostly small to medium sized cars are presented. The engine size or their equivalent powers of 1.6L to 2.4L sedan cars are included in the scenarios.
Battery Life		Battery life is a feature of the electric vehicle. Nowadays most EVs use Lithium-ion batteries and their life span ranges from 10 to 12 years. After 10 years the capacity of the battery varies between 85% and 95%.
Noise		The noise here is the Engine Noise. The noise from EVs comes mainly from tyre roll and wind resistance. Thus, EVs generate less noise as compared to petrol or diesel cars.

6. B. Household Choice Experiment - 1

1. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $50,000	Price = $36,000	Price = $53,000	Price = $46,000
	Driving range = 140km	Driving range = 800km	Driving range = 400km (including 30km electric)	Driving range = 800km
	Fastest charging available - 1.5h (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging at home (30 min)	n/a
	Running cost = $1.4/100km	Running cost = $7.5/100km	Running cost = $6.0/100km	Running cost = $7.5/100km
	Equiv. 2.4L	2.4L	Equiv. 1.6L	2.0L
	Life cycle Emissions = 11kg/100km	Life cycle Emissions = 21kg/100km	Life cycle Emissions = 17kg/100km	Life cycle Emissions = 23.5kg/100km
	Battery capacity after 10 years = 85%	n/a	Battery capacity after 10 years = 85%	n/a
	No engine noise	Medium engine noise	Medium engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

2. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $42,000	Price = $36,000	Price = $45,000	Price = $38,000
	Driving range = 140km	Driving range = 500km	Driving range = 500km (including 30km electric)	Driving range = 800km
	Fastest charging available - 1.5h (to add 40% of battery capacity)	n/a	n/a	n/a
	1,000 public stations available	n/a	Charging at home (30 min)	n/a
	Running cost = $2.0/100km	Running cost = $7.5/100km	Running cost = $4.0/100km	Running cost = $9.0/100km
	Equiv. 2.0L	2.0L	Equiv. 2.0L	2.0L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 21kg/100km
	Battery capacity after 10 years = 90%	n/a	Battery capacity after 10 years = 85%	n/a
	No engine noise	Medium engine noise	High engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

3. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $42,000	Price = $44,000	Price = $45,000	Price = $30,000
	Driving range = 100km	Driving range = 700km	Driving range = 500km (including 30km electric)	Driving range = 1,000km
	Fastest charging available - home 4 hours (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging at home (30 min)	n/a
	Running cost = $1.7/100km	Running cost = $10.0/100km	Running cost = $5.0/100km	Running cost = $6.0/100km
	Equiv. 1.6L	2.0L	Equiv. 2.4L	2.4L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 17kg/100km	Life cycle Emissions = 26kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 80%	n/a
	No engine noise	High engine noise	Low engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

4. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $34,000	Price = $28,000	Price = $37,000	Price = $30,000
	Driving range = 100km	Driving range = 600km	Driving range = 600km (including 30km electric)	Driving range = 800km
	Fastest charging available - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	1,000 public stations available	n/a	1,500 public stations available	n/a
	Running cost = $1.7/100km	Running cost = $7.5/100km	Running cost = $6.0/100km	Running cost = $9.0/100km
	Equiv. 2.0L	2.0L	Equiv. 2.4L	2.0L
	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 21kg/100km	Life cycle Emissions = 17kg/100km	Life cycle Emissions = 23.5kg/100km
	Battery capacity after 10 years = 85%	n/a	Battery capacity after 10 years = 85%	n/a
	No engine noise	High engine noise	Low engine noise	Medium engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

5. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car	***Petrol car***	***Plug-in hybrid car***	***Diesel car***
	Price = $34,000	Price = $44,000	Price = $53,000	Price = $38,000
	Driving range = 140km	Driving range = 700km	Driving range = 400km (including 30km electric)	Driving range = 1,000km
	Fastest charging available - 1.5 hours (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	500 public stations available	n/a
	Running cost = $1.4/100km	Running cost = $12.0/100km	Running cost = $5.0/100km	Running cost = $6.0/100km
	Equiv. 1.6L	1.6L	Equiv. 1.6L	1.6L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 15kg/100km	Life cycle Emissions = 23.5kg/100km
	Battery capacity after 10 years = 85%	n/a	Battery capacity after 10 years = 80%	n/a
	No engine noise	Medium engine noise	Medium engine noise	Medium engine noise
Most preferred				
Least preferred				

6. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car	***Petrol car***	***Plug-in hybrid car***	***Diesel car***
	Price = $42,000	Price = $28,000	Price = $45,000	Price = $30,000
	Driving range = 100km	Driving range = 600km	Driving range = 600km (including 30km electric)	Driving range = 800km
	Fastest charging - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	1,000 public stations available	n/a	500 public stations available	n/a
	Running cost = $2.0/100km	Running cost = $12.0/100km	Running cost = $6.0/100km	Running cost = $7.5/100km
	Equiv. 2.0L	2.0L	Equiv. 2.4L	2.0L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 26kg/100km	Life cycle Emissions = 15kg/100km	Life cycle Emissions = 21kg/100km
	Battery capacity after 10 years = 90%	n/a	Battery capacity after 10 years = 80%	n/a
	No engine noise	Low engine noise	Medium engine noise	High engine noise
Most preferred				
Least preferred				

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8. C. Background Questions

1. What is your combined household income, before tax?

- ◯ Less than $45,000
- ◯ $45,001 to $75,000
- ◯ $75,001 to $100,000
- ◯ $100,001 to $150,000
- ◯ $150,001 to $200,000
- ◯ Over $200,000

2. When do you intend to change your existing car?

- ◯ By next year
- ◯ In the next 1-3 years
- ◯ In the next 3-5 years
- ◯ In more than 5 years

3. What type of car would you purchase?

- ◯ New Car
- ◯ Used Car

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9. Thank you.

Thank you for taking the time to complete this survey, your opinion is important. If you have any further questions or comments, please feel free to contact Ms Fakhra Jabeen (6488 5698).

If you want to participate in the random draw please enter your email address below:

1. Email:

2. Please feel free to provide comments/feedback about this Electric Vehicles Survey. (Optional)

<< Prev | Done >>

APPENDIX H: HOUSEHOLD SURVEY INSTRUMENT SET II

7. B. Household Choice Experiment - 2

1. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $42,000	Price = $36,000	Price = $53,000	Price = $46,000
	Driving range = 140km	Driving range = 600km	Driving range = 600km (including 30 km electric)	Driving range = 1,000km
	Fastest charging - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging 30 min (home)	n/a
	Running cost = $1.4/100km	Running cost = $7.5/100km	Running cost = $4.0/100km	Running cost = $6.0/100km
	Equiv. 2.4L	2.0L	Equiv. 1.6L	2.0L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 26kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 80%	n/a
	No engine noise	Low engine noise	High engine noise	High engine noise
Most preferred				
Least preferred				

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $42,000	Price = $36,000	Price = $45,000	Price = $30,000
	Driving range = 140km	Driving range = 800km	Driving range = 600km (including 30 km electric)	Driving range = 800km
	Fastest charging - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging 30 min (home)	n/a
	Running cost = $2.0/100km	Running cost = $10.0/100km	Running cost = $4.0/100km	Running cost = $9.0/100km
	Equiv. 2.0L	1.6L	Equiv. 1.6L	2.0L
	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 26kg/100km	Life cycle Emissions = 15kg/100km	Life cycle Emissions = 21kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 90%	n/a
	No engine noise	High engine noise	Low engine noise	Medium engine noise
Most preferred				
Least preferred				

3. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $34,000	Price = $28,000	Price = $45,000	Price = $46,000
	Driving range = 120km	Driving range = 800km	Driving range = 400km (including 30 km electric)	Driving range = 900km
	Fastest charging - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging at home (30 min)	n/a
	Running cost = $1.4/100km	Running cost = $12.0/100km	Running cost = $6.0/100km	Running cost = $6.0/100km
	Equiv. 1.6L	2.4L	Equiv. 2.4L	2.0L
	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 13kg/100km	Life cycle Emissions = 26kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 90%	n/a
	No engine noise	Low engine noise	Medium engine noise	Medium engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

4. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $34,000	Price = $44,000	Price = $53,000	Price = $46,000
	Driving range = 100km	Driving range = 700km	Driving range = 600km (including 30 km electric)	Driving range = 900km
	Fastest charging - home 4 hours ~~(to add 40% of battery capacity)~~	n/a	n/a	n/a
	1,500 public stations available	n/a	n/a	n/a
	Running cost = $1.7/100km	Running cost = $12.0/100km	Running cost = $6.0/100km	Running cost = $6.0/100km
	Equiv. 2.0L	1.6L	Equiv. 1.6L	1.6L
	Life cycle Emissions = 11kg/100km	Life cycle Emissions = 21kg/100km	Life cycle Emissions = 15kg/100km	Life cycle Emissions = 26kg/100km
	Battery capacity after 10 years = 85%	n/a	Battery capacity after 10 years = 80%	n/a
	No engine noise	Low engine noise	High engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

5. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $42,000	Price = $36,000	Price = $45,000	Price = $46,000
	Driving range = 140km	Driving range = 700km	Driving range = 600km (including 30km electric)	Driving range = 800km
	Fastest charging - 12 min (to add 40% of battery capacity)	n/a	n/a	n/a
	500 public stations available	n/a	Charging at home (30 min)	n/a
	Running cost = $3.4/100km	Running cost = $12.0/100km	Running cost = $6.0/100km	Running cost = $9.0/100km
	Equiv. 2.0L	2.0L	Equiv. 2.4L	2.0L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 31kg/100km	Life cycle Emissions = 17kg/100km	Life cycle Emissions = 23.5kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 95%	n/a
	No engine noise	Low engine noise	Medium engine noise	High engine noise
Most preferred				
Least preferred				

6. Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:

	Electric car	*Petrol car*	*Plug-in hybrid car*	*Diesel car*
	Price = $34,000	Price = $36,000	Price = $37,000	Price = $38,000
	Driving range = 120km	Driving range = 700km	Driving range = 500km (including 30 km electric)	Driving range = 1,000km
	Fastest charging - home 1.5 hours (to add 40% of battery capacity	n/a	n/a	n/a
	1,500 public stations available	n/a	Charging 30 min (home)	n/a
	Running cost = $2.0/100km	Running cost = $10.0/100km	Running cost = $6.0/100km	Running cost = $9.0/100km
	Equiv. 2.0L	1.6L	Equiv. 2.0L	2.4L
	Life cycle Emissions = 12kg/100km	Life cycle Emissions = 26kg/100km	Life cycle Emissions = 15kg/100km	Life cycle Emissions = 21kg/100km
	Battery capacity after 10 years = 95%	n/a	Battery capacity after 10 years = 85%	n/a
	No engine noise	Medium engine noise	Medium engine noise	Low engine noise
Most preferred				
Least preferred				

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APPENDIX I: PRIOR ESTIMATES USED IN EXPERIMENTAL DESIGNS

EV	A	A	A	A	A	A	A	A	A	A
Parameter		x21	x22	x23	x24	x25	x26	x27	x28	x29
		x21	x22	G3	G4	G5	x26	G7	G8	G9
Prior	-0.2	0.111	0.0005	-0.002	-0.115	0.02	1.06	-0.23	-0.025	0.0002
Petrol	B	B	B	B	B	B	B	B	B	B
Parameter		x31	x32		x34	x35		x37	x38	x39
		x31	x32		G4	G5		G7	G8	G9
Prior	0.1	0.111	0.0005		-0.115	0.02		-0.23	-0.025	0.0002
Hybrid	C	C	C	C	C	C	C	C	C	C
Parameter		x41	x42	x43	x44	x45	x46	x47	x48	x49
		x41	x42	G3	G4	G5	x46	G7	G8	G9
Prior	-0.1	0.111	0.0005	-0.002	-0.115	0.02	1.06	-0.23	-0.025	0.0002
Diesel	D	D	D	D	D	D	D	D	D	D
Parameter		x51	x52		x54	x55		x57	x58	x59
		x51	x52		G4	G5		G7	G8	G9
Prior	0	0.111	0.0005		-0.115	0.02		-0.23	-0.025	0.0002

APPENDIX J: DESIGNS FOR HOUSEHOLD SURVEYS

EV

Choice Set	Engine Size	Range	Charging Time	Running Cost ($/100km)	Battery Capacity after 10 years	Purchase Price ('000 $)	Number of Charging Stations
1	2.4	80	1.5	1.4	0.65	50	500
2	2.4	120	0.2	1.7	0.8	42	1,500
3	2.4	160	4	1.7	0.95	50	500
4	2	80	1.5	1.7	0.95	50	1,000
5	2.4	80	4	2	0.8	50	1,500
6	1.6	160	0.2	2	0.65	42	1,000
7	2	160	4	2	0.65	50	1,500
8	1.6	80	0.2	1.4	0.95	42	1,000
9	2.4	120	1.5	1.7	0.95	34	500
10	1.6	80	4	2	0.65	42	500
11	1.6	120	4	1.7	0.65	50	1,500
12	2.4	160	0.2	1.4	0.95	34	500

