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Understanding consumer’s intentions to electric vehicle adoption and preferences for charging infrastructure in Innsbruck, Austria.

Master’s Thesis

A thesis presented in part fulfilment of the requirements of the Degree of Master of Science in Transportation Systems at the Department of Mobility Systems Engineering, Technical University of Munich.

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Abstract:

Sustainable mobilities have become an indispensable necessity for sustainable economic growth and smart city initiatives. To this point, the potential of electric vehicles plays an important role as an integral option for the smart city initiatives. Within the framework of the project 'PECASO', a survey with the sample size (N=496) was conducted which consisted of two different ownership groups (EV owner and non EV owner), this research focuses to fill the gap on the user's perception and intentions, attitude towards the behavior of electric vehicle adoption, the different socio-economic attributes that influences the people's choice in adoption of the EV and preferences for the charging infrastructure in Innsbruck city. This research utilizes the constructs from the Extended Theory of Planned Behavior to understand the underlying latent intentions of the focused groups. Hence in this case, a forced discrete choice, with unlabeled alternatives as a choice experiment has been setup to this end. The results from the MNL model indicates that, both of the focused group prefer nearby distances of the charging stations, positively prefer the reservation of the spot in charging station, higher charging speed and perceive negatively the incremental costs associated with charging EV in charging stations. Furthermore, a HCM ordered logit model has been developed to understand the latent construct of ETPB of the focused groups. The main results show that, the barrier towards the adoption intention for the non-EV owners' group is driven by the functionalities of EV (longer charging time, driving range) and EVCS (insufficient charging infrastructures) and in case of the EV owner's group the repurchase intention for EV, is mainly driven by the social influence or the subjective norms. Respondents are willing to pay more with included reservation of spot in short term public charging facilities in nearby distances. Hence, for more wider network of the EV establishment of the charging stations more specifically fast/rapid charging needs to be scattered to the different location based on the demand of EV's. Moreover, a robust planning for the installation of fast charging infrastructures, within a reliable coverage by inclusion of reservation time and different amenities surrounding EVCS must be considered for widespread EV adoption as future extension plans. These initiatives will require more balanced and close cooperation from the Government, automotive industries, stakeholder associations, city authorities, and charging service providers to reach the goal of smart city.

Keywords: Electric vehicle, EVCS, ETPB, MNL, hybrid choice model, charging infrastructure,

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List of Abbreviations

EV: Electric Vehicle/s

EVCS: Electric Vehicle Charging Stations

EVSE: Electric Vehicle Supply Equipment

HEV: Hybrid Electric Vehicle

PHEV: Plug in Hybrid Electric Vehicle

AFV: Alternative Fuel Vehicle

CGV: Conventional Gas Vehicle

MNL: Multinomial Logit Model

HCM: Hybrid Choice Model

OL: Ordered Logit

SP: Stated Preference

SEM: Structural Equation Modeling

ETPB: Extended Theory of Planned Behavior

WTP: Willingness to Pay

DWLS: Diagonally weighted least square

ML: Maximum Likelihood

EAFO: European Alternative fuel observatory

CBD: Commercially Business district

VBN: Value belief Norm

DIT: Diffusion of Innovation Theory

NAM: Norm Activation Model

DC: Direct Current

AC. Alternate Current

ICLV: Integrated Choice and Latent Variable

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1. Background & Motivation

1.1. Introduction:

Different alternative modes of transport have been focused on recent years due to the higher amount of GHG emission worldwide. Transport sector is one of the main emitters of the Carbon dioxide or the Greenhouse gas emissions of which 41% comes from the passenger cars globally (Tiseo, 2021). A concept of sustainable mobility has been emerged to tackle this threat of carbon emissions from these transport sector. In addition to this, restrictive CO_2 emission policies and rising of the fuel prices has led the automotive industry, changed the way in terms of manufacturing more fuel efficient and sustainable modes of transport. The different alternative solution for this sustainable mobility includes the different car sharing schemes, electro-mobility, or the electric vehicles (EV's) etc. To counteract the negative notion on the electric vehicles, the government subsidies have been incentivizing for the BEV purchasing. The introduction of such policies has led to the promotion of the electromobility that also includes the development of the charging infrastructure at different designated locations with different schemes that also includes the reduced prices for parking. For example, Dundee in UK offers free parking flexibilities in almost all car parking areas (Heidrich, Dissanayake, Lambert, & Hector, 2022). Additionally, Oslo in Norway offers access to the bus lanes for EV (Heidrich et al., 2022). Such examples for EV uptake in cities depend much upon the different situational & contextual factors. Recent study by (Heidrich et al., 2022) discussed different perspective including the situational factors, contextual factors, barriers & enablers etc to revolutionize EV's in the cities.

Moreover, the strict policies in Europe for CO_2 emission have been changing the mindset of the individuals in terms of different alternative mobility concepts. To offset the CO_2 emission, the European Alternative fuel observatory, (EAFO) has set up a road map targeting the year of 2050 for making a carbon neutral continent (EAFO & Sandra, 2021). According to the statistics provided by the EAFO, by the end of 2020 around 2.24 million of EV's and PHEV's were owned in 27 different EU member states (EAFO & Sandra, 2021). Following these statistics in fig 1, about 94.3% share come from the passenger cars whereas the light commercial vehicles take upon the 5.4% of the share (EAFO & Sandra, 2021). To make a successful integration of the electric vehicles in urban mobility concepts and increasing the adoption rate also depends upon the publicly accessible charging points or established infrastructures.

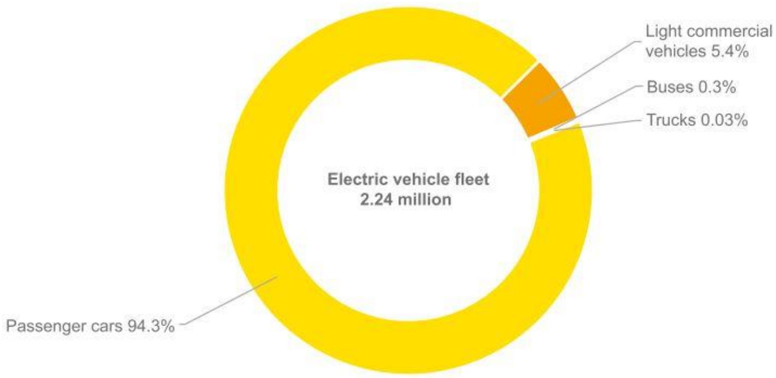


Figure 1: EV fleet in 27 EU member state as of December 2020, (adapted from EAFO & Sandra, 2021)

Hence, in this case the European commission has already expected to reach a 1 million public charging points to serve the growth of EV's by 2025 (EAFO & Sandra, 2021). As of the recent progress in 2020 regarding the charging infrastructure, the 27 EU member states jointly have around 226,000 publicly accessible charging points, which constitutes to 89% of the normal recharging points and 11% of the fast charging points (EAFO & Sandra, 2021). The optimal distribution of these charging points is based on the public demand, hence becomes an important question for future uptake of electric vehicles in different EU member states. Although implementation of such sustainable mobility solution, especially for the adoption of electric vehicles in context of the Innsbruck city in Austria often poses functional and financial barriers or challenges in terms of the charging infrastructure availabilities for electric vehicles, higher cost acquisition, driving range etc. The above-mentioned limitations/barriers in context of the Innsbruck- Austria have been addressed in detail in further section of this introductory part.

1.1.1. Present status of electric vehicle in Austria:

According to (Austriatech, 2021) with the statistics from federal states of Austria, there were around 5099 registration of electric vehicles with Salzburg having a highest share of 16.96% in battery electric vehicle registration. With tesla model 3 being the most popular model for BEV which comprises around 24% of the market share for the users in Austria (Austriatech, 2021).

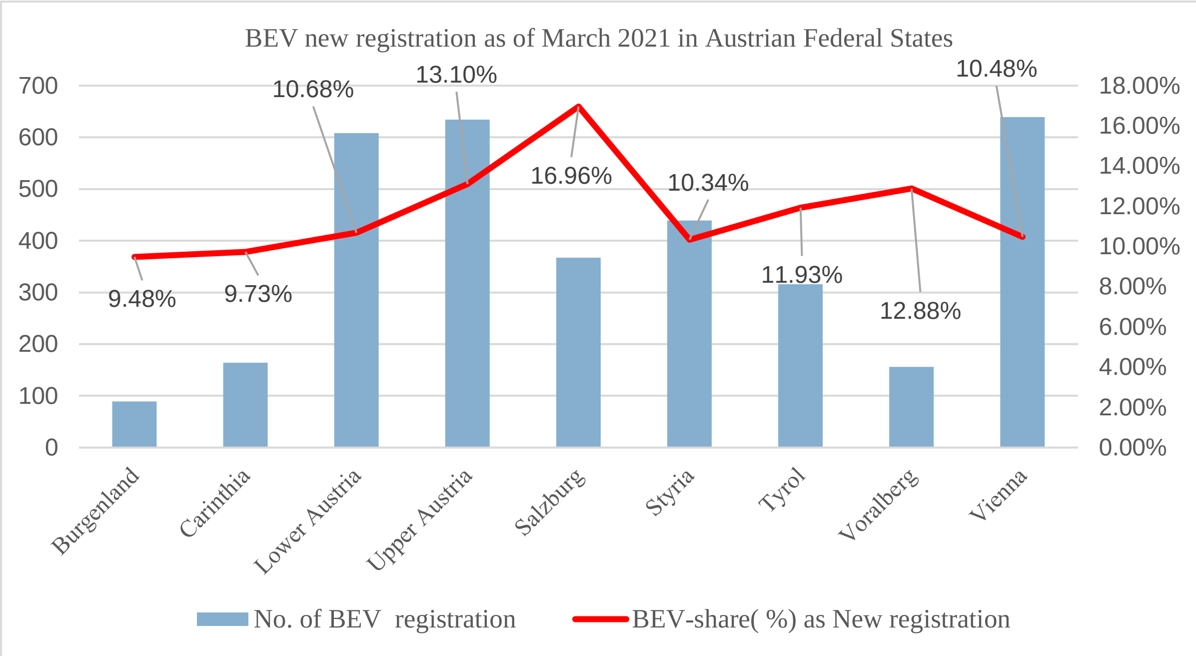


Figure 2: New EV registration in Austrian Federal states -M1 category, own elaboration (adapted from Austriatech, 2021)

Comparing the share of electric vehicles among the states in Austria, Tyrol observed to be slightly above average. The average EV registrations for the Austria is approximately 11.56% (Austriatech, 2021). The above (fig 2) depicts the share of new registration of EV as the M1 category by the federal sates of Austria.

1.1.2. Present status of charging infrastructures in Austria:

The charging network for EV's is developed and constantly being updating throughout Austrian federal states. The charging network is comprised of different modality including the normal charging points and fast charging points. Normal charging points are considered to be up to 22KW charging power whereas the fast charging points are considered to be higher than 22KW charging power (Austriatech, 2021). During the first quarter of 2021, there were around 6660 (around 84%) normal charging points and 1299 fast charging points (around 16% approx.) (Austriatech, 2021). This makes a combination of total 7959 charging points in Austria which results in 9 EV's per charging points (Austriatech, 2021). The following figure depicts the scenario of publicly accessible charging points with the data from (E-control, 2021) in federal states of Austria (Austriatech, 2021):

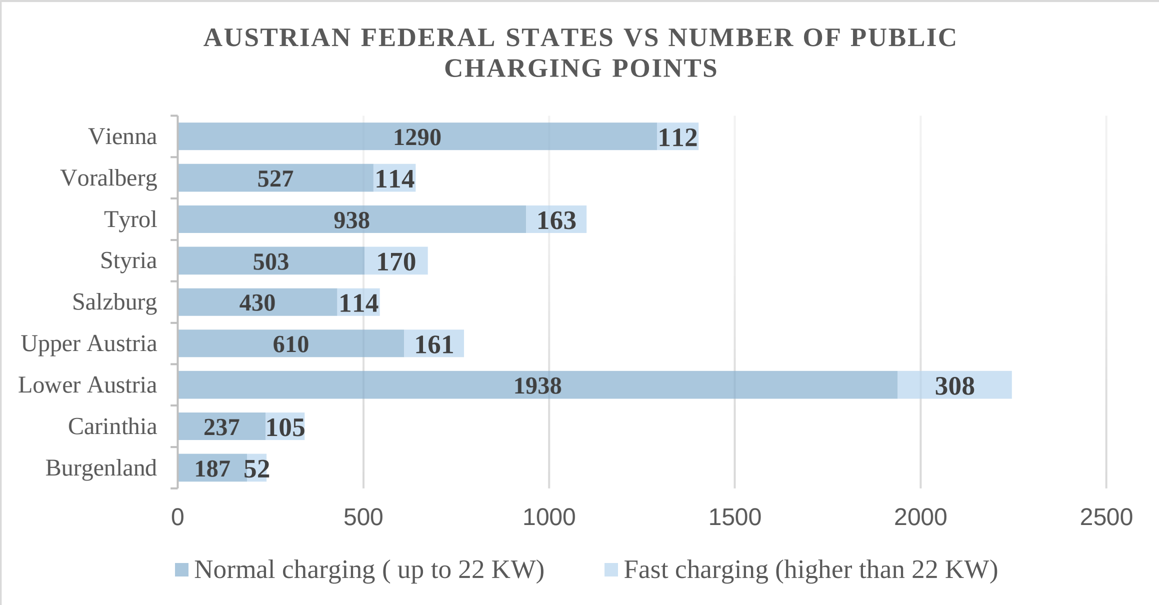


Figure 3: Publicly accessible charging points in Austrian Federal states, own elaboration (adapted from Austriatech, 2021)

In the above figure, the state Tyrol has around 938 normal charging points with up to 22KW charging power (Austriatech, 2021). The publicly accessible to fast charging points are still very less in Tyrol state, which is around 163 (14.8% approx.) (Austriatech, 2021). The location of these charging points is dispersed in different location ranging from supermarkets, parking garages, commercial areas, residential blocks, motorways, and highways etc. Some of the charging stations are currently offering free services and most of the locations included are in the multi-story car parks in shopping malls (E-control, 2021). Moreover, there are quite number of companies providing services of charging infrastructure for electric vehicles. The cumulative charging points provided by the different companies such as IKB, Green Energy Center etc. makes the charging network umbrella of the Innsbruck city. The (figure 4) depicts the distribution of the charging infrastructure with different power modalities by IKB (Innsbruck municipal operations) in Innsbruck city in shown in appendix section (A7):

1.1.3. Heatmap visualization of the charging infrastructures in Innsbruck:

Based on the existing charging infrastructure, a heatmap visualization has been created with the existing coordinates of the IKB service provider. The heatmap below (see Fig 5.) depicts the existing scenario of the currently present charging infrastructure. The map shows that the higher concentration of the publicly accessible charging points is within the city center and lower concentration of EVSE on other sides of the city. The IKB is equipped with the combination of the rapid, fast, moderate, and slow charging points in different areas of Innsbruck. According, to IKB there are total 70 publicly accessible charging station with different tariff structures that combines the different power modalities (IKB, 2022). The establishment of such facilities is based on the electric vehicle user's demand and proximity to the points of interests and public services. Since, the center of the city is equipped with wide range of facilities, as such the higher number of the public charging stations is focused on the city center. A typical picture of the EV charging park, where multi-modality charging options allows user to charger different electric operated transport vehicles near Innsbruck central station is shown below:

Figure 4: EV Charging Park (near Innsbruck central station, Own captured, Site Visit)

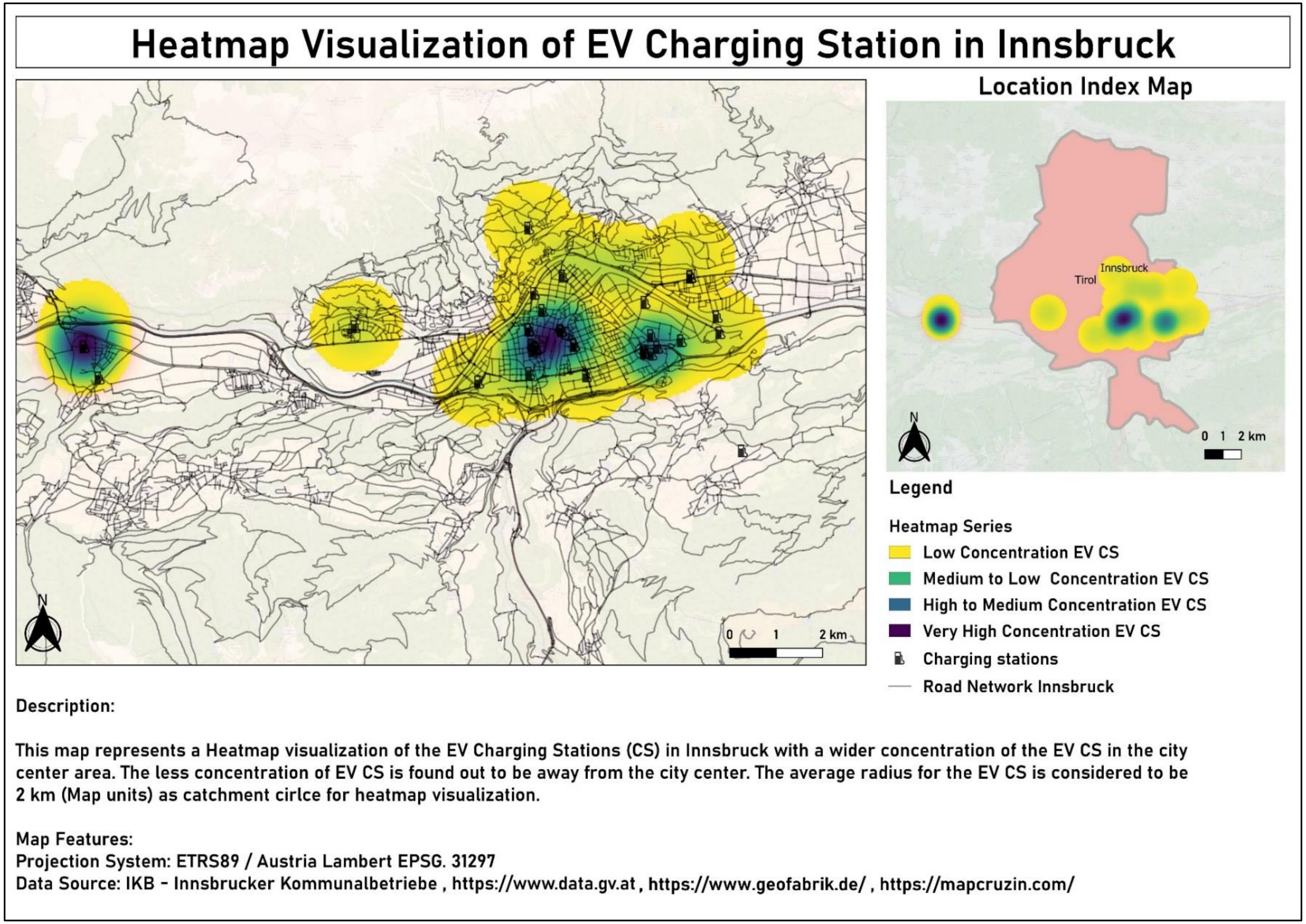


Figure 5: Heatmap of existing charging infrastructure of IKB, Innsbruck (Own illustration, based on the data (IKB, 2022)