Petrol

Choice Set	Engine Size	Range	Running Cost ($/100km)	Emissions	Noise	Purchase Price ('000 $)
1	1.6	800	12.5	21	1	36
2	1.6	600	10	31	2	28
3	2.4	600	7.5	21	1	36
4	2.4	700	7.5	21	1	36
5	1.6	800	7.5	31	2	44
6	2	800	7.5	31	2	44
7	2	800	10	21	1	28
8	1.6	600	7.5	26	1	28
9	2.4	800	7.5	31	3	28
10	2.4	700	12.5	31	1	28
11	2.4	600	12.5	21	3	28
12	2.4	800	10	26	2	36

PIH

Choice Set	Engine Size	Range	Charging Time	Running Cost ($/100km)	Emissions	Battery Capacity after 10 years	Noise	Purchase Price ('000 $)	Number of Charging Stations
1	2	400	4	5	17	0.95	2	37	1,500
2	1.6	500	4	5	17	0.95	3	37	500
3	2.4	600	0.2	6	17	0.65	2	45	1,000
4	1.6	600	0.2	6	15	0.8	1	37	1,500
5	1.6	600	0.2	4	15	0.65	1	37	1,000
6	1.6	600	4	4	13	0.65	1	53	1,500
7	1.6	400	0.2	4	15	0.65	3	53	1,000
8	2.4	400	4	4	13	0.65	1	37	500
9	2	400	1.5	5	17	0.95	1	53	500
10	1.6	400	1.5	4	13	0.8	3	53	1,500
11	2.4	600	0.2	4	13	0.95	3	53	500
12	2	500	4	5	13	0.95	1	45	1,000

Diesel

Choice Set	Engine Size	Range	Running Cost ($/100km)	Emissions	Noise	Purchase Price ('000 $)
1	2.4	900	7.5	26	1	46
2	1.6	800	9	23.5	2	46
3	2.4	800	9	26	1	30
4	2	1000	9	23.5	2	30
5	2.4	800	6	23.5	2	38
6	1.6	800	9	21	1	30
7	2.4	1000	7.5	26	2	30
8	2.4	800	9	26	3	30
9	2.4	1000	7.5	21	3	38
10	1.6	900	6	21	3	30
11	1.6	1000	6	26	1	38
12	2	1000	7.5	26	3	38

APPENDIX K: CHOICE ANALYSIS: TRADING VS. NON-TRADING BEHAVIOUR (BEST ONLY DATA)

The multinomial-logit model does not incorporate correlations in the unobserved utilities across multiple choice tasks and is inappropriate for analysing “quasi-panel data”. Consequently, a panel Mixed Logit (panel-ML) model has been estimated on these data, both on the mail-out full estimation sample and on a second sample including only traders on the Best choice (290+59 in Figure 7.1). Whereas the alternative specific constants ASCs were set as random parameters, all taste weights and error components were non-random. In which case equation 3.13 is rearranged as follows:

$$U_{jtn} = (ASC_j + \omega_{jn}) + \sum_{k=1}^{K} \bar{\beta}_{jk} X_{jtnk} + \varepsilon_{jtn} \qquad \textbf{Eq. k.1}$$

and the random parameter $(ASC_j + \omega_{jn})$ **is the sum of a location or sample mean component** ASC_j, and the random effect ω_{jn}.

The results for the random effects choice model are presented in Table k.1. Investigating the full estimation sample with the attitudinal data, the estimates indicate a preference for low running cost (β=-0.251; *t=8.83*), quiet vehicles (β=-0.382; *t=7.41*) with low purchase price (β=-0.066; *t=9.32*), and fast EV charging (β=-0.0040; *t=5.65*). For Petrol and Diesel vehicles large engine sizes (β=1.550; *t=7.88*) were preferred.

Table k.1: Parameter Estimates for Panel-ML with Random Effects in Mail-Out Sample: All vs. Traders

Variables	Mail-Out Best Only All		Mail-Out Best Only Traders		Mail-Out Best Only All – With Attitudinal Data		Mail-Out Best Only Traders– With Attitudinal Data	
Random Parameters (RP) in Utility Functions ***ASC*** $_{\mathbf{Alternative}}$	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	0.363	0.25	0.0891	0.06	-3.31***	3.38	-2.31***	2.75
ASC_{Diesel}	-3.66***	7.39	-3.30***	6.79	0.252	0.33	-0.574	0.82
ASC_{Petrol} [a]	-3.18***	6.29	-2.84***	5.72	0.612	0.8	-0.262	0.37
St. Dev. of random effects RP/limits of triangles of random effects RP	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**
ASC_{EV}	2.39***	15.17	1.53***	12.8	2.12***	14.85	1.36***	12.15
ASC_{Diesel}	2.21***	12.47	1.67***	11.43	1.97***	12.18	1.49***	10.92
ASC_{Petrol}	2.19***	12.96	1.43***	10.48	2.08***	12.8	1.37***	10.2
Attributes $_{\mathbf{Alternatives}}$	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**	**Beta**	**|t|**
PRICEK: Purchase $Price_{Generic}$	-0.0675***	8.58	-0.0645***	8.32	-0.0664***	9.32	-0.0636***	9.04
EMISSIONS: $Emissions_{Generic}$	-0.00425	0.30	-0.00562	0.40				
RUNCOST: Running $Cost_{Generic}$	-0.253***	8.65	-0.249***	8.57	-0.251***	8.83	-0.248***	8.75
CHTIME: Charging $Time_{EV}$	-0.00404***	5.71	-0.0041***	5.80	-0.0040***	5.65	-0.00405***	5.76
BAT_LIFE: Battery Life $_{EV}$	0.125	0.08	0.191	0.12				
RANGE: Range $_{\mathbf{EV}}$	-0.0122***	3.47	-0.0121***	3.41	-0.0120***	3.59	-0.0119***	3.58
RANGE: $Range_{Petrol,Diesel,PIH}$	0.00035	0.82	0.00039	0.90				
ENGINESIZE: $EngineSize_{Petrol,Diesel}$	1.48***	7.22	1.406***	6.85	1.55***	7.88	1.47***	7.49
NOISE: $Noise_{Generic}$	-0.396***	7.37	-0.398***	7.45	-0.382***	7.41	-0.386***	7.53
Covariates $_{\mathbf{Alternatives}}$					**Beta**	**|t|**	**Beta**	**|t|**
EC: Preference for $Environment_{EV}$					1.29***	4.33	1.008***	4.19
SN: Social $Norms_{EV}$					0.479***	3.98	0.225**	2.34

Rely on Single Car$_{EV}$					0.514***	5.09	0.355***	4.62
Often use EV$_{EV}$					0.363***	3.12	0.227**	2.55
EC: Preference for Environment$_{PIH}$					0.926***	4.64	0.7003***	3.88
SN: Social Norms$_{PIH}$					0.177**	2.04	*0.0729*	*0.97*
PU: Perceived Uses of Technology$_{PIH}$					0.124	1.1	0.0625	0.65
Rely on Single Car$_{PIH}$					0.205***	2.96	0.168***	2.88
Number of estimated parameters	15		15		21		21	
Number of observations	2,694		2,154		2,694		2,154	
Number of individuals	**437**		**349**		**437**		**349**	
Log-likelihood	-2,795.302		-2,496.891		-2,734.94		-2,457.42	
AIC/N	2.086		2.33		2.04		2.30	
ρ^2 (Pseudo-R^2)^b	0.251		0.164		0.27		0.18	

[a:] ***Plug-in Hybrid is the reference fuel and vehicle technology;***
[b:] **McFadden Pseudo R^2;**
*****, **, * indicate significance at 1%, 5%, and 10% level respectively.**

The negative parameter estimate on EV driving range (β=-0.0120; *t=3.59*) was not expected. This counter intuitive result is investigated by collecting another round of data using scenarios that include two electric vehicles (Chapter 8).

The comparison of the findings from the full sample (437) was achieved in Table k.1 by removing *Non-traders (B)* from the sample, leaving 349. The parameter estimates had a higher level of significance for the latter, as indicated by the *t values* being larger for the charging time and noise variables. The estimates between the sample without non-traders and the full sample were consistent; however there were differences in the attitudinal data. The attitudinal estimates for the full sample were more reliable as compared to *Non-traders (B);* this reflects non-traders' strong pro-environmental behaviour and their influence from friends and fashion. People who chose PIH in the full sample were more influenced by social norms (β=0.177; *t=2.04*), while it is not so obvious in the traders only sample.