1.1.4. Policy Incentives and measures for Electric Vehicles in Austria:

Austria is paving its path for more sustainable mobility solutions by providing the different Governmental subsidies to increase the rate of EV adoption. According to (EAFO, 2022) the Government has planned different purchase subsidies, tax rebates etc. Table 1 depicts the scenario of the target group with purchase subsides by Austrian Government:

Target Group	Car Type	Purchase subsidies	Subsidies from Government	Rebate from the industry	Condition
Private Customers	BEV, FCEV	5,000 €	3,000 €	2,000 €	Price 50,000€ incl. VAT and for PHEV minimum range of 50 km
Business, Municipalities	BEV, FCEV	5,000 €	3,000 €	2,000 €	
For all	PHEV	2,500 €	1,250 €	1,250 €	

Table1: Purchase subsidies of BEV,PHEV & FCEV for target groups by Austrian Government, (EAFO, 2022)

Furthermore, the Austrian Government also provides different benefits that includes the registration benefits, ownership benefits, and other financial benefits ranging from private individuals to the companies as well. Table 2 depicts the scenario of the target different benefits covered by the Austrian Government:

Benefits (VAT + TAX)	Measures
Registration Tax	Cars below 141g/km are registration tax free
Ownership Tax	BEV's 100% tax exempt, except VAT
Financial	Exemption of parking charges, Free parking
Company Tax	0% tax for private usage of the company car
VAT	Company BEV's exempt from VAT

Table 2: Different benefits for BEV’s and measures undertaken by Austrian Government, (EAFO, 2022)

Moreover, the Austrian Government has also announced different changes in the policy schemes that would increase the EV penetration rate by providing more incentives specially for EV’s (EAFO, 2022). The Austrian Government also provides incentives for the infrastructures required for charging these electric vehicles. Again, this incentives for infrastructure are divided in to two distinct categories. The categories include the private individuals setting up a wall box (for private home charging) with a subsidy up to six hundred euros and 1800 euros for setting up the charging stations in multi-storey buildings / parking garages (EAFO, 2022). Hence, such measure for purchase subsidies and different incentives by the Austria federal states has been undertaken to enhance the BEV adoption in the large catchment of the transport industry.

1.1.5. Current challenges for EV in Austria-Land Tyrol:

The Austrian federal Government has imposed strict mission so called the mission 2030 adopting its climate and energy strategy in order to meet its sustainable development goals (SDG's) in various sectors including the transportation domain to limit the GHG gas emission. The aim is to achieve energy efficiency by 2030, use of renewable energy and reduction of greenhouse gas (Integrated National Energy and Climate Plan for Austria, 2019). In addition to mission for 2030, the land Tyrol has introduced the electromobility strategy with the motto called '***How Tyrol drives in 2050'*** with introduction of various incentivizing policies (European Commission, 2016). Hence, for faster adoption of BEV, the Austrian federal Government has declared various incentives and subsidies along with different tax and financial benefits. So, this can be said that one of the main challenges for Austrian federal Government in transport sector is to foster the growth of BEV in order to mitigate GHG emission from the private transport sector by providing lucrative policies and subsidies for electro mobility.

A recent study by Groschopf, Schönfelder, & Leovac (2020) has investigated preferences of the users and challenges of battery electric vehicle market in Austria. The authors (Groschopf et al., 2020) have provided a comprehensive analysis from the sample of Austrian population, clustering different user segments by individual use patterns on BEV. Clustering across the different user segment by associating with the use and ownership of BEV's, the authors (Groschopf et al., 2020) have illustrated individual preferences, their perceived challenges and resulting opportunities. The results obtained from the study of (Groschopf et al., 2020) has identified three different clusters for the BEV users which are known as Cluster 1 (Heavy users), those using the BEV in intensive way, Cluster 2 (Urban hoppers) , often using the BEV as their first car traveling for short distances. Cluster 3 includes (Moderate users) functions as the middle of the both cluster group by using the BEV to a lesser extent than the group in cluster 1 (Groschopf et al., 2020). Furthermore, (Groschopf et al., 2020) have studied the barriers and challenges for BEV market in Austria and concluded that "*BEV users perceive a lack of cost transparency for charging as well as little interconnectivity between charging infrastructure providers and standardization of billing processes*". In addition to this, the respondents struggle for more and better information of the existing charging infrastructure (Groschopf et al., 2020). In line with this, a previous study by Priessner, Sposato, & Hampl, (2018) has focused on analyzing different adopters for EV, that includes the early adopters, potential adopters and non-adopters for EV despite the commonly cited barriers for EV adoption such as the range limitation, acquisition costs and charging points with the results drawn from the survey sample of (n = 1000) Austria citizens. Likewise, the study applies a cluster analysis to understand the four different profile of the potential EV adopters (Priessner et al., 2018). Additionally, (Priessner et al., 2018) provides two insightful research regarding the effectiveness of the EV policy incentive. According to (Priessner et al., 2018), "*EV policy incentives were found not to distinguish between early adopters and non-adopters, which means that non-adopters and early adopters are equally likely to live in regions with strong EV government policies*". The authors (Priessner et al., 2018) further concludes that the policy makers can increase the incentives targeting to the particular group (potential EV adopters) or may provide incentive packages to the special service providers such as the car sharing companies. Moreover, the data for the above mentioned study suggests that the EV's are not perceived as ICE in terms of performance, convenience, and price by the non-adopters (Priessner et al., 2018).

Moreover, authors Gühnemann, Kurzweil, & Mailer (2021) have mentioned in their study that Austria being situated in an alpine region considered to be a touristic destination place for the travelers as well as a key income source which narrates about 17.5% of the direct GDP in Austrian province of Tyrol (according to tourism satellite statistics of Austria for Tyrol). The authors (Gühnemann et al., 2021) mentioned in their research that, within the territory private vehicles perform around 75% of holiday trips in Austria which has a substantial effect on the climate change pattern. But a successful transition to alternative mobility forms requires policy measures, expansion of the charging infrastructures, taxes on CO_2 and GHG emission . Hence, one of the big challenges from the tourism point of view is to avoid forms of mobility that have adverse effect on environment such as the decreasing the possession of car trips by conventionally operated vehicles to most climate friendly mobility forms by use of EV's in tourism sector (Gühnemann et al., 2021).

1.1.6. Problem identification:

At present, due to more technological advancement in automotive industry and more stringent policies for climate change around the world, the demand for BEV had risen and a fierce competition has been seen in the recent years. Innsbruck, being the fifth largest city of the Austrian federal states, a mesmerizing touristic destination with alpine demographics and different forms of mobility services according to the recent fact check on mobility of Austria, that unveils interesting research on how much an average trip made by the commuters in Austria. Surprisingly, it was found that the average trip made by commuters in Austria is around 34 km/day (Federal Ministry for Climate Protection Environment Energy Mobility & Innovation Technology-(BMK), 2021). With this range, a BEV is well equipped to meet the demand of the inhabitants or the car owners of the Innsbruck. Moreover, even if the range is not only the great concern, but the city of Innsbruck also has a wider coverage of charging stations only within the CBD areas. A large portion of the city lacks adequate charging stations. However, charging stations in Innsbruck are equipped with different power modalities from slow to fast charging EVSE. One of the examples of the well-known charging service provider is IKB (Innsbruck Municipal Services) in Innsbruck city with coverage of the charging stations at different location that includes the residential areas, CBD areas and some in highways. Despite the different disadvantages of the EV's from the existing infrastructural perspectives, there exists different incentives, subsidies, and policies from the government, different commercial/private stakeholders offering greater benefits upon tax, registration, and VAT to support the adoption of Battery electric vehicle (BEV).

1.2. Research Motivation:

Innsbruck being a fifth largest city of Austria located in Tyrol state, the adoption of EV's is comparatively less compared to the other cities or state in Austria as mentioned in the figure 1. Despite much of the structured effort in policy incentives and subsidies (Table 1 & 2) in electromobility sector by the Austrian federal Government, the adoption rate hasn't seen a growth trend compared to the other federal states in Austria. Although, a huge number of people in Austria own conventional cars and 94% of the car trips are shorter than 50 km/day (VCÖ - Mobility with Future, 2019), with BEV which is suitable for covering this range and daily needs of the commuter in Innsbruck, possesses an interesting gap in the research agenda to discover what certain factors plays a potential role in driving away the barriers for the EV adoption and what different expectations from the consumers point of view would increase the EV uptake. Moreover, to reach the goal of smart city and to achieve the 'SDGs' is also of paramount importance for Innsbruck city. Hence, investigating the essential factors for fostering the EV uptake with pre-defined policy incentives from the Austrian federal states it would be worthy to explore the preferences of the respondents of different distance based charging point locations through the choice experiment procedure and to observe the willingness to pay for these different types of charging infrastructures from the inhabitants of the Innsbruck sample.

1.3. Objective & Research questions pertaining to study:

1.3.1. Objective of the research:

Understanding the user's intention for EV adoption and charging infrastructure preferences using a discrete choice experiment on distance-based charging station in a Stated preference survey considering the attitudinal statements, existing travel habits or characteristics & socio demographics that helps in reflecting the latent factors for choice preferences of the respondents in Innsbruck, Austria.

1.3.2. Research questions:

Based on the defined objective, the following research questions is expected to answer from the analysis:

I. What are the expectations and challenges relating to the adoption of EV's from both the existing and potential users' perspective?

II. How users perceived the utility of the preferred charging location?

III. What are the factors underlying the willingness to pay for both the short terms and long terms charging facilities?

1.4. Research Framework:

The below flowchart depicts the procedure of the research framework which has been carried out in this for this research area:

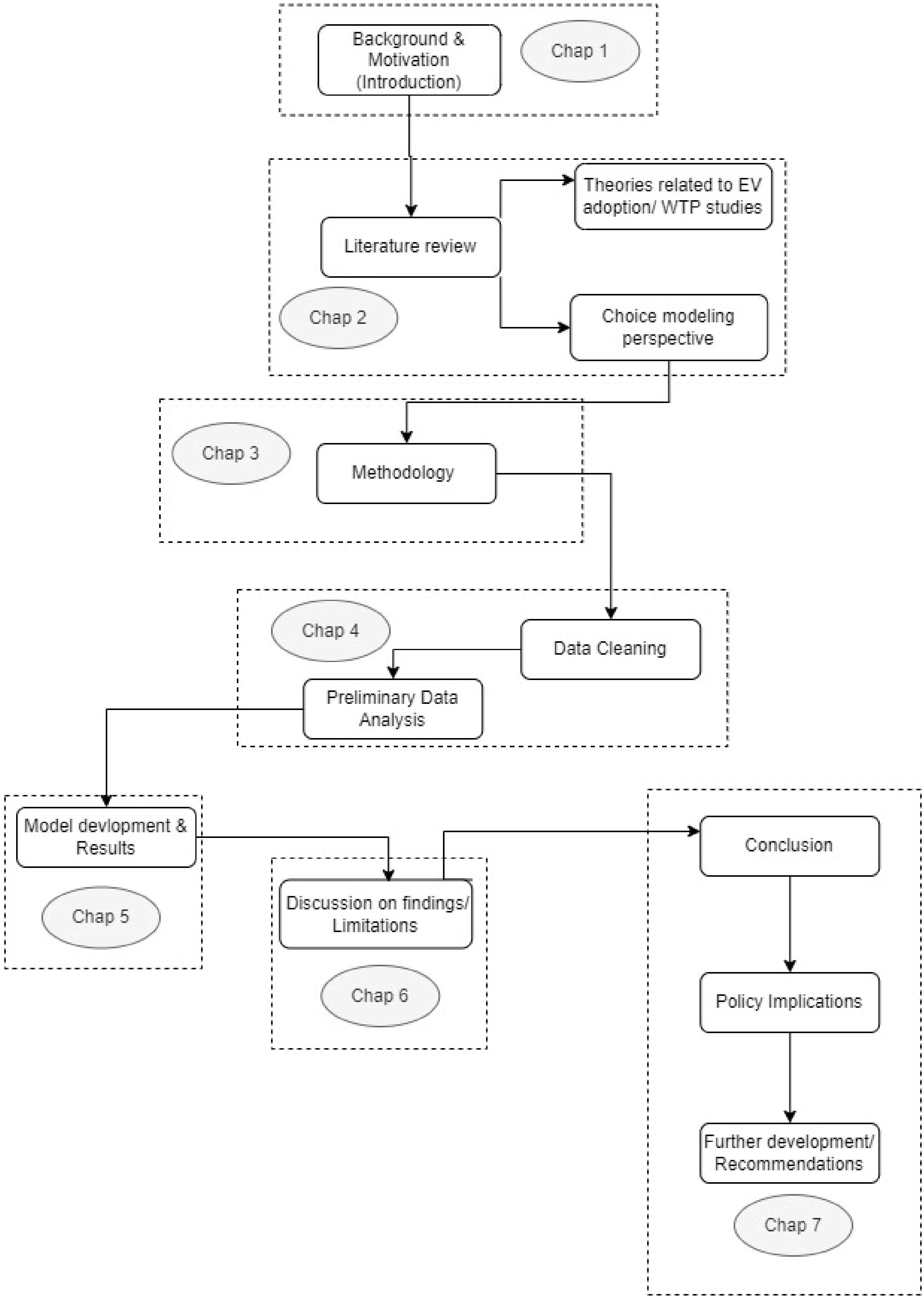


Figure 6: Research Framework

2. Literature Review

2.1. Literature segmentation:

The Literature review has been divided into different segments for better understanding of the distinct aspects for EV adoption. This part of the research section usually deals with the previous studies to understand the potential barriers of the EV adoption by citing different examples made by the different authors. Hence, this section is divided into three distinct parts: The first part involves review of the 'Theories' used in previous literatures to understand the human perceptions, behaviour, adoption psychology, rate of adoption for different users in a sample population. The second part continues with different key barriers and significant factors for EV adoption around the different geographical regions with different socio-economic backgrounds. The third part focus on the key element in identifying the factors that an individual or the sample of the population are willing to pay (also called marginal rate of substitution) given the parameters such as the installation of the charging infrastructures and other attributes relating to EV adoption.

2.2. Theories related to EV adoption:

2.2.1. Theory of Planned Behavior (TPB) & extended version

Different theories have been used in order to understand the perception of human's behavior for electric vehicle adoption. The different societal factor has a great impact that influence people's choices for electric vehicle adoption. This theory (TPB) developed by Icek Ajzen (1991) in 90's has been widely used in many studies for understanding the users perception for electric vehicle adoption. This theory is based on theory of reasoned action which is the function of the variables such as Perceived behavioral control (PBC), Subjective norm (SN) and Attitude towards behavior (ATB) (Icek Ajzen, 1991). All of these three variables reflect the behavior intention which in turn reflects the actual behavior of the user. The control beliefs give rise to the PBC, normative beliefs result in subjective norm and behavioral beliefs which produces the favorable and unfavorable attitude towards behavior (Ajzen, 2002). All of these beliefs are guided by human action and thus it reflects the actual intention to perform an actual behavior (Ajzen, 2002). Hence explaining these functions of TPB where, PBC measure the self and response efficacy that exerts individual beliefs for performing a behavior. In addition to this, Attitude towards behavior (ATB) reflects the positive and negatives attributes of the behavioral beliefs to perform a behavior. Moreover, Subjective Norm (SN) measures the normative beliefs that will be influenced by surrounding people or important person or the influence from the society to perform a behavior. All of these underlying factors have a greater influence for behavioral intention and actual behavior control.

A previous study by Yan, Qin, Zhang, & Xiao (2019) has utilized (TPB) theory of planned behavior as a theoretical framework to scrutinize the potential consumers in the city of Beijing. From this study (Yan et al., 2019) has concluded that different constructs exerting the positive and negative attribute of the TPB (PBC, ATB, SN) influences user's choice on actual behavior for purchasing the electric cars. Another study by Ahmed, Catchpole, & Edirisinghe (2020) have used the Theory of planned Behavior (TPB) from a socio-psychological perspectives in form of attitudinal questions using the TPB construct in order to investigate the mode choice behavior of the Australian users. The findings of the study (Ahmed et al., 2020) shows that, different users has different positive beliefs towards the mode they used. The public transport users have more concern regarding the reliability of the public transportation whereas the young commuting users finds it more reliable to use private transport as their main mode of transportation due to the reliability of this particular mode (Ahmed et al., 2020). From this point of view, it can be understood that the human action is particularly dependent on the beliefs to perform an actual behavior. Albeit, authors Haustein & Jensen (2018) have also utilized the theory of planned behavior in addition to the 'personal norm' and 'perceived mobility necessities' relating to affective and symbolic motives as an extension of the theory of the planned behavior to understand the potential psychological factors for purchase of electric vehicles.

The authors Haustein & Jensen (2018) has also mentioned about the advantage of Theory of planned behavior is the inclusion of the additional factors. And as such, the authors find environmental norms and symbolic-affective measures as a relevant factors to be included in their study as an extended version of the theory of planned behavior (Haustein & Jensen, 2018). Nevertheless, the study by Shalender & Sharma (2021) have also utilized the extended theory of planned behavior to predict the adoption intention of the electric vehicle in India. The authors Shalender & Sharma (2021) included 'Environmental concern' and 'Personal Norm' as an additional factor to the original TPB model which results in extended TPB model that allows the authors to interpret better for EV purchasing intention in India. In this study, the psychological factors have been chosen based on the extended version of theory of planned behavior by the inclusion of the construct 'Environmental Concern' for adoption of EV which is relevant for this study. Hence, the original model of the Theory of planned behavior can be illustrated in the following schematic diagram:

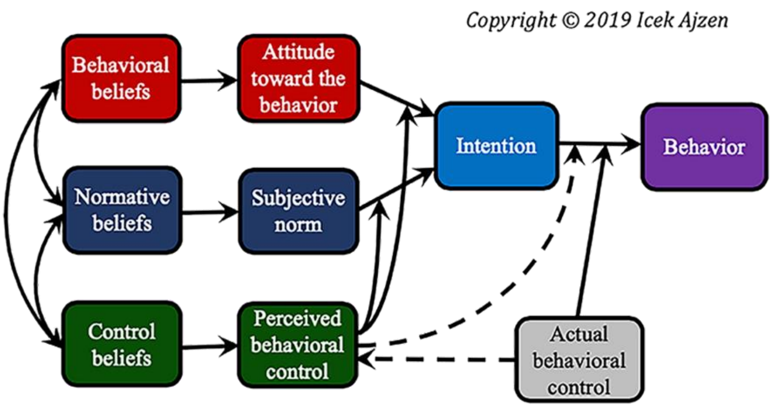


Figure 7- Different Components from Theory of Planned Behavior (adapted from Ajzen, 2019)

2.2.2. Norm Activation Model/Theory (NAM):

Another theory that has been widely used for understanding the user's perception in adoption of sustainable modes of transport such as the alternative fuel vehicles (AFV) namely:- BEV and PHEV. This model focuses on explaining the altruistic and environment friendly behavior of individual. From this theoretical framework, the researchers have tried to understand the sustainability concepts in transportation research and policy control in light of the underlying factors of NAM model. The NAM model developed by Schwartz (1977) uses the personal norms as a core to predict individual behavior. Previous study by Nordlund, Jansson, & Westin (2016) have used the theoretical framework of 'NAM' model and 'Value Belief Norm '(VBN) theory by Stern, Dietz, Abel, Guagnano, & Kalof (1999) to predict the intentions of the sample population to switching to environment friendly transport modes such as electric or hybrid vehicle. The results obtained from the study (Nordlund et al., 2016) has found that the Norm activation model or theory has supported their problem in defining the intention to purchase the alternative fuel vehicles (AFV). Furthermore the results by (Nordlund et al., 2016) also indicated that the self-efficacy, higher awareness and personal norm are more important to the users of PHEV/EV/HEV than the conventional car owners as an openness to change. Another recent study by (Asadi et al., 2021) has used 'NAM' and 'TPB' to identify the factors effecting the actual behavior towards the adoption of electric vehicles in Malaysia. The results by the study of (Asadi et al., 2021) has found out that the underlying factors such as perceived value, attitude, ascription of responsibility, subjective norms or societal influence, personal norms, awareness of the consequences etc. have a positive influence on people's intention for EV adoption.

2.2.3. Diffusion of Innovation Theory (DIT):

A widely use of ‘Diffusion Innovation Theory’ which have been developed by E.M rogers in 1962 defines how the ideas or the innovation diffuses among the groups of people. This diffusion of the process is further defined as the communication channel where the participants exchange or share their ideas in order to reach a mutual understanding mentioned by the authors Rogers, Singhal, & Quinlan (2019). For the diffusion of the innovation, there are mainly four key elements that includes Innovation, communication channel, time and the social system (Rogers et al., 2019). Rogers has divided this unit of adoption into five units and the rate of adoption to each of this unit has also been mentioned. As such, the adopters do not adopt the innovation at the same time in a social system. Since, this social system creates a boundary upon which the innovation takes place (Rogers et al., 2019). The adopter categorization has five scales of adopter categorization, shows the distribution of different adopter categories when a new innovation is being adopted (Rogers et al., 2019). A short summary of the ‘DIT’, is described below (Rogers et al., 2019):

For the first stage of adopters which are known as the ’innovators’ are the ones those who are willing to take the risks and very much interested to the new ideas or the innovation. The second stage are the ones known as the ‘early adopters’ that represents the innovators and they are willingness to embrace new possibilities or the opportunities within the social system. ‘Early majority’ are the third kind of adopters that tends to adopt new innovation. The fourth kind of the adopters are called, ‘late majority’ which are willing to adopt a new innovation that comes lately after a new technology, or the innovation has been widely accepted or used across the individuals. The last and the fifth kind of adopters are called ‘Laggards’ are those which are very skeptical to change. This certain groups are bound by the tradition and adoption of the new innovation or technology is in fact remains very slow in this group of the individuals. Many researchers have tried to understand from the theoretical framework of Diffusion of Innovation Theory for the adoption of electric vehicle or switching to a new different mode as a regular one. Previous study by Peters & Dütschke (2017) has focused on understating the underlying factors in changing towards the more sustainable modes of transport. This study of Peters & Dütschke (2017) tries to understand the underlying factors from the theoretical framework of ‘Diffusion of Innovation’ theory. The authors Peters & Dütschke (2017) has figured out the four distinct groups of the adopters which are very much likely to be different from one another through the socio-economic attributes. The study in Germany by Peters & Dütschke (2017) further provides the statistics of these four group of EV adopters based on the online web survey with a sample size of 1548, in one of the show case region for EV. The results from this study of Peters & Dütschke

(2017) finds out that the due to different technological issues owing for an EV adoption the sample population relies much on the compatibility with the daily life as the main factor influencing peoples decision in purchasing or choosing electric vehicle as their sustainable modes of transport. Another similar study where, Peters & Dütschke (2014) have used the diffusion innovation theory along with the technology acceptance model (TAM) to explain the range of different groups for EV adoption in Germany and found out that, early adopters in Germany are most likely to be the 'middle aged' men in a 'multi-vehicle household' living with families. This group of the sample size of the population stated as the early adopters drawn from the online survey of 969 respondents. Moreover, a recent study by authors Tomasi, Zubaryeva, Pizzirani, Dal Col, & Balest (2021) to understand the propensity of choosing EV in cross border alpine regions. The authors (Tomasi et al., 2021) has chosen three areas and considered them in different categories for the adopters by categorizing them as 'Canton Ticino (as leader)', 'South Tyrol (as early adopter'), and the province of 'Verbania-Cusio-Ossola' (as laggard).

2.3. Barriers and influential factors for EV adoption:

2.3.1 Recent studies relating to EV adoption in different countries :

A lot of studies have been conducted regarding the adoption of EV in different countries as an alternative mode of transport compared to the conventional gas vehicle (CGV). This alternative fuel vehicle can be divided into three parts which are known as the Plug-in Hybrid electric vehicle (PHEV), Hybrid Electric Vehicle (HEV) and Battery Electric vehicle (BEV). The definition of each of these categories are as follows:

PHEV: These vehicles have both combustion engine and battery pack are charged using a plug-in cable with a charging board outsource to the electrical grid typically known as the charging station.

HEV: These vehicles have both combine options of being able to charge with small battery pack (usually use for travelling smaller distance) and ICE (internal combustion engine) to run the motor or the engine.

BEV: These vehicles are fully dependent on the battery pack for their mobility which can be charged using a cable in the charging station or at home charging facilities.

A study by Jia & Chen (2021) includes 837 drivers from Virginia with the data obtained from the department of the motor vehicles. The authors Jia & Chen (2021) have found out several consistent findings among the two different data sets obtained. However, the age effects do not corresponds to this findings and it remains inconsistent with these two different sets of data (Jia & Chen, 2021). The combined analysis of these two different data sets has given insights for the potential factors for electric vehicle adoption (Jia & Chen, 2021). The stated preference survey by Jia & Chen (2021) has resulted that, the owners of the EV who are more susceptible towards the new technology adoption, environmental concerns, are also aware about the climate change. Furthermore, the study also finds that gender has an impact while the preference has been made between EV's (PHEV and BEV). In addition to this other socio demographic variables such as the higher income level, higher educational level has an impact while making the choice decision for the utility of EV as stated in the study of (Jia & Chen, 2021). The authors Jia & Chen (2021) have also found out the significant correlation between the adoption of EV and financial rebates by the Government. The study by Jia & Chen (2021) also pointed out some interesting correlation between the battery range and type of the EV. While the authors Jia & Chen (2021) have also pointed out some of the influential factors such as the DC fast charging stations, AC charging infrastructure density, monetary attributes etc. which found out to be significant factor for the successful adoption of EV. Hence, different factors influencing EV adoption have been discussed in different subsections.

Government Policy incentives:

Government Policy incentives plays a vital role for the fast EV uptake given that other functional barriers are resolved. A recent study by Kumar, Chakraborty, & Mandal (2021) have developed four different models which includes the development of the charging infrastructure and purchase subsidy from the Government as well as the EV manufacturer to investigate the users preferences for the adoption of the EV in India. The results obtained from the study of (Kumar et al., 2021) shows that, to maximise the EV demand as well as to increase the share of EV, two of the proposed four different models are essential with the model named as 'MG'- where the Government as a whole provides the subsidies for the charging infrastructure as well provides the purchase subsidies for EV's to consumer and the model named as 'M'-where the EV manufacturers invests in setting up the charging infrastructures and Government provides subsidy to the EV consumers. The authors (Kumar et al., 2021) concluded that for a favourable EV ecosystem, Government subsidy plays a vital role for the positive inclination of EV demand.

Another interesting study conducted by J. Wang & Matsumoto (2021) has found out the introduction of the subsidy program in Japan has promoted the consumer to choose electric vehicles, which results in achieving higher sales on hybrid electric vehicles. The number of ‘HEV’ have been increased in last 14 years from 2004 to 2018 (0.13 million to 7.5 million) (J. Wang & Matsumoto, 2021). The main reason behind this certain inclination of the HEV sales is due to the increased technology in fuel economy and Japanese Government’s series of Eco-Car Program subsidies (J. Wang & Matsumoto, 2021). Three different period have been mentioned and studied by the authors J. Wang & Matsumoto (2021) that includes the event ‘Before starting of Eco-Car Program’, ‘During the Eco-Car program’ and ‘After the Eco-Car program’. The result indicates that, with an increase of the price by 1 JPY, the probability for the HEV choice over the CGV increases by 0.04% for the event or the 1st period. Similarly for the event of 2nd and 3rd period the probability increases by 0.55% and 0.34% retrospectively (J. Wang & Matsumoto, 2021). Hence, it dictates that the Government policies such as the tax rebates or environmentally friendly programs helps to induce consumer choice preferences to a greater extent.

The adoption of Battery Electric vehicles in the regions with German speaking Swiss Cantons, where there is no strong policies for BEV was studied by Brückmann, Willibald, & Blanco (2021). Authors (Brückmann et al., 2021) have developed a generalized mixed effects logit model based on the (RP) revealed preference data and found that the individuals with higher affinity to the technologies, politically prefering green party while living in their own houses and high income tends to be strong predictors for adoption of EV early. Hence, this paper (Brückmann et al., 2021) has provided an insights for the individuals with high end income, living in their own houses and have particularly awareness to the environment are most likely to adopt BEV where there is a lack of strong policies to support EV uptake.

Charging Infrastructure:

Study from Santos & Davies (2020) has suggested that the development of the charging infrastructure play a vital role for the quick penetration of EV based on the responses obtained from the experts and stakeholders from around the Germany, Netherlands, Spain, UK and Austria. The second most significant factors for the EV adoption was found from the study of Santos & Davies (2020) is to be the purchase subsidies. More-over the authors Santos & Davies (2020) has also mentioned about the other relative incentives such as the taxation subsidies, climate change policies fostering a positive influence towards the EV adoption.

The effect of home charging facilities upon the EV adoption has been clearly studied by Bühler, Franke, Cocron, & Schleinitz (2014). (Bühler et al., 2014) deployed a field trial test relying on the public charging station in Berlin with eighteen EV drivers for six-month long duration and had been compared exactly with eighteen home charging EV users to compare the perceptions and EV related attitudes. The results driven by the study (Bühler et al., 2014) indicates that, the private charging or the home charging does not have a potential effect on EV adoption. In other words, the study (Bühler et al., 2014) reveals that lack of home charging facilities does not potentially reduce people's intention to purchase an EV. Although the study (Bühler et al., 2014) was conducted with a smaller sample size and the sample population are mostly governed by the lower mileage. Further study by (Bühler et al., 2014) has suggested that, sample study can be conducted for higher mileage population in order to investigate the effects of home charging on wide range of EV adoption. Owing to the charging facilities for EV, research has also been focused on the Smart Charging facilities and its acceptance factors by the users of EV.

A study by Will & Schuller (2016) with a sample size of 237 electric vehicle adopters at an early stages suggests that integration of the renewable energy sources with the grid stability are the most important factor for the smart charging acceptance. The survey in this study by Will & Schuller (2016) has been designed considering the potentiality of the monetary incentives expressing in two ways such as the discounted price on per kwh and discounted price on monthly base price on electricity bill as well. Using a structural equation modelling, the authors Will & Schuller (2016) have discussed the different hypotheses in light of their research for acceptance or rejection of the formulated hypotheses. The results shows that the monetary incentives are no longer an influential factor for EV adoption when it comes to the smart charging (Will & Schuller, 2016). The users in this sample are more focused towards the varied amounts of the compensation to their monthly individual charging costs (Will & Schuller, 2016).

The study in Netherlands by Brey, Gardien, & Hiep (2021) for further optimization of the charging facilities so called the smart charging also revealed some interesting insights from the opinion of the EV drivers. The authors (Brey et al., 2021) study consists of 1800 EV drivers and in order to understand the key barriers in charging at home or away along with investigating the concepts regarding the smart charging. The results of this study (Brey et al., 2021) shows that the respondents are well familiar with the smart charging and want to adopt the controlling session of the charging. In this context of the conducted study by (Brey et al., 2021) suggested that a legal framework is required in

European legislation that connects the needs to meet the demands of the EV users as well the grid operators. Moreover, the researchers (Brey et al., 2021) also investigated the possible reason that contributes for not charging smartly includes, the fear associated with not charging completely and not having control over the charging session. An integration of the renewable energy such as the solar energy and wind energy for producing the electricity at an optimum cost such that the EV users find it safe, affordable, and reliable to ensure the usage of the smart charging is also a vital point to be considered.

Socio-Demographics:

For the successful EV adoption other than the financial incentives or Government policies, Socio-demographic plays a vital role. A study by Higueras-Castillo, Molinillo, Coca-Stefaniak, & Liébana-Cabanillas (2020) has used a cluster analysis with the socio demographic attributes such as the age, income , gender along with the green moral obligation with two different attributes of EV such as the price and range to understand the potentiality of the early EV adoption in Spain. The results obtained from the respondents of the sample size of 404 from the study of (Higueras-Castillo et al., 2020) has developed a group of cluster analysis by segmentation profile where the female respondents tends to inclined more towards the adoption of electric vehicles with high green moral obligation. Among the most important predictor variables, driving range found to be the most important variable in this study. This study has utilized a new way of understanding profile based EV adopters based on Green moral obligation (Higueras-Castillo et al., 2020). Meanwhile a study conducted by (Tomasi et al., 2021) to understand the propensity of choosing EV in cross border alpine regions. The findings of the study by (Tomasi et al., 2021) indicates that the policies should consider socio-demographic profiles and social practices along with physical infrastructure for the EV uptake in the Alpine regions.

Other factors:

Apart from the socio demographics, many studies have found out different attributes that contribute to understand the underlying factors for EV adoption. Studies from the author Rotaris, Giansoldati, & Scorrano (2021) has conducted a stated preference study with a sample size of 1394 respondents from Italy and Slovenia to understand the underlying hidden factors for EV adoption. The authors (Rotaris et al., 2021) have considered following attributes purchasing price, driving range, fuel economy, fast charging time and the consecutive distances between the charging facilities including the free parking time. (Rotaris et al., 2021) have developed a hybrid choice model with ordered probit for measurement model that constructs the important variables as described above along with the latent construct such as the environmental concern and environmental association. The result from the study (Rotaris et al., 2021) shows that the Italian respondents are much aware of the purchasing price of BEV where the respondents from the Slovenian sample are more aware of the driving range. Moreover, the distance between the charging stations is non-significant for the Italian respondents where in fact the variable becomes negative and significant for the Slovenian respondents (Rotaris et al., 2021). The possible fact behind this reason mentioned by the authors (Rotaris et al., 2021) is due to high density of the charging station with a respondents living nearby the charging stations for the Slovenian sample. Interaction effects has also been tested in (Rotaris et al., 2021) by inclusion of the socio-economic variables (age , gender, income) and as such gender which turn out to be negative and statistically significant for the Slovenian respondents only (females have a higher utility for BEV compared to males). No statistical significant result has obtained for income effect from both of the sample (Rotaris et al., 2021).

A study by Mandys (2021) have utilized a stated preference dataset of UK developing a ordered logit and binomial logit regressions to reveal the underlying key barriers and factors as well for EV adoption. Study by Mandys (2021) shows that, the important factors for the propensity of EV adoption for the respondents in the UK are basically individual with education, living alone more towards the southern parts of the country. In addition to this, driving range, purchasing price, environmentally friendly behaviours and performance are the key factors for potential EV adopters (Mandys, 2021). Moreover, the study of Mandys (2021) also suggested that, the two most important barriers plays a vital role as the hindrance path of EV adoption are the higher cost and range of these electric vehicles.