By allowing for a random effect (the random ASC's in the model), the estimation function accommodated the heterogeneity in the relative importance of the unobserved components of utility. As displayed in Figure k.2, the posterior estimates on the AEV parameter are substantially higher for non-traders (here estimated without the attitudinal data). By estimating a more dispersed random effect, the likelihood estimator was able to proceed by essentially ignoring the attribute importance weights for the non-traders due to *very high* ASCs. Looking at the profiles of EV *Non-Traders (B),* it was found that this group does not differ in general from the total sample. However, their attitudes distinguished from the trading responses with their significantly different predisposition to buy an EV as their next car (3.77 for EV *Non-Traders (B)* vs 2.70 for traders), the perception that their travel needs could be satisfied without a second car with ICE (3.54 for EV *Non-Traders (B)* vs 2.87 for traders), and their stated frequency of using EV if they owned one (4.15 for EV *Non-Traders (B)*, 3.55 for traders).

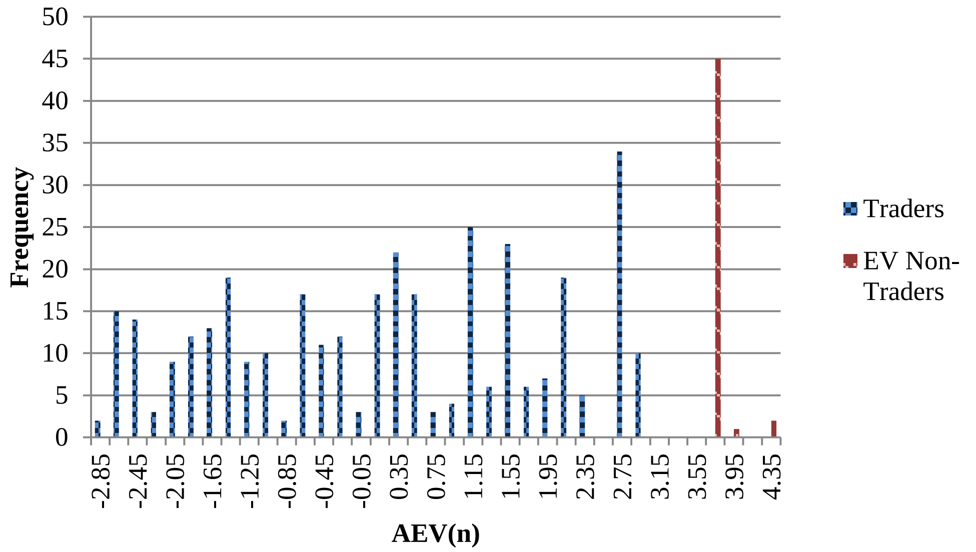

Figure k.1: Random Effect Estimates for EV ASC

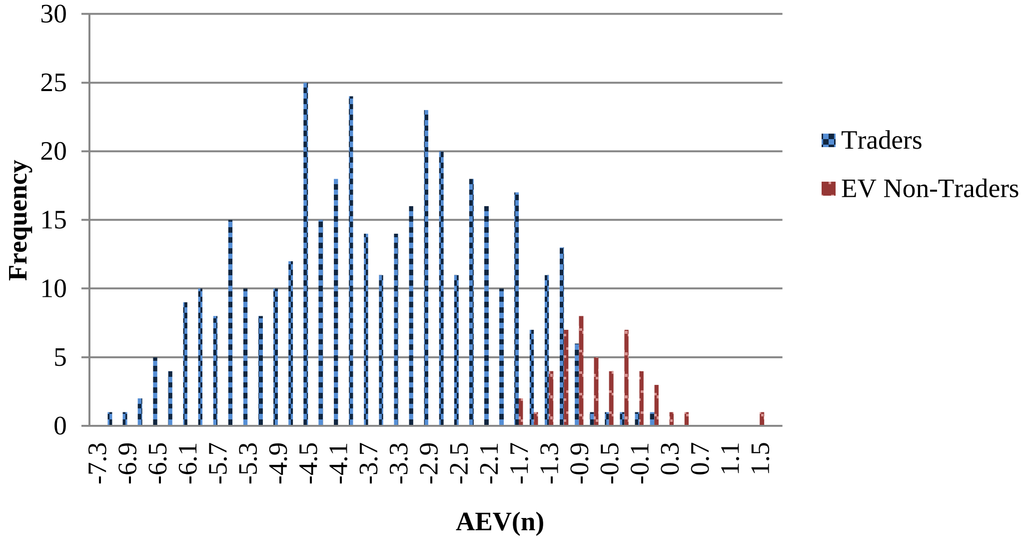

Figure k.2: Random Effect Estimates for EV ASC (With Attitudinal Data)