Ziegler (2012) had studied the user preference in Germany by investigating the individual characteristics and the stated preferences for different type of propulsion systems in the vehicles. The findings from the Ziegler (2012) shows that youngest individuals are the potential buyers of alternative propulsion technologies. The empirical analysis of the study of Ziegler (2012) includes potential car buyers (N=598) in Germany, based on the Multinomial Probit model signifies a negative impact on purchase price, CO_2 emission and fuel costs which in turn waves a path for the direction of EV adoption through the subsidization of the alternative propulsion technologies and higher taxation on the diesel or the conventional gas vehicles. A similar line of study by Tamminen (2021) in Finland with 409 respondents having finish driving license to the stated preference survey in a discrete choice experiments between the plug-in hybrid vehicle (PHEV) and Battery electric vehicles (BEV). The author Tamminen (2021) has shown that the primary reason or the barrier for the people not adopting the electric vehicles are the purchase price, driving range and problems associated with the charging. Respondents from the sample of the study prefer more PHEV over BEV as the range uncertainty does not bothers while driving longer distances (Tamminen, 2021). The study of Tamminen (2021) suggests that for achieving the carbon neutrality by the Finnish Government, necessary steps in incentivizing for switching from PHEV to BEV should be needed in further research.

Authors Gehrke & Reardon (2021) have utilized a unique data of 8 years of the electric vehicle buyers and their utilization in Massachusetts to understand the Geo spatial pattern of the EV adopters as well as the environmental factors behind their adoption intention. The study by Gehrke & Reardon (2021) finds a positive inclination of the EV buyers as an urban phenomena in which individuals living in single family homes with higher income at a neighbourhood scale had been the early adopters of EV. With proper incentives and charging stations availability through the policy action will increase the EV adoption (Gehrke & Reardon, 2021) .

Further study by Chu, Im, Song, & Park (2019) has investigated the psychological and behavioural factors that effects users decision making for EV adoption. For this the study by (Chu et al., 2019) has been conducted between the respondents from China and Korea in four major cities. The authors (Chu et al., 2019) have revealed that the environmental concern is the biggest important factors for the respondents from China for the adoption of electric vehicles where as the most important aim of purchasing EV in Korea is to minimize the operating costs. The results from (Chu et al., 2019) also indicates that both sample group has a common reference barrier for EV adoption which are remarkably known as the battery charging and driving range. The authors (Chu et al., 2019) have suggested that the Government assistance is required for further conveniences of EV adoption for speedy uptake.

2.4. Willingness to pay for different factors for EV:

2.4.1 Studies relating to WTP for EV adoption in different countries:

Different researchers have tried to investigate the different perspectives of the vehicle attributes and their underlying factors for the willingness to pay measures. Much research has been already conducted to understand the sensitivity parameter where the marginal WTP shows a diminishing attitude and in which people are willing to pay for different measures in order to adopt the electric vehicle.

Using a stated preference methodology, where the respondents are asked to choose in between the choice scenarios or tasks based on hypothetical questions that has different level of attributes. From the estimated coefficient, WTP can be derived and estimated. Usually this is done by taking the ratio of the estimated coefficient parameter to its price coefficient which yields the marginal WTP measure.

The authors Ito, Takeuchi, & Managi (2019) has revealed some insights for the marginal WTP in case of the cruising range and the infrastructure establishments. The study by the authors (Ito et al., 2019) has revealed that, the WTP for the cruising range of 300 km for HEV and EV is respectively 53.36$ and 18.56$, for the one additional kilometer of range from the estimation of the random parameter logit model. Due to the diminishing attitude of the marginal WTP, hence as such it diminishes with respect to the cruising range (Ito et al., 2019). Particularly (Ito et al., 2019) has found that the respondents consider the REV and SEV, mainly for the shorter driving range such as the daily shopping trips. For the estimation of the WTP attribute in regards with the range, the authors (Ito et al., 2019) have used the following equation (only EV range is shown here):

$$WTP^{EV}{}_{Range} = -\frac{(\mu_R + \gamma_{EV})Range + \mu_{R2}\, Range^2}{\beta_{-price}}$$

Where, the $\beta_{\_price}$ is the price parameters coefficient and $\mu_R, \mu_{R2}, \gamma_{EV}$ denotes the mean coefficient of range, square of the range and interaction term of range and considering the dummy variable (EV=1, otherwise 0).

Another study by (Plenter et al., 2018) has investigated that the major impediment for the adoption of the electric vehicle is due to the poor availability of the charging infrastructure in Germany. A privately owned charging facility will be helpful to overcome this problem (Plenter et al., 2018). Hence, the study of (Plenter et al., 2018) focuses on choice based conjoint analysis to obtain the Willingness to pay (WTP) for different charging location and their point characteristics. (Plenter et al., 2018) have calculated as well as recommended the WTP for the charging service per hour. According to (Plenter et al., 2018) with three different modality of 3.7KW, 11KW and 22KW the recommended price were 3.49 €, 4.99 € and 7.99 € per hour respectively. These price schemes are recommended for the city areas only. The study has also revealed the different price schemes for different charging location points based on CBC analysis (Plenter et al., 2018).

Meanwhile the study of Peters & Dütschke (2014) based on the online survey of sample size, (N= 969) has compared the four different consumer groups with difference in taste heterogeneity regarding the EV purchase likelihood. The result form this survey of Peters & Dütschke (2014), indicates that the major influential factors for willing to purchase EV is the daily personal needs. The four different consumer groups differ in their WTP measure on the survey response (Peters & Dütschke, 2014). The actual EV users are willing to pay around 35% premium on an average whereas the purchase intention group are willingness to pay 20% premium on an average (Peters & Dütschke, 2014). The situation is bit diverse among the affine group with 19% found to be willing to pay for the premium and lastly the group with no purchase interest on EV are willing to pay 16% for the premium on an average (Peters & Dütschke, 2014).

Investigating into deeper insights for the willingness to pay attributes the study by (Ensslen et al., 2016) has focused on the responses from the fleet managers of 109 German organizations including the medium to small size organization. The study have analyzed the different services which are interconnected with the operation and charging of electric vehicles (Ensslen et al., 2016). In order to determine the subsequent factors for EV adoption the project , "Get eReady" for e-mobility service has been adopted by (Ensslen et al., 2016). Moreover, in this mobility project of 'Get eReady' the different relevant services for EV adoption has been accumulated to the fleet managers and other decision makers so as to investigate the attractiveness and relevance of these services (Ensslen et al., 2016). Among these the stated relevant e-mobility services include basic connected charging services, CO_2 minimized charging, using of other organizations EVSE (charging infrastructure) etc. Moreover, the findings of (Ensslen et al., 2016), WTP for using other organization EVSE within the charging network of power modality (> 3.3 KW) is 3.95€/hour.

Much research has also been explored in finding out the WTP for vehicle to grid (V2G) connection for electric vehicles. This could be a potential solution to the problem that will arise due to the incremental load of large scale EV integration. A study by B. Huang, Meijssen, Annema, & Lukszo (2021) has focused on stated choice experiment based on two different arcs of concepts that includes, the EV recharging time (at present) and recharging (fast) in order to evaluate the (WTP) for vehicle to grid (V2G) connection technology and their contracts among the Dutch EV drivers. The result from the study by the authors (B. Huang et al., 2021) shows that the EV drivers are willing to pay additionally 6€ per month for every 1% (minimum) of the battery level under the context of the current recharging time. While the other context of the fast recharging time, the value of WTP reduces to 3€ per month (B. Huang et al., 2021).

2.5. Review on Choice Modelling Perspectives:

2.5.1. Choice Modeling:

The context of the choice modeling is to model the decision process of the individual based on the revealed preference or the stated preference survey on different situation. The components of choice modelling also depends on the choice set which includes a set of alternatives upon which the individual makes the decisions (Train, 2003). Based on the decision making the choice probabilities are defined which is in turn derived from utility maximizing behavior (Train, 2003). Hence, these choice set are known as the set of alternatives which must follow three characteristics that includes: the choice set or the alternatives must be mutually exclusive, they must be exhaustive and finite as well (Train, 2003). Hence, the choice set is consisting of the mutually exclusive and exhaustive alternatives which is fit for discrete choice model analysis (Train, 2003). This discrete choice model which are usually derived from the maximizing behavior of the utility or known as the utility maximizing behavior are made by the decision maker (Train, 2003).

2.5.2. Radom Utility Choice Theory / Random Utility Model:

Random utility models define the choice of an individual, provided that there exist a discrete sets of alternatives (Horowitz et al., 1994). These utility models can be described as the utility function (Horowitz et al., 1994). Hence, the individual chooses the alternatives that maximizes the utility of the individuals (Horowitz et al., 1994), a classical random utility approach developed by 'McFadden' in 1974. Hence, this utility depends upon the different attributes of the alternatives through which the modeler can observe the effects such as the Gender, age etc. (Horowitz et al., 1994). Although the modeler can observe the deterministic part yet, some of the attributes in which the modeler cannot capture or directly observe the effect (includes special circumstances or occasion under which the respondents has chosen) (Horowitz et al., 1994). Hence, this observed part of the utility function are expressed by explanatory variables whereas the unobserved part as the random variables, has given rise to the 'Random utility model' (Horowitz et al., 1994). Thus, a utility function which consists of the deterministic part and error term as a random variable can be expressed as the following equation:

$$Ui_j = \beta{\cdot}X_j + \varepsilon_j$$

Where,

Ui_j = Utility of the j^{th} alternative for the i^{th} individual,

β = Coefficient / parameter associated with the attribute X_j (being characterized by alternatives or the socio demographic attribute of the decision maker/ respondents)

ε_j = Error term / random variable associated (unobserved part of the utility function) which thereby brings the uncertainty into the choice modeling.

Following the above mentioned equation, the utility maximization rules states that the individual choses the alternatives that has the highest utility with no uncertainty where the decision maker certainly choose the alternative with highest ranked given the observed choice scenario (Koppelman & Bhat, 2006). Hence, the utility model that results in certain prediction of the choice are termed as the deterministic utility model (Koppelman & Bhat, 2006). In addition to this, the above mentioned equation the modeler does not have any information regarding the error term or the random component of the utility function which is represented as , ε_j (Koppelman & Bhat, 2006).

Hence, in this regard a wide range of the distribution has been used for the representation of the error term distribution over the individuals and alternatives which is used to describe and predict further choices (Koppelman & Bhat, 2006). Owing to this wide range of distribution, these assumptions has led to the introduction of the probit and logit models (Koppelman & Bhat, 2006). However due to the complexity, interpretability, and limited practicability of the Probit models such as the MNP (Multinomial Probit Model) that depends upon a probabilistic choice model an alternative assumption of the distribution led towards the development of the logit model such as Multinomial Logit Model (MNL) (Koppelman & Bhat, 2006).

2.5.3. Multinomial Logit Model (MNL) and Nested Logit Model:

Another form of expression for the Logit model is the multinomial logit model, which is considered to be the easiest and widely used in discrete choice analysis. There are certain assumptions for the unobserved part of the utility function usually the (error term) that captures the information which can’t be modeled by a modeler. These specific assumptions are (Koppelman & Bhat, 2006):

1. The error term (ε) is Gumbel/ or the extreme value distributed .

2. The error term follows a 'IID' (identically and independently distributed) across the alternatives

3. The error term follows a 'IID' (identically and independently distributed) across the decision makers/ individuals

Amongst these certain assumptions the most common assumption for the error term is that it follows a normal distribution (Koppelman & Bhat, 2006). However, such assumption in which the error term follows a normal distribution leads to Multinomial Probit model and thus in this case the computational effort rises making it complex to be used in discrete choice analysis (Koppelman & Bhat, 2006). Moreover, the Gumbel distribution has been selected over the normal distribution is due to the computation advantage that closely approximates the normal distribution where the maximization is important (Koppelman & Bhat, 2006). Moreover, it produces a closed form probabilistic choice model which however means that for calculating the probability it does not require a complex numerical integration or the simulation methods (Koppelman & Bhat, 2006). Additionally, the second and the third assumptions are related to the location and variance of the distribution such as the μ and σ^2 which indicates the location and variance of the normal distribution (Koppelman & Bhat, 2006). Hence, considering all of the above mentioned assumptions leads to the structure of Multinomial Logit model (MNL) (Koppelman & Bhat, 2006). Therefore, the following expression of the probability of choosing an i (i= 1,2,3….j) from the set of the alternative j is given by:

$$P_r(i) = \frac{\exp(Vi)}{\sum_{j=1}^{j} \exp(Vj)}$$

Where,

$P_r(i)$ = probability of choosing an i alternative by the decision maker, $V(i)$ = systematic component of the utility of the alternative i , $V(j)$ = systematic component of the utility of the alternative j (Koppelman & Bhat, 2006).

Although, by far MNL is considered to be the easiest and widely used in discrete choice analysis, but this type of the logit model has also some limitations and exhibits the property knows as the 'IIA' or the independence of irrelevant alternative. Moreover, when the unobserved factors are correlated over time, the logit models cannot handle such situation (Train, 2003).

Hence, the 'IIA' property indicates that the ratio of the probabilities of choosing two alternatives does not depend on the presence of the third alternatives or attributes of the alternatives (Koppelman & Bhat, 2006). For instance, this can be simply illustrated by the following mathematical equation with the alternatives i and k as (Train, 2003)

$$\frac{\Pr(i)}{\Pr(k)} \quad = \frac{exp^{Vni} / \sum_{j}^{j} exp^{Vnj}}{exp^{vnk} / \sum_{j}^{j} exp^{Vnj}}$$

$$= \frac{exp^{Vni}}{exp^{Vnk}}$$

$$= exp^{Vni-Vnk}$$

The above mentioned ratio of the probabilities of two alternatives is independent of other alternatives (Train, 2003). In other words, it can be said that the probability of choosing of these alternatives i and k are the same and does not matter if there is any other presence of the alternatives or the attributes of the alternatives (Train, 2003). Since, the mentioned ratio of the probabilities are independent of the alternatives except alternatives i and k, hence it is termed as the IIA property (Train, 2003). As mentioned by (Train, 2003), the limitation of logit model arises when it tries to incorporate the taste variation with respect to unobserved variable or purely random. Hence, in such cases in order to incorporate the taste variation more complex model such as the probit or the mixed logit models comes to play (Train, 2003). To overcome this limitation of the IAA property of the MNL model, 'Nested logit' model comes into play. The Nested logit model is characterized by grouping of the subset of the alternatives so called 'nests. As mentioned by authors Koppelman & Bhat (2006) in each of these nests, the alternatives that exhibits most similar properties are nested together with respect to the excluded properties than they are with other alternatives. Hence by grouping of the similar alternatives it relaxes the property of the 'IIA' and 'IID' partially, since the 'IIA' only exists within the bounded nests of the alternatives but not with the other alternatives.

2.5.4. Complex model in discrete choice platforms:

Other different model has been proposed by different researchers that provides in defining the preference heterogeneity in order to capture more information regarding the latent variables and their constructs. Hence, this kind of model provides more flexibility where the analyst reveals some useful information by the estimation of main effects or interaction effects of the variables and thereby increases the precision interpretability. A typical example of this kind of model has been discussed in the following sections to provide a brief idea regarding the advance models in discrete choice platform.

2.5.4.1 Hybrid choice model (HCM):

Hybrid choice model is another type of extension of the discrete choice models that predominantly considers including the attitudinal variables, with latent factors which are unobserved and the socio demographic variables. The complexity arises when the analyst tries to observe the latent factors while computing for the choice behavior. But in reality, prediction of the choice behavior is quite difficult since it depends on lot of other complex factors such as the latent attitudes, taste, beliefs, value, and perceptions that may influence in people’s decision making process (J. Kim, Rasouli, & Timmermans, 2014). These unobservable factors and their causal relationship are difficult to identify. Hence, HCM attempts in identifying such factors which are unobservable by including them in discrete choice analysis (J. Kim et al., 2014). This expanded version of the discrete choice model aims to integrate a various type of model which can be estimated at a simultaneous process.

In order to explain the unobservable factors such as the latent factors it is necessary to identify them through the set of the attitudinal indicators (J. Kim et al., 2014). In doing so, it allows the latent constructs to be the function of indicator by establishing the cause and effect relationship between the latent and explanatory variables (socio-demographics) in the utility function of the choice analysis (J. Kim et al., 2014). Thus, such integration of the latent constructs gives the structure of the Integrated choice latent variable model or also known as ICLV model (J. Kim et al., 2014). Hence the framework for the Hybrid Choice model according to (Ben-Akiva et al., 2002) is illustrated as below:

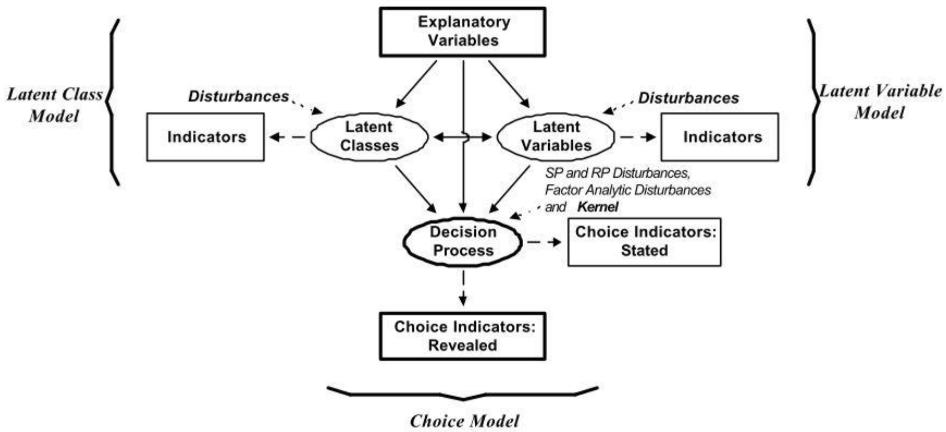


Figure 8: Framework for Hybrid Choice Model (adapted from Ben-Akiva et al., 2002)

From the above mentioned adapted (fig 10): it shows that the traditional RUM (random utility maximization theory) takes place along the vertical axis of the figure where the observable explanatory variables are included for the decision making of the individuals that leads towards the revealing of the choice preferences (Ben-Akiva et al., 2002). Researchers along this year have tried to provide more insightful information when it comes to the choice modeling by considering the latent class segmentation and unobservable latent factors leading to the extension of the hybrid choice model. Thus, the extensions that includes as mentioned by (Ben-Akiva et al., 2002) are :

I. The inclusion of the flexible disturbances in order to mimic any desirable error (factor analysis as an example).

II. The modeling of the latent psychological factors such as the attitudes and perceptions by combining the 'hard information' (retrieved from the socio demographics data) with 'soft information', (retrieved from the latent attitudinal factors) over the population heterogeneity.

III. Lastly, addition of the latent class segmentations that helps to delivery useful information in revealing the choice preferences based on market segmentation and different decision protocol.

Estimating such model becomes cumbersome and complexity arises with the revealed preference data (Ben-Akiva et al., 2002). Hence, additional indicators have been adopted in the framework of HCM in order to facilitate or establish a causal relation and thereby providing aid in estimation of the behavioral relationship (Ben-Akiva et al., 2002). These includes the SP survey questionnaire relating to the attitudes and perceptions (Ben-Akiva et al., 2002).

However, it has to be noted that, the requirement of the HCM does not involve the classical assumption of the random utility maximization or RUM theory (Ben-Akiva et al., 2002). Several researchers have suggested of replacing the RUM model with RRM or else with integration of both hybrid 'RUM-RRM' model (J. Kim et al., 2014). Hence in this case, as mentioned by the authors (J. Kim et al., 2014) in their paper, Random regret model ('RRM') states that the " individuals try to avoid a situation where one or more non choses alternatives outperform the chose one in terms of one or more attributes and characteristics" (J. Kim et al., 2014). Saying that, the widely used RRM framework model is that it takes the form of MNL model where the utility is replaced by the negative value of the anticipated regret (J. Kim et al., 2014). Although, the earlier efforts in order to incorporate the latent variables in discrete choice model in the utility function by inclusion of the error free attitudinal indicators (J. Kim et al., 2014). This approach has some limitation that leads to an inconsistent estimates since it does not consider that latent variables contains measurement error (J. Kim et al., 2014). A way to overcome the limitation is to deploy a factor analysis of the latent variables (unobserved variables such as the attitudinal factors) and then adding them in the utility function in a sequential manner (J. Kim et al., 2014). But this again leads to some inefficient estimates of the latent variables since it does not capture the choice indicators or the actual choice behavior of the respondents (J. Kim et al., 2014). Hence, to overcome such problem, 'SEM' or the structural equation modeling has been used which consists of the two parts. The first part is the measurement model, and the second part is the structural model. Measurement models measure the latent variables by considering as the endogenous latent variable whereas the structural model tests the hypothetical dependencies between the latent variables based on the path analysis. Therefore, SEM is able to estimate the causal influence by establishing the causal relationship between the endogenous latent variables simultaneously (J. Kim et al., 2014). In saying that, a basic model that incorporates the latent variable into a discrete choice model is employed by 'MIMIC' model or also knows as multiple indicators multiple causes model. As mentioned by the author (J. Kim et al., 2014) in their research works *"The MIMIC model is a set of simultaneous equations based on linear-in-parameter specifications, in which a latent variable is measured by multiple indicators and regressed on several observable exogenous variables"*.

As such, this kind of model is embedded with a series of structural and measurement relationships. Hence, in this case of the measurement indicators are used to identify latent variables (J. Kim et al., 2014). This indicators are often answered in a questionnaire survey by respective respondents regarding the different attitudes (J. Kim et al., 2014). The structural and measurement equation hence can be expressed in terms of utility function is as follows (J. Kim et al., 2014) :

$$U_{in} = \beta_z\,(i) * X_n^z(i) + \beta_L\,(i) * X_n^L(i) + \beta_M\,(i) * X_n^M(i) + \varepsilon_{in\,,} \quad \varepsilon_{in\,,} \sim G(0, \sigma\varepsilon_i)$$

Where,

U_{in}= Utility function of the ith alternative of nth individuals.

$\beta_z, \beta_L, \beta_M$ = are the unknown parameters for socio demographic, alternative attributes, latent attitudes (for estimation)

$\varepsilon_{in\,,}$= is the error term with mean zero and standard deviation $\sigma\varepsilon_i$. Here, the logit model is assumed to be ('IID') Gumbel distribution with error term.

X_n^z, X_n^L, X_n^M = are the attributes of the alternatives of nth individuals and of the ith alternative

Hence, the likelihood function obtained from the logit model, (including the measurement and structural components of the MIMIC model) yields a joint likelihood function (J. Kim et al., 2014). Thus, the solution of this joint likelihood can be obtained by considering the integrals (since it does not have any close form solution) over the latent constructs or the variables which are unknown (J. Kim et al., 2014). This allows to estimate the full model, and the indicators identifying the latent variables with given distribution of the measurement and structural equation it follows, provides efficiency in estimating (J. Kim et al., 2014). A notable example in this case are the authors (Bansal, Kumar, Raj, Dubey, & Graham, 2021), who have used the (ICLV) model in their modelling approach that integrates a discrete choice model and latent constructs of structural equation modelling in order to understand the EV adoption trend among the Indian consumers. Furthermore, in context of HCM model, a study by the authors Bolduc & Alvarez-Daziano (2010) have used different approaches of estimation that includes the classical estimation procedure, Bayesian estimation procedures for HCM models.

2.6. Estimation of the Logit Models

2.6.1. Maximum Likelihood Estimation Theory:

Logit models are estimated based on the maximizing the likelihood function. This involves on maximizing the function such as the likelihood function, simulated maximum likelihood function or squared moment conditions (Train, 2003). The error term of the Logit models is assumed to be multivariate extreme type 1 distribution with additional restrictions (Hensher, Rose, & Greene, 2015a). Hence, the logit models are estimated by maximizing the likelihood function. For further understanding of the topic on simulated maximum likelihood, it has been discussed on the later section 2.6.2. Estimation of the likelihood function involves two step procedure (Koppelman & Bhat, 2006).

1. Developing the joint probability density function which is known as likelihood function.
2. Parameter estimation which maximizes the likelihood function.

The likelihood function can be expressed as follows adapted from (Koppelman & Bhat, 2006) :

$$\mathrm{L}(\beta) = \prod_{\forall\, t\varepsilon\, T}\prod_{\forall\, j\in J}(P_{jt}(\beta))^{\wedge}\delta jt$$

Where,

δjt= 1, if the respondent chooses the j alternative otherwise, 0

T = individuals or the respondents

P_{jt}= Probability that t respondent chooses the j alternative.

It is a common practice for the above mentioned likelihood function to be considered by maximizing the log of the likelihood function. The reason behind this is that the product of the large number of probabilities tends to produce very smaller values (Hensher, Rose, & Greene, 2005). Hence, the idea is to take the log of the likelihood function first and then combining them by multiplying a series of log probabilities results in a large negative number (Hensher et al., 2005). Hence the above mentioned equation, the final log likelihood function can be expressed as following (Koppelman & Bhat, 2006):

$$\frac{\partial(LL)}{\partial\beta_k} = \sum\nolimits_{\forall\, t\varepsilon\, T}\delta jt\left(X'_{jt} - \sum\nolimits_{j't}P_{j't}X_{j't}\right)$$

$$= \sum\nolimits_{\forall\, t\varepsilon\, T}\ \sum\nolimits_{\forall\, j\varepsilon\, J}\left(\delta jt - P_{jt}\right)X'_{jt}$$

The above mentioned equation yields a maximum value for the estimated parameter since the second derivative of the mentioned equation yields a negative value (Koppelman & Bhat, 2006). Various software packages are available to estimate parameter by providing the desired solution of the maximized log likelihood function.

2.6.2. Simulated Maximum Likelihood Estimation Theory:

In some cases, estimation of the models become complex and cumbersome for which the models need to be following the simulation of the choice probabilities when the models do not have any tractable solution, or they said to be in open form. The complex integral equations do not have any closed analytical form (Hensher et al., 2015a). Hence, in this case, they have to evaluated by Pseudo- Monte Carlo (PMC) or Quasi-Monte Carlo methods (Hensher et al., 2015a)[1]. This procedure of the estimation is known as the simulated Likelihood estimation or simulation assisted estimation. Simulation method consists of drawing from the densities by averaging the total results with taking R draws for each of the statistic (Train, 2003). For example, the following equation in which the analyst wants to have an approximation for the estimation is given by:

$$t = \int t(\varepsilon).f(\varepsilon)d\varepsilon$$

From this equation, the analyst is interested in t (.) statistic and f (.) is the density (Train, 2003). For the approximation of above mentioned equation through simulation, the analyst has to take draws of the density f (.) (Train, 2003). Often the tasks of drawing from densities is simple but the ways of taking draws may provide better approximation results to the integral rather than depending upon the random draws (Train, 2003). Since Monte Carlo simulation is only an approximation and thus it requires a large number of draws to approach to a true value for its approximation. Hence, there are some ways to reduce such large number of draws for the approximation. These, draws are often called the smart draws which include Halton draws, Sobol draws, and Gaussian draws etc. These draws yield a similar approximation with a smaller number of draws and thus saves time in computation.

[1]*For further and deeper insights on this topic of simulation assisted estimation and smarter draws, readers are requested to follow* (Hensher et al., 2015a), *Applied choice analysis 2nd edition book of chapter 5-6 and Discrete choice methods with simulation, second edition (Train, Kenneth E. , 2003)*

2.7. Unlabelled choice alternatives:

Choice settings can either be handled as labeled alternatives and unlabeled alternatives. The labeled alternatives are those which have label in their alternative’s names such as most of the examples that are related to the mode choice study usually end up having name for the alternatives. On the other hand, the unlabeled alternatives are those in which the alternatives do not convey message to the respondents regarding the choice alternatives or else it does only convey message of the appearance of different alternatives within each of the choice task as mentioned by the authors (Hensher, Rose, & Greene, 2015b).

Typically, this includes the route choice studies, vaccination studies etc. In this thesis framework, understanding the latent psychological behavior of the respondents, and willing to pay for the different locations of the charging infrastructure whether it be a long term or short term charging facilities was the main target and hence unlabeled choice alternatives has been selected in this study that incorporated different distance based charging station options. The estimation of utility function for the unlabeled alternatives is different from the labeled alternatives. The situation becomes more intricacy when the design of the experiment is restricted i.e., including only the generic terms. Hence, in case of the generic parameter estimation, the alternative specific parameters cannot be estimated. Moreover, the only way to include any covariates is to create a meaningful interactions with the attributes of the choice experiments that varies across the alternatives (Hensher et al., 2015b). Furthermore, as mentioned by the author (Hensher et al., 2015b), 'ASC' (alternate specific constant) should be included in J-1 alternatives when the unlabeled choice experiment is of concern. However, the 'ASC' can be removed from the utility function if the results found out to be statistically insignificant (Hensher et al., 2015b). In addition to this, in course of calculation of the WTP (willingness to pay) the inclusion of the 'ASC' term does not eventually matter as they are ignored in such type of calculation (Hensher et al., 2015b).

2.8. Hierarchical stages for model development:

The below figure depicts the different stages of the modeling framework that has been considered for this research study. In order to analyze the survey data of the sample population the following framework (fig 9) has been considered for the further analysis of this study:

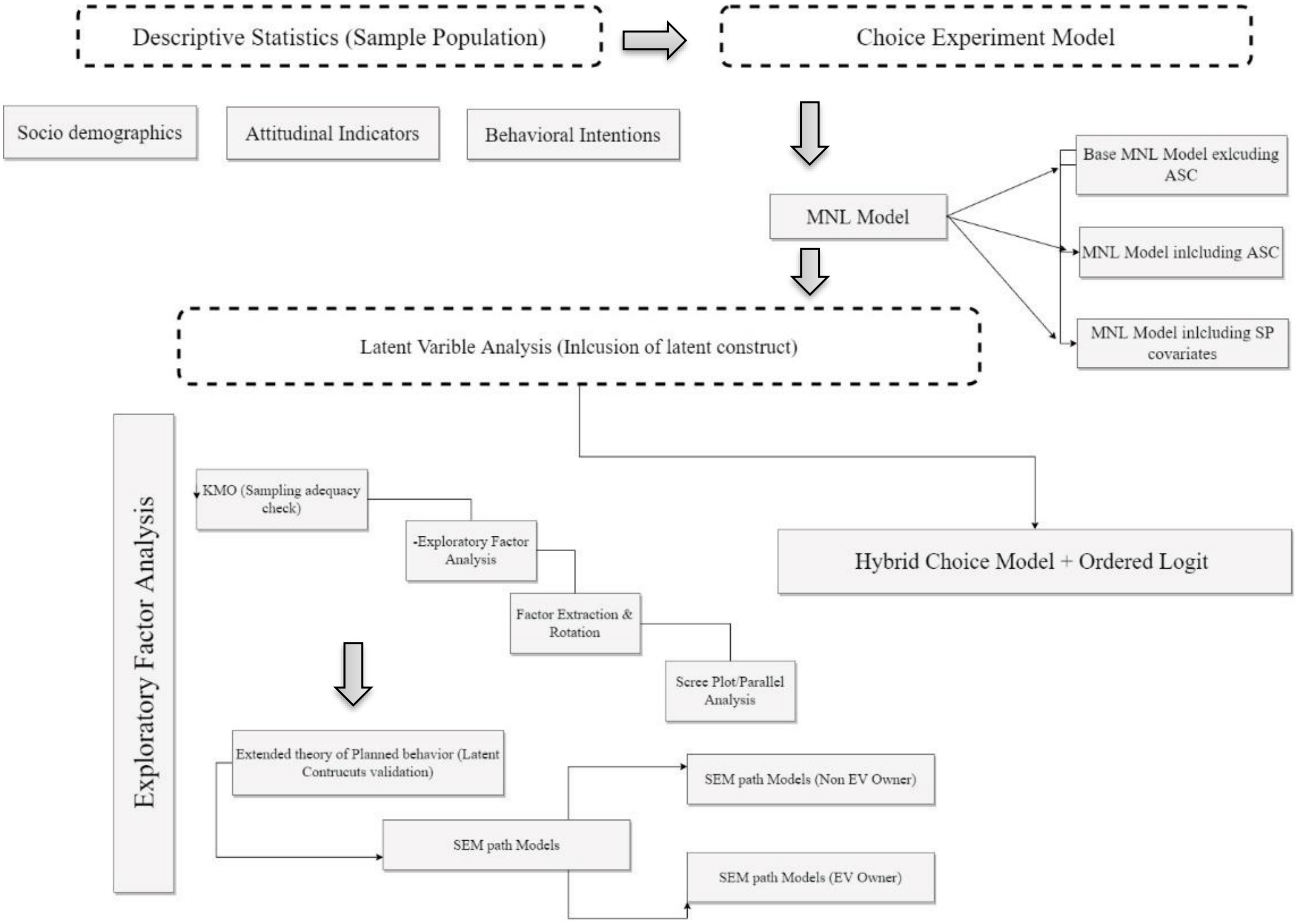


Figure 9: Hierarchical stages in model development

3. Methodology Framework

3.1. Stated Preference Survey (Focus group & sample size) :

The research methodology is formulated based on mixed-method approach or also known as the multi-methodology. Hence, this methodology uses more than one method of data collection in a research study (Leech & Onwuegbuzie, 2009). The two step design approaches has been applied, which includes the qualitative interview at first and followed by the literature review to develop a stated preference questionnaire survey for quantitative analysis within the framework of the project ‘PECASO’ (Sarker & Morshed, 2020). Stated preference data are collected in an experimental way where the respondents provide their response based on a given hypothetical choice situations given to them. For this study, in order to understand the consumers intention to electric vehicle adoption and charging infrastructure preferences, the focus group has been divided into two groups. These are: (i) EV owners, (ii) Non EV owners. This means that only respondents having the driving license and currently learning will be able to take the survey. The study does not include the participants outside of this focus area. A targeted sample size has been determined based on the reviewed literature with approximately, N = 400-500. The survey consists of four different parts that include the following : (i) Travel habits, (ii) Attitudinal questionnaires, (iii) Choice preferences based on hypothetical scenarios (iv) Questions on socio-demographic characteristics. The graphical illustration of the framework for this study is depicted as follows:

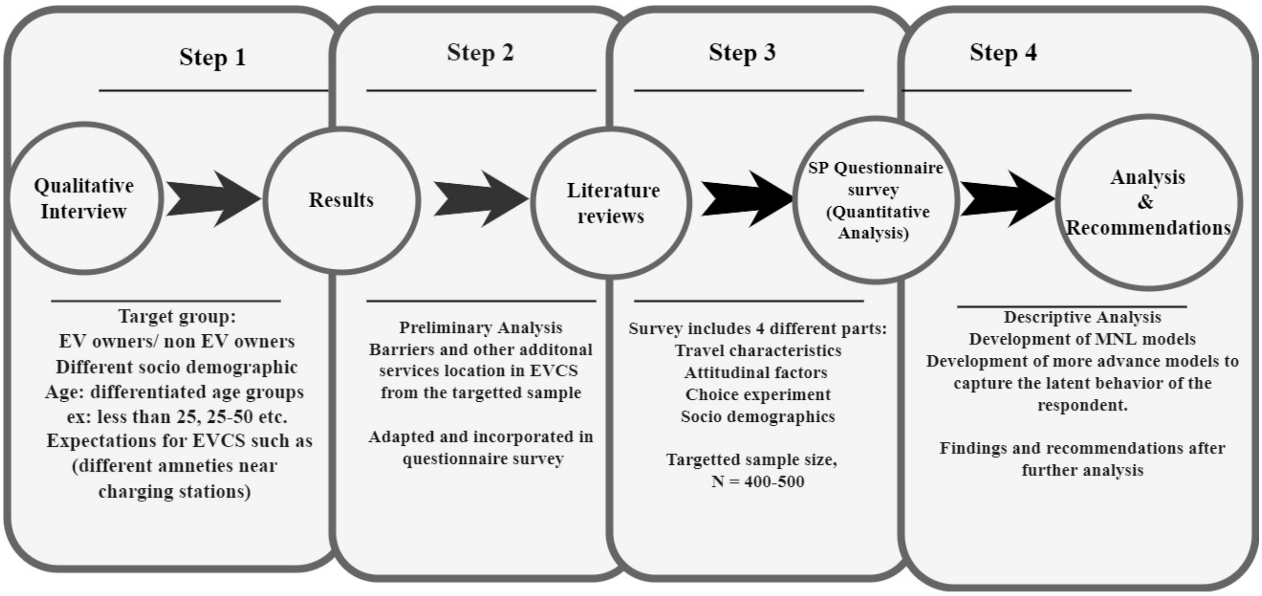


Figure 10: Survey procedure

The first part of the survey focuses on the general travel habits of the respondents from both the focused groups. Section (ii) of the questionnaire survey is based on the constructs of Theory of planned behavior (extended version) with additional constructs to understand the consumer's choice intentions for EV adoption and charging stations preferences. Section (iii) of the questionnaire survey is added with experimental design based on the five different hypothetical choice tasks and scenario. Lastly, the section (iv) comprised of the socio demographic questionnaires for comprehensive understanding of the respondent's choice based on their socio economic factors. These four parts of the survey has been described more in detail in the next chapter.

3.1.1. Experimental design (labeled vs unlabeled):

A main foundation for the stated choice preference survey is the experimental design. This experimental design includes different effects one variable upon another variable such that the manipulation of levels of one or another takes place (Hensher et al., 2005). Each of the individual attribute level is termed as treatment and the combination of this attributes each with the unique level is termed as treatment combination or in marketing literature this is termed as profiles (Hensher et al., 2005). Moreover, the experimental design may consist of labelled and unlabeled experiments. Experiments using the generic titles to represent the alternatives are known as the unlabeled experiment. This type of experiment does not convey any information to the respondents other than just a generic title. Experiments that are using a fixed title for the alternatives are termed as the labeled experiment. In this study, unlabeled choice based conjoint experiment has been adopted, where the alternatives have been named a generic title of option 1 , option 2 or option 3. The benefit of choosing such unlabeled discrete choice experiment, is that the respondents choose an alternative based on the tradeoffs between the attribute levels. As such, the respondents from the sample population are not initially biased in their choices to a certain labeled alternative while conducting experiment with an unlabeled or the generic alternatives. The main purpose of this research study is to understand the consumers preferences instead of forecasting purpose, which is based on the attribute's tradeoffs between the different alternatives. Hence, the unlabeled experiment has been chosen to conduct the study. Moreover, in an unlabeled experiment, not violating the IID (error terms are independent and identically distributed) assumption is more robust than in a labeled experiment due to the fact that the alternatives are less correlated with the attributes (Hensher et al., 2005). A hierarchical stages has been involved to generate the stated preference experiments as mentioned by authors (Hensher et al., 2005) that include from the initial stage of problem refinement till the construction of the survey instrument. The selection of the stimuli (attributes, alternatives, and their levels) has been discussed in detail in further section of this chapter. Having identified the attributes, alternatives and their respective levels, the specific design for the choice experiment is the next target. There are different number of classes of design available, of which the most widely used design has been discussed shortly.

3.1.2. Types of experimental design :

A number of different design class is available depending on the type of design. Full factorial design allows an analyst to generate all possible treatment combination. That been said, it allows to use all possible treatment combination of each attribute and alternatives with unique levels. A fraction or the subset of this treatment combination is termed as the fractional factorial design. Such example of the design includes the orthogonal, random & efficient designs. A design is assumed to be orthogonal if the sum of the factors over the columns is equal to zero (Hensher et al., 2005).

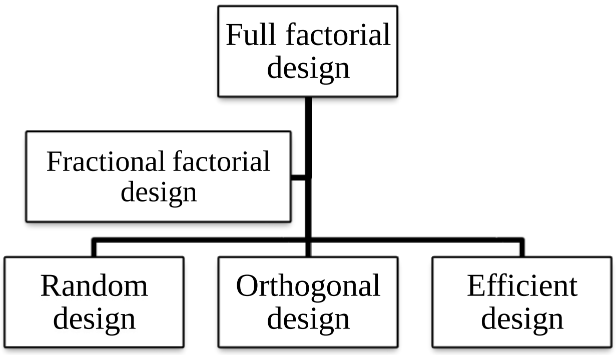


Figure 7: Experimental design category (own illustration)

The random design of the fractional factorial design randomly selects the subset from the full factorial design. In case of the orthogonal design given a choice set, the aim is to reduce the correlation of the attribute levels (ChoiceMetrics, 2018)[2]. The efficient design aims to minimize the standard error of the estimated parameters form the subset of the factorial design (ChoiceMetrics, 2018)[2]. As such, for this type of design it is necessary to have an assumption of the a-priori estimates and thus leads to more complex form of design class[1].

[1] *[* For further and deeper insights on this topic of types of design class, readers are requested to follow* (Hensher et al., 2005) *Applied choice analysis book of chapter 6]*

[2] *For experimental design, readers are requested to follow Choice Metrics, 2018 or 2020 (User Manual and reference guide Ngene-1.2-1.3)*

3.1.3. Method of Choice based conjoint analysis (CBC-discrete choice experiment):

In order to evaluate people's willingness to adopt electric vehicle and understanding the user's behavior and main challenges towards the widespread implications of EV, a choice based conjoint analysis method has been adopted using the 'Sawtooth' software (Sawtooth Software, 2017). Moreover, to collect the consumer preferences, choice based conjoint methodology have been utilized in form of the discrete choice method. In CBC experiment, the respondents face the different choice scenarios including a set of the attributes and alternatives. These whole set of combination of alternatives and attributes combined together to form a task also known as the choice scenario. The different alternatives which are used to compare between each other, are known as concepts in CBC experiment. Additionally, in case of the CBC experiment, blocking of the experimental design is done by the 'questionnaire version'. Each of the version generated in design via Sawtooth software, yields blocking for each of the respondents. Hence, for this study 2 blocking has been applied making 6 choice tasks for each respondent per block.

Furthermore, for the choice task generation method, a 'Complete Enumeration' method has been chosen. This gives a 'D-efficient' experimental design by the software considering null priors along with prohibitions (Sawtooth Software, 2017). This certain type of design strategy considers all possible concepts such that the concepts within the task are kept different unless any prohibition between the attribute level is indicated (Sawtooth Software, 2017). Since there is no inclusion of the 'none' alternatives, hence the respondents would have to select only one option out of the given three alternatives. The experimental design that has been used in this research study along with the given level of prohibitions, compromised the D-efficiency of the design to some extent. This D-efficiency design illustrates the strength of the design relative to the other. Hence, for example the experimental design (attributes and their level combinations) is shown along with the prohibition matrix in the appendix section (A2). For this study, a typical example of the choice task is shown below in the figure:

Figure 11: Example of randomly selected choice task designed in Sawtooth software

3.1.4. Questionnaire survey design:

The aim of this survey is to identify the main factors influencing the users' decision for EV adoption and outcome of the survey will help the researcher to determine the existing barriers for EV adoption and other relevant factors. Based on the two different focus group such as the EV owners (experience as own car) and non- EV owners (respondents does not have experience in driving EV as their own car), the survey includes the four different parts. These four different parts are:

I. **Travel habits:** In this section of the questionnaire survey, the respondents were asked to fill out the questions regarding their travel habits, location of their stay in order to capture the information from the focus area. Moreover, this section of the survey consists of the how user experience driving an electric vehicle. This particular question in the survey works, as the bridge between the EV owners' group and other non-EV owners' group. Following the questions, the two different groups are directed to the designated attitudinal questionnaires. The section also asks the respondents about their travel modes to determine the frequency of their travel from the daily transport modes and range of distance they cover (only applicable for the car users).

II. **Attitudinal questionnaires:** This section is populated with the attitudinal statements derived from the theory of the planned behavior developed by (Ajzen, 2019). This theory is based on theory of reasoned action with an addition to an extended version by including the 'Environmental Concern (EC)'. All of these four latent constructs reflect the behavioral intention which in turn reflects the actual behavior of the user. Hence, the attitudinal statements that are presented in this survey is formulated in order to obtain a direct measure (in a scale of strongly disagree to strongly agree) for these beliefs (mentioned in figure 2 of the literature review section). Each attitudinal statement being measured with psychometric response scale of 5 point (Likert scale) ranging from [Strongly disagree (1) – Strongly Agree (5)], that allows the responders to specify their level of argument. In addition to these attitudinal factors mentioned above, two different attitudinal constructs have been developed in order to distinguish the individualistic attitude between EV owner and non EV owner. These designated attitudinal factors are called as the 'Repurchase Intention' of EV (only the respondents of the EV owner able to see the question in the survey) and non-EV owner group 'Adoption Intentions' (only the respondents of the non-EV owner able to see). The attitudinal constructs have been mentioned in the appendix section (A8).

III. **Hypothetical choice scenarios:** The choice preference has been based on the discrete choice experiment for each consecutive task. As such, each of the respondents from overall choice tasks, get to respond on a subset of choice task in a 'Complete Enumeration' design method (Sawtooth Software, 2017). For this study, a discrete forced and unlabeled choice experiment have been chosen. Hence, in this case the total number of choice tasks would be (Level^ attribute) L^A = (3^4) = 81 choice sets. The minimum number of the choice task is evaluated using the formula (J-1)xS (min no. of choice tasks)=K (no. of parameters to be estimated); that yields 3 choice tasks (ChoiceMetrics, 2018). In order to explore more advance model, a set of 12 choice tasks has been chosen (fractional design), so that each respondent would be able to see six choice tasks in order to put less cognitive burden and to ensure an optimal time to complete the survey by the respondents. In each of the scenario, a combination of profiles or alternatives named as Option 1, Option 2, Option 3 is presented mentioning the monthly package price for charging EV at charging station. The package price includes the small reservation charges and three times charging per month with maximum of 80% charging possibility in each of the alternatives as shown, the distance of the nearest charging stations from home or workstation, reservation and waiting time in the charging station and charging time is associated with it. Each of the respondents have to select one option from the six scenarios presented to them. The selection and the calculation of the different attributes and their levels that is associated with each of the choice task have been discussed in section (3.1.7) of this methodological chapter.

Note that, *the final choice experiment is done based on the Complete enumeration design methodology (by sawtooth software) with restricted level design in order to make the choice tasks more realistic and reasonable.*

IV. **Questions on socio-demographic characteristics:** In this respective section of the survey, the respondents were asked regarding their socio demographic portfolio that includes income, gender, working status, educational figures, household size etc. This part of the survey questionnaire is important in order to evaluate the respondents background data that makes the choices on the hypothetical scenario and helps to determine the distinction between each respondent responses. Lastly, based on the personal interview facilitated earlier in this project 'PECASO', questions were asked to the respondents (which has been incorporated in the SP survey) about the additional services in the charging stations, that respondents experienced while charging their EV (See appendix **A3** for word cloud text analysis,).

3.1.5. Stimuli refinement (Attributes & their levels):

Based on the extensive literature reviews for the electric vehicle adoption, four different attributes have been chosen to address the research question and identifying the main problem of this research study. A forced discrete choice experiment has been developed excluding the none-option for the alternatives. Respondents are faced to choose a single option (RUM theory) from the given hypothetical choice tasks. Since the consumer expectation regarding the vast acceptance of the electric vehicle relies upon the packages and other additional benefits provided by the electric vehicle charging service providers, a combination of all benefits in form of a 'package' has been developed with the generic title using the alternative names as Option 1, Option 2, & Option 3. The distance of the charging infrastructure is entirely dependent upon the demand of the particular area and the users of the electric vehicles. In order to introduce distance as an attribute for the choice experiment for different type of charging modality or power, a study by K. Huang, Kanaroglou, & Zhang (2016) focused on the design of public charging points network by measuring the distance of the charging points. The authors (K. Huang et al., 2016) based on the ranges describes about the level 2 & 3 charging stations. Such as the charging station equipped with level 2 charging power usually takes hours to fully charge are considered to be within the walking distance and such type of charging stations are usually places near shopping centers, dinning etc. (K. Huang et al., 2016). Whereas the level 3 charging stations which are much faster will require 30 min-60 min for full charging is placed within the driving range (K. Huang et al., 2016). Hence, in this study the respondents face the option of choosing the 'location first' from the list of location prior to the choice experiment. As such, the different distances such as 500 m, 1000m, 1500m have been considered in this study. Moreover, based on the existing infrastructure of Innsbruck city by IKB establishments, a distance based isochrones and walking time isochrones map has been developed in order to understand the proximity of the existing EV charging stations. The isochrone shows (Fig 12) that a minimum number of the charging stations can be reached within a proximity of 500m whereas a maximum number of the charging stations are within the range of the 1500m from each of the isochrone centroid.

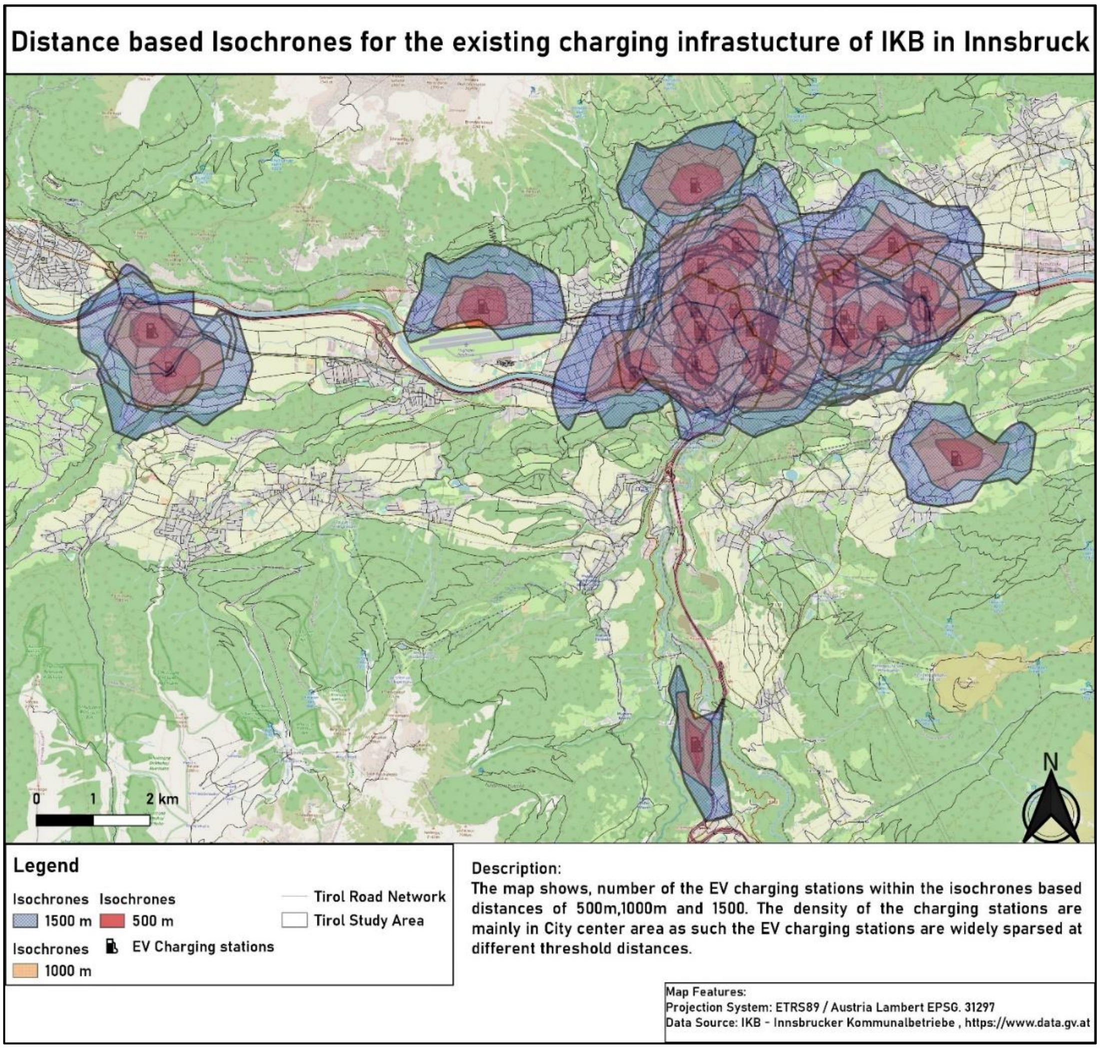


Figure 12: Distance based isochrone map (own illustration)

In the next (Fig 13), walking based isochrone map has been created in order to visualize how many charging stations can be reached from each of the centroid of the isochrones within a threshold walking time of 5 min, 10 min, 15 min with average human walking speed as assumed. The visualization helps to show that the higher walking time threshold provides the users to reach most of the electric vehicle charging station followed by the walking time threshold of 5 mins to 10 mins from each of the centroid of the isochrones. Most of the electric vehicle charging stations are centered within the city center. A very few charging stations can be seen on motorways or the highways.

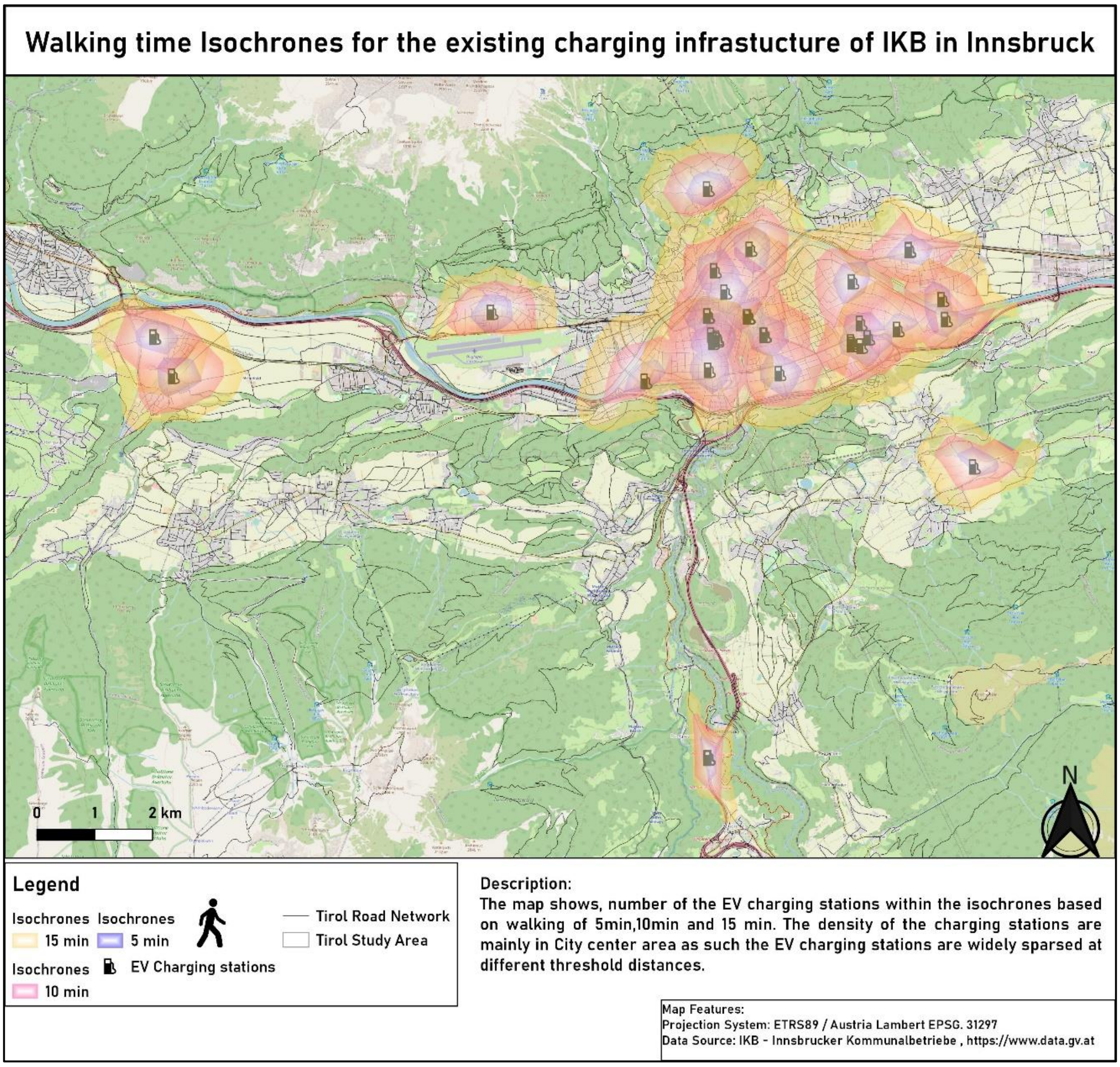


Figure 13: Isochrone based on the average human walking time (own illustration)

The attributes that have been considered in this research study includes-

i. **Distance of the charging station or charging infrastructure (in meters) :** The levels that has been considered for this first attribute are – 500m, 1000m, 1500m. The attribute levels are pivoted by the reference: -50%, 0% (reference level, +50%). This attribute has been created for this experiment in order to understand from the consumers' point of view, the acceptable distance of the charging infrastructure or the charging station from home or work area (hypothetical assumption).

ii. **Reservation / Blocking in the charging station (in min) :** This is the second attribute of the choice experiment for this study. The levels that have been considered here are 'No' (0 min), 15min, 30min. Similarly, the attribute levels are pivoted by the reference: -50%, 0% (reference level, +50%). With a growth of electric vehicle, charging stations in future. The service providers need to adopt such policies that allows the user to reserve a place for a certain time through their mobile application. Subsequently, the EV owners being notified in advance if a certain charging station is already being occupied or empty.

iii. **Charging speed:** The third attribute for the choice experiment is the charging speed. The levels of the charging speed are slow, moderate, fast. Consequently, the moderate charging refers to the 11-22KW power supply, fast charging refers to the 22-75KW (kilowatt) and the rapid charging refers to greater than 75KW of the power modality. The charging time for the EV varies with these subsequent power modalities. As per the charging service provider (Innsbruck Kommunal Betrieb) IKB, most of the charging station in Innsbruck are being equipped with these power modalities (see appendix section **A7** for distribution of existing charging station power modality).

iv. **Monthly package price in (€= euros) :** The last attribute for this study, is the monthly price. The levels for this particular attribute are- 55€, 75€, 90€ respectively. The prices mentioned here are according to the charging rates provided by (Innsbruck Kommunal Betrieb) IKB, which are considered with 3 times payment on a monthly basis for each of the alternatives. This attribute is significantly important to calculate the Willingness to pay measure for this research study.

Some of these attributes included in this study are the results of the extensive literature reviews found out to be as a significant factor for EV adoption and rest of the attributes and their levels are created for this experiment and research study. Hence, the following table shows a summarized alternative, attributes, and their levels.

Item	Attributes	Levels	Remarks/Source
1.	Charging station distance	500m,1000m,1500m	Developed for this experiment & & GIS isochrone catchment analysis
2.	Reservation time	No, 15min ,30min	Developed for this experiment (considering futuristic assumption)
3.	Charging speed	Moderate, Fast, Rapid	Developed for this experiment (based on existing charging modality of IKB)
4.	Monthly Price [a]	55€, 75€, 95€	Developed for this experiment and calculated from price list of (IKB, 2022)

Table 1: Attributes and Levels of Choice experiment

3.1.6. Detailed calculation of attribute levels

In this section, the calculation of the chosen attributes which has been defined in light of this research study and choice experiment have been discussed. Four different attributes have been chosen that satisfies the problem definition and answers the research question. These four attributes include: distance between the charging station in (m), reservation time in (min), charging speed or the power modality and monthly price in (€). Some of the levels of this chosen attributes have been calculated and some of them have been created for this experimental design. The below table shows the calculation of the different attributes: The below table shows the detailed calculation of the monthly price attributes:

Power	Item	Up to 80% Charging
Moderate [b]	Charging Time (min)	400
	3 times monthly Price in (€)	(400 * 0.06) * 3= 72 ~ 75
Fast [b]	Charging Time (min)	90
	3 times monthly Price in (€)	(90 * 0.35) * 3= 94.5 ~ 95
Rapid [b]	Charging Time (min)	50
	3 times monthly Price in (€)	(50* 0.35) * 3= 52.5 ~ 55

Table 2: Calculation of the attribute levels

Source[b]: (EMC, 2022) *~ *figures are rounded*

3.1.7. Formulation of the hypotheses:

A set of hypotheses has been proposed for better interpretation of the model's outcome,

(Evaluated at P value ≤ 0.05)

H1: People with part time working professionals likely to be sensitive with monthly cost of EV charging at public charging infrastructure.

H2: People who are self-employed likely to be less sensitive with monthly price of EV charging at public charging infrastructure.

H3: Number of people in household size has an effect monthly cost of EV charging in charging station.

H4: People with lower educational background tends to be sensitive with monthly cost of EV charging at the station.

H5: EV owners are sensitive to cost involved in charging their EV at public charging stations.

H6: Non-EV owners (using EV as company car) are sensitive with the cost involved in charging their EV at public charging stations.

H7: EV owners (using EV as own car) are more susceptible to the distances of the Charging infrastructures.

H8: Non EV owners (using EV as company car) are more susceptible to the distances of the Charging infrastructures.

H9: Age has a significant association with the cost of charging EV at public charging stations.

H10: Higher number of cars in household has significant association with distance of the EV charging infrastructure.

H11: Income has a significant association with the cost of charging EV at public charging stations.

H12. Respondents who use (cars as driver) for their travel modes are sensitive to the cost of EV charging at charging station.

H13a : Respondents using ‘Car Sharing’ as their travel modes are sensitive to the cost of EV charging at the stations.

H13b : Respondents using bicycle as their travel modes are more sensitive to the cost of EV charging at the stations .

H14: Functional barriers of electric vehicles has significant impact on EV owners.

H15: Positive attitude towards EV adoption, has a positive impact on non EV owners .

H16: Non EV owners are positively influenced by the Environmental concerns of EV .

H17: Subjective norms has a positive influence on non-EV owners for EV adoption .

H18: The constructs of the ETPB have a significant impact on EV owners purchase intentions .

H19: The constructs of the ETPB have a significant impact on non-EV owners’ adoption intentions.

4. Preliminary Data Analysis

4.1. Survey Circulation and Data Collection:

The duration of the data collection started from March ended in the mid of April. The survey has been circulated through the online platform in form of a weblink/ QR code, such as ‘Innsbruck informiert‘ (online bulletin portal) in Innsbruck to get responses from different households. Additionally, the survey has also been circulated in the local newspapers (MeinBezirk.at) and as well in the employers list of University of Innsbruck (UIBK), Medicine University Innsbruck, Management center Innsbruck (MCI) via weblink/ QR code, in order to get further responses. In addition to this, the survey has also been circulated through the newsletter subscription list of consultation company ‘Energie Tirol’ that deals with the energy issues in Innsbruck city. This widespread circulation of the survey allows to capture a wide variety of information from the above mentioned focus groups. A total of 606 responses has been collected during the mentioned time frame and of which 496 responses are completed indicating around 83% response rate from the sample population which has been chosen for the further data analysis. The average time of completion of the survey was 20 mins. The valid responses are those which commutes to Innsbruck, and hence commuting to Innsbruck represents a 100% of the frequency count. Hence, the respondents having no driving license are terminated from the questionnaire survey.

4.1.1 Data Cleaning:

Firstly, the incomplete responses have been filtered out for the further data analysis. Secondly, in order to detect the outliers, a boxplot has been created to understand the distribution of the data with mean , first quartile, third quartile, inter quartile range (IQR), median (black line), and other statistics. Data with 1.5 times of the interquartile range (IQR) above the upper quartile and lower quartile are considered to be outliers (indicated as circles) in the dataset. The socio-demographics variables have been tested using the boxplot to identify any outliers in the dataset. Hence, the final data that has to be treated further for modeling purpose stands on 496 valid responses. The variables that have been tested through boxplot distribution is shown in (see appendix A1):

4.2. Descriptive statistics (Socio-demographics):

The descriptive statistics contains the description of the chosen responses by the respondents from the sample population that includes the socio demographic data, mobility behavior of both the focused group, location preferences and travel characteristics etc. From (Table 1), it is evident that, the survey has been responded by the age group between 18-25 (41.32%), followed by age group of 26-35 (27.82%). A small share of the age group between 36-45 (14.72%) can be observed in responding the survey. A symmetrical share can be observed between the gender of both male (49.6%) and female (48.6%) in the sample population. The highest household share can be observed for each family is two (35.5%), followed by household size of four (29%). Considering the education level, most of the respondents in the survey obtained a technical college or university degree with a share of 57.46%. This is then followed by the respondents obtained a Secondary school/Matura with a share of 38.31%. Regarding the employment status of the sample population, 36.69% of the population are employed as a full time employee. Around 42.54% of the sample population are student. The rest of the sample population are retired (1.01%), self-employed (1.21%) & others (3.02%). The income status shows that around 48% of the sample population have below average income level which represent the scenario, of the sample population are students mostly. Around 28% of the complete respondents have an average income level (2000-3000€) per month (Österreich-unterwegs, 2013/2014).With a very few shares of 13% of the population have above average income level. A recent mobility survey conducted by Omnitrend GmbH (2019), shows the number of car available in the different households. The following (table 3) depicts the scenario in the summary form of the descriptive statistics:

SL No.	Sample demographics N=496	Sample Items	% Of shares in survey sample	Population (Innsbruck city) N= 131,059	Source (years)
1	**Gender**	Male	49.60%	49.5%	(Stadt Innsbruck, 2022)
		Female	48.60%	50.5%	
2	**Education levels**	Compulsory school	0.20%	21.0%	(Statistik Austria, 2019)
		Apprenticeship/middle school	2.02%	19.5%	
		Secondary school/Matura	38.31%	25.3%	
		Technical college/University	57.40%	22.4%	
		Others	1.41%	11.8% (not applicable)	
3	**Employment status**	Part Time	14.92%	32.0%	(Statistik Austria, 2019)
		Full Time	36.69%	52.0%	
		Pupil / Student	42.54%	13.5%	
		Apprentice	0%	-	
		Household	0%	-	
		Retired	1.01%	19.8%	
		Self-employed	1.21%	9.80%	
		Others	3.02%	15.65%*	
4	**Income categories**	Below average	48.80%	Avg Income 2000-3000€/month	(Österreich-unterwegs, 2013/2014)
		Average	28.40%		
		Above average	13.10%		
		Others	9.70%		
5	**Age Groups**	<17 years	0%	Under 15 years = 11.7%	(Statistik Austria, 2021)
		18-25 years	41.33%	15-64 years= 69.7%	
		26-35 years	27.82%		
		36-45 years	14.72%		
		46-55 years	9.48%		
		56-65 years	5.65%		
		66 & above	0.81%	65 or up = 18.6%	
6	**Ownership category for EV**	EV owners	8.47%	2.19%	(Statistik Austria, 2021)
		Non EV Owners	91.53%	97.8%	(Statistik Austria, 2021)
7	**Household Size**	1	14.50%	Avg household size = 2.1	(Statistik Austria, 2019)
		2	35.50%		
		3	21.00%		
		4 or more	29.00%		
8	**Car Availability**	0	23.00%	26.2%	(Omnitrend GmbH, 2019)
		1	43.80%	55%	
		2	24.40%	18.8% (2 or more)	
		3	5.40%		
		4 or more	3.40%		

Table 3: Socio demographics of Innsbruck sample vs population sample

4.2.1 Travel characteristics:

In this section , the descriptive statistics of the travel characteristics involves in analyzing the travel pattern of the sample population of the Innsbruck inhabitants. From figure 14, it is evident that around 68% of the respondents living in Innsbruck with a smaller number of shares living outside of the Innsbruck is 32%. Since the survey has been focused on the respondents having the driving license , hence a 99% of the population have the driving license. More than 70% of the respondents have their driving license age with more than five years (fig 14).

Regarding the car availability of the households, around 43.8% of the sample population have at least one car available followed by 24% of the population have at least two cars available. When the question asked regarding the EV experience, a very small percentage of sample population of the respondents which is equivalent to 8.47% have their own EV while the majority of the respondents does not own an EV but do have experience of other forms of electric vehicle.

Most of the respondents in Innsbruck, make shorter trips with their cars on a single day, hence the respondents average kilometer travel is less than 20 km with a percentage of more than 70%. This is in line with the literature from the statistics office of Austria. A small percentage (14.7%) of the respondents usually travels more than 30 kilometers on a single day (fig 14).

Descriptive statistics of the **Travel Characteristics variables** from the responses of the sample population of Innsbruck inhabitants:

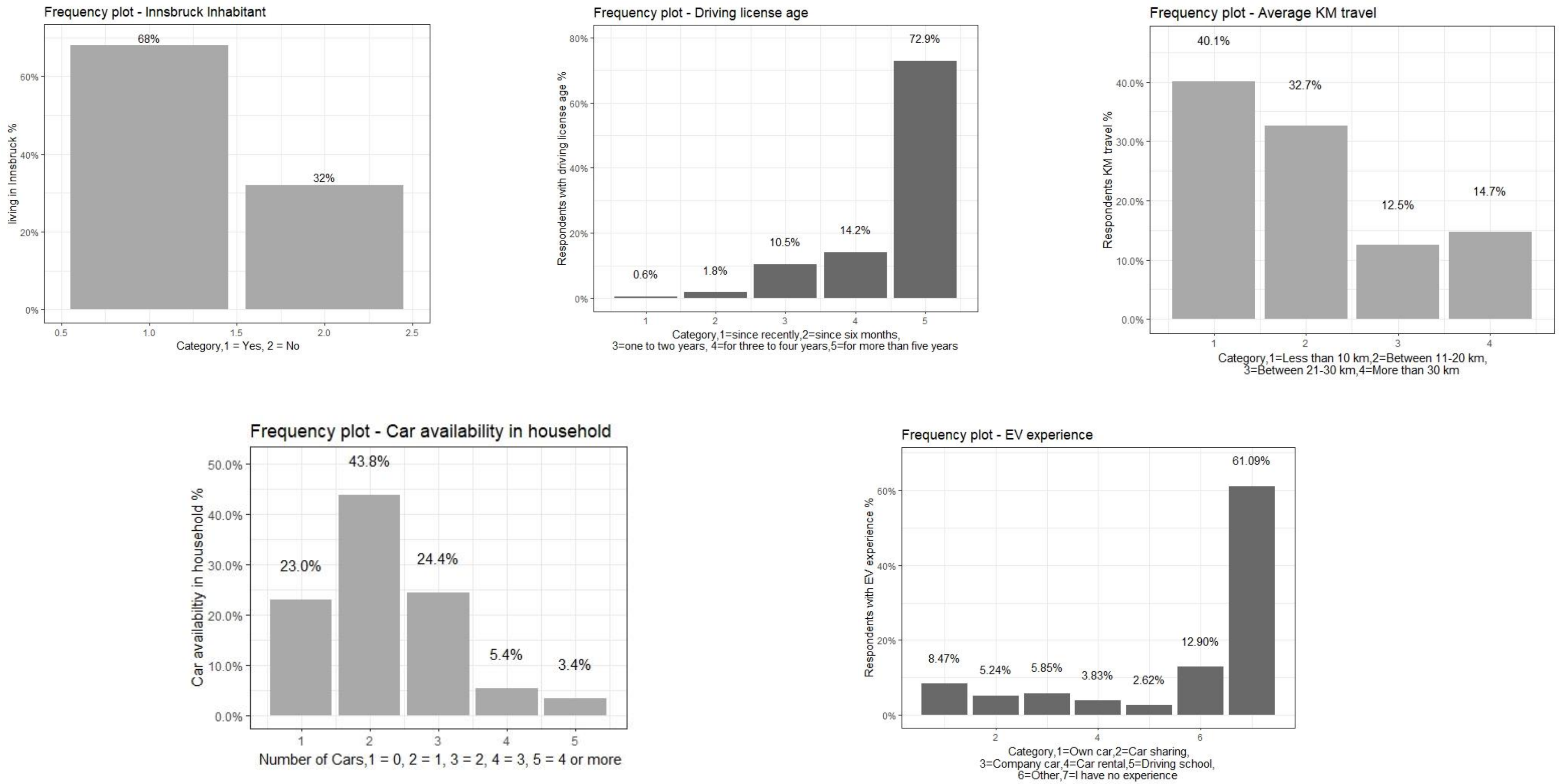
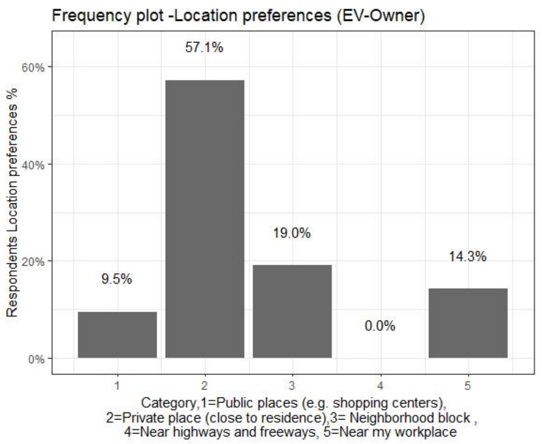


Figure 14: Descriptive statistics of travel characteristics of sample

4.3. Location preferences of the focused group:

Prior to the experimental choice situation, the respondents were asked to choose the preferred location for the charging station location and afterwards they have been redirected to 'Choice tasks' part of the survey. Thus, the frequency plot of the two focused groups, resembles almost similar location preference in terms of the EV charging station location preference. Both of the groups, more than 50% voted for private place near to the residence as their main preferred location for EV charging (fig 15). Secondly, neighborhood block has been chosen as the second most prominent location for EV charging by both of the focused group which constitutes to more than 15%. This retains the fact that the respondents as EV owners or non-EV owners prefer having the charging station near by their walking distances which is one of the biggest expectations from both the existing and potential users' perspective.

Even around 11.7% of the non-EV owner from the sample population also preferred choosing workplace as their one of the preferences for EV charging which almost resembles the similar scenario in case of EV owner that constitutes to 14.3%. While, in terms of the location preferences for motorways, or highways, non EV owner seems to be slightly preferring such location for EV charging than the EV owners. However, this might explain that those population tend to travel more kilometers than others. Lastly, both of the focused group, has preferred less likely to be charging their EV in public places such as the shopping centers and the total percentage for choosing such location by the EV owner is 9.5% and 11.7% for non EV owner. The following (figure 15) depicts the location preferences between these two distinct groups for EV charging.



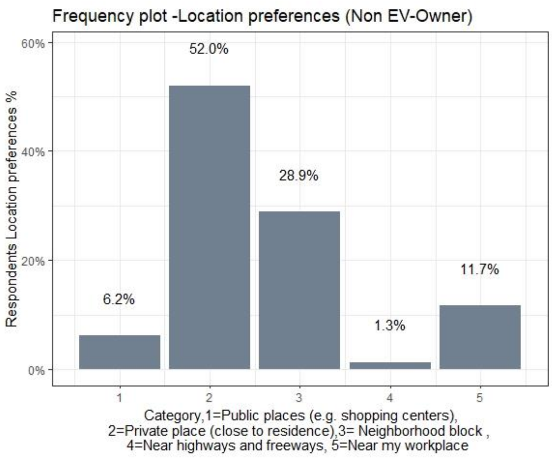


Figure 15: Location preferences of the focused group

4.4. Mobility behavior of the focused groups

4.4.1. EV Owner & non EV Owner:

In this survey, as mentioned previously a distinction has been made between the focused group (EV owner and non-EV owner). By asking the respondents in which form do they have experience of driving an electric car. The answers of the respondents with "Own Car" are termed as the EV owner while the rest of the answers corresponds to the non-EV owner. A descriptive statistic has been performed in order to reveal the mobility pattern of these two distinct groups. From the above descriptive analysis of the EV experience, shows that in the sample population, 91% (N= 454) of the respondents does not have EV experience as own car. Only, 8.5% of the respondents have experience of driving EV as owner which makes 42 respondents out of 496 respondents. In the following figures, each of the distinct group shows how they experience different travel modes such as- car as a driver, car as a passenger, usage of public transport, usage of bicycle and car sharing. From figure 15, it shows that (24%) of EV owner prefers in using their own car as driver nearly with 1-3 times per month. EV owners (29%) also responded to travel mode they experience of using 'car as passenger', and also public transportation (PuT) around 21%, using them 1-3 times per month basis.

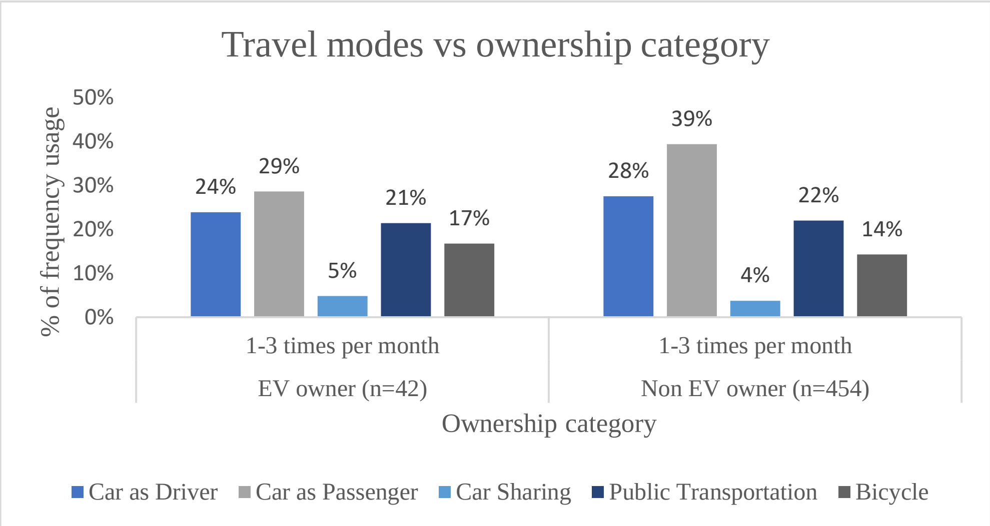


Figure 16: Travel modes of respondents (1-3 times/month)

However, in (fig 16) 28% non EV owners experience 'Car as a driver', followed by 39% 'Car as a passenger', 22% in public transportation (PuT), and 14% as bicycle users. From (fig 17), it shows that the (38%) EV owner prefers in using their own car as driver nearly with 1-3 times weekly compared to 27% of non EV owner. The EV owners (45%) also responded to travel mode use of 'car as passenger', compared to 27% of non EV owner.

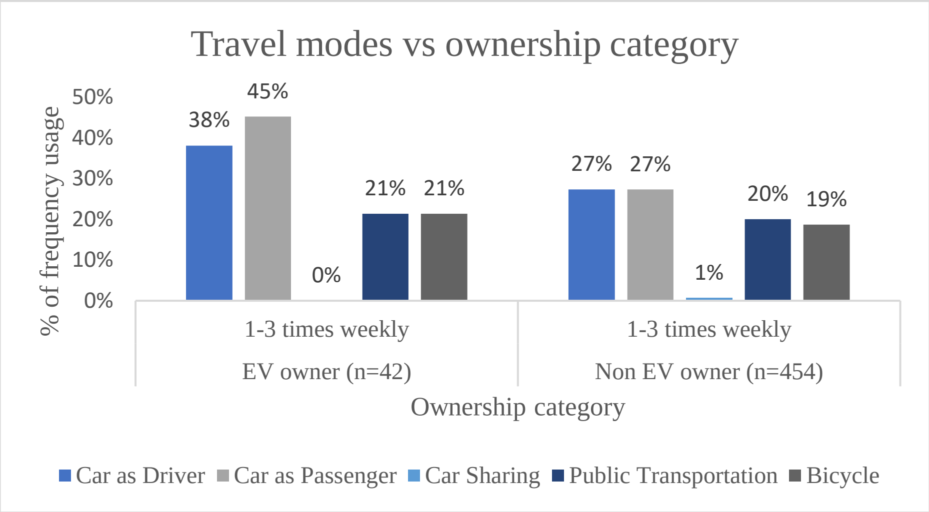


Figure 17: Travel modes of respondents (1-3 times/weekly)

Preferences for public transport as well seem to be under the preference list of the EV owner. Car sharing reveals as the least preference for the EV owners amongst the different travel modes of their daily mobility pattern. Interestingly EV owners have a greater willingness for using their bicycle as their one of the travel modes. From the figure 17, it depicts that around 29% of the EV owners use bicycle as their one of the travel modes for 4-7 times in a week. Non EV owners, are more inclined towards the public transport mode by using 4-7 times a week compared to the EV owners. The usage of bicycle as a mode of transport is also higher in case of non EV owner compared to the EV owners (fig 18).

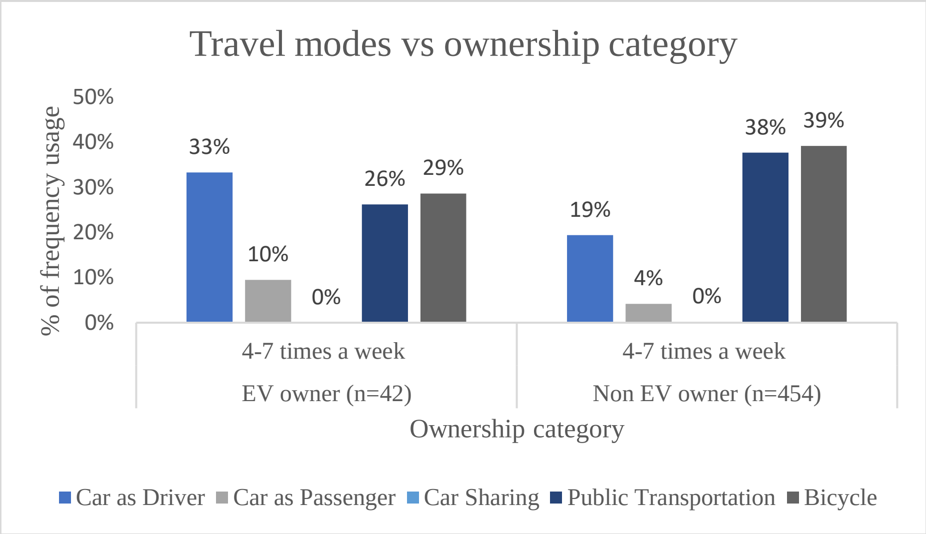


Figure 18: Travel modes of respondents (4-7 times/weekly)

The following (fig 19) represent the mobility behavior of the focused group of the sample population of the respondents (never / seldomly uses such transport modes). Around 29% of the sample population seldomly or never experience ‘car as a passenger’ in case of non EV owner and 17% in case of EV owner.

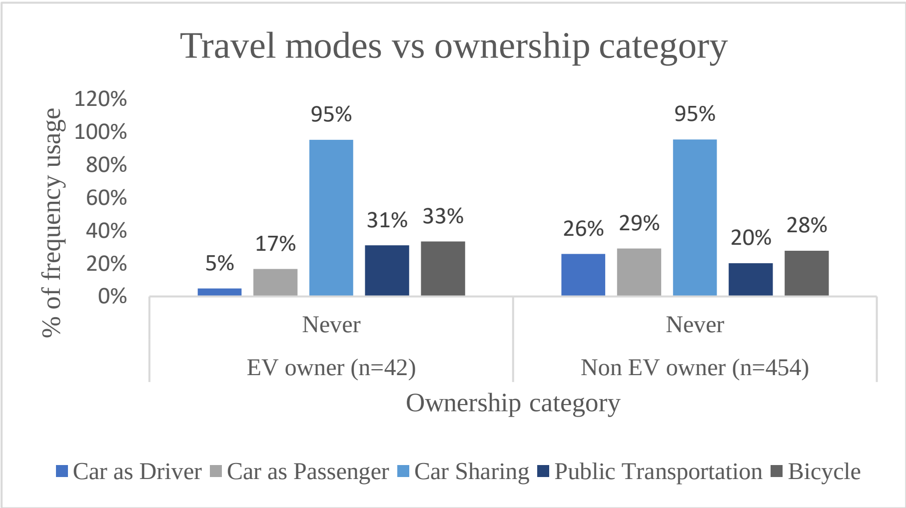


Figure 19:Travel modes of respondents (Never/Seldom)

Both of the focused groups, has lesser preference for car sharing mode as their travel mode. From this sample population descriptive statistics both of the focused groups generally do not have much affinity towards the car sharing programs or schemes (fig 19).

4.4.2. Additional services provision in EV Charging Station:

Both of the focused group has been asked regarding their additional facilities in the EV charging stations. The different additional services that were include are adopted and modified from the qualitative interviews that were undertaken in the framework of the *'PECASO'* project (Sarker & Morshed, 2020) (a text cloud analysis have been performed, see appendix section A3) for this project and also from the point of view of the EV policy implication as well as consideration for future expansion of the EV charging stations (EVCS). In the following section, fig 20 depicts the focused group regarding the additional facilities in the EV charging stations:

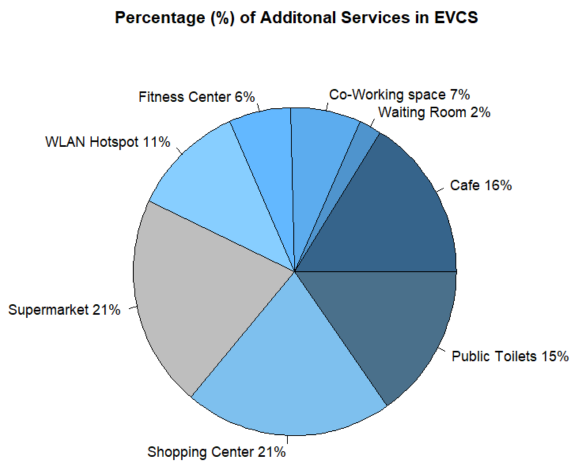


Figure 20: Pie chart illustration of additional services in EVCS

The different additional service items that were listed in this survey includes Café, waiting room, co-working space, fitness center, WLAN hotspot, supermarket, shopping center and public toilets. Respondents were asked to choose the best three additional services as they prefer of having additional service provision being an EV owner and non EV owner. From the above illustration (fig 19), it is seen that respondents prefer in having shopping center (21%) and supermarket (21%) as the highest priority. The additional service in EVCS is then followed by the public toilets, cafeteria, WLAN (internet connections).

4.5. Descriptive statistics of attitudinal statements of focused group

4.5.1. EV owner :

The survey was designed by the inclusion of latent constructs (**refer to appendix section A8 for sources**) from the determinants of the Theory of planned behavior (extended version), to response some of the attitudinal factors for the EV adoption for both of the focused group based on the Likert scales. From the below (fig 21), it is evident that the EV owners are more likely to disagree with the perceive behavioral control (PBC1) item which focuses on the "Purchase subsidies of the EV and tax exemption of the Government", the result indicates that 53% of the sample population of EV owners, tends to disagree the statement, while only 26% of the EV owner agree with the statement. Furthermore, statements regarding the insufficient charging infrastructure for EV (PBC3), reveals that around 46% of the EV owners have agreed while 19% of the EV owner is neutral about the situation and 36% of the EV owners disagree with the statement. When the respondents were asked regarding the charging time duration in the charging station, a majority of the EV owner, 74% of the sample population disagree with the statement.

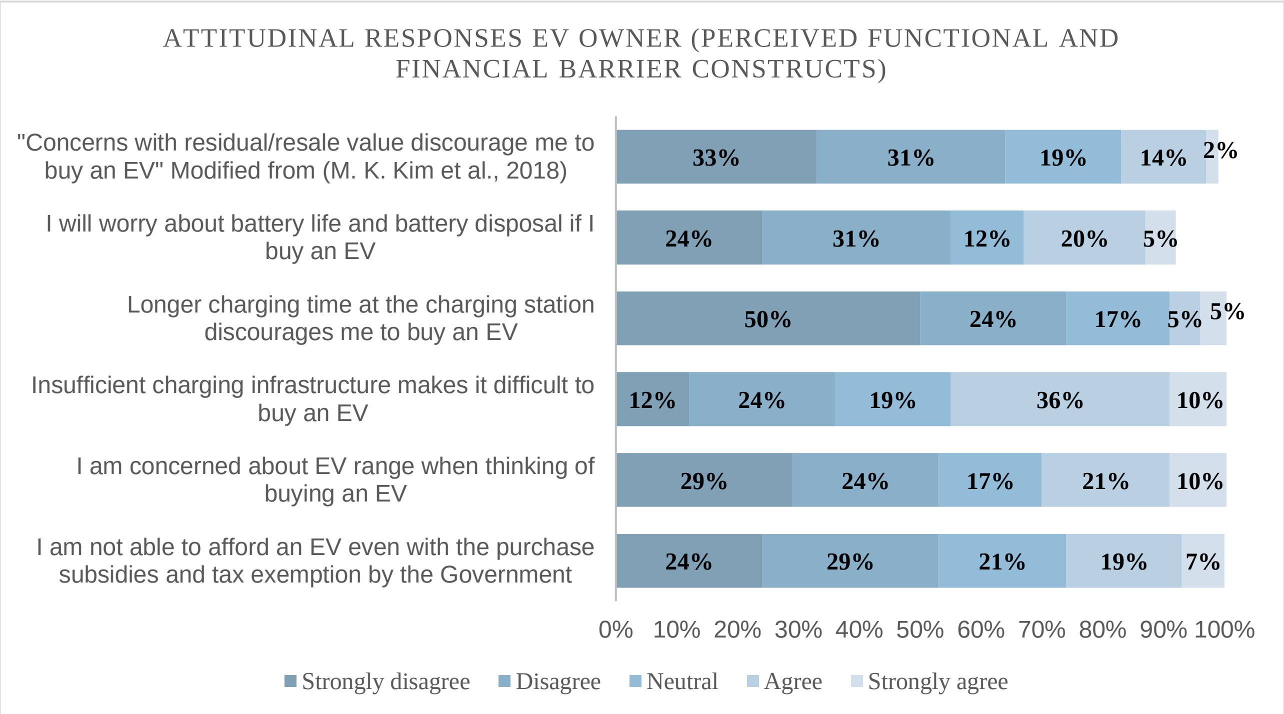


Figure 21:Likert plot of attitudinal statements responses of the EV owner

Note: *Attitudinal statements presented here and in the later sections have been properly sourced as well in the appendix section (08) of thesis part.*

Moreover, when the EV owners have been asked about the statements of attitude towards behavior concerning the positive effects of EV, good performance price ratio etc., almost 80% of the EV owner agreed with the statement while 18% of the EV owner disagreed with the statement (fig 22).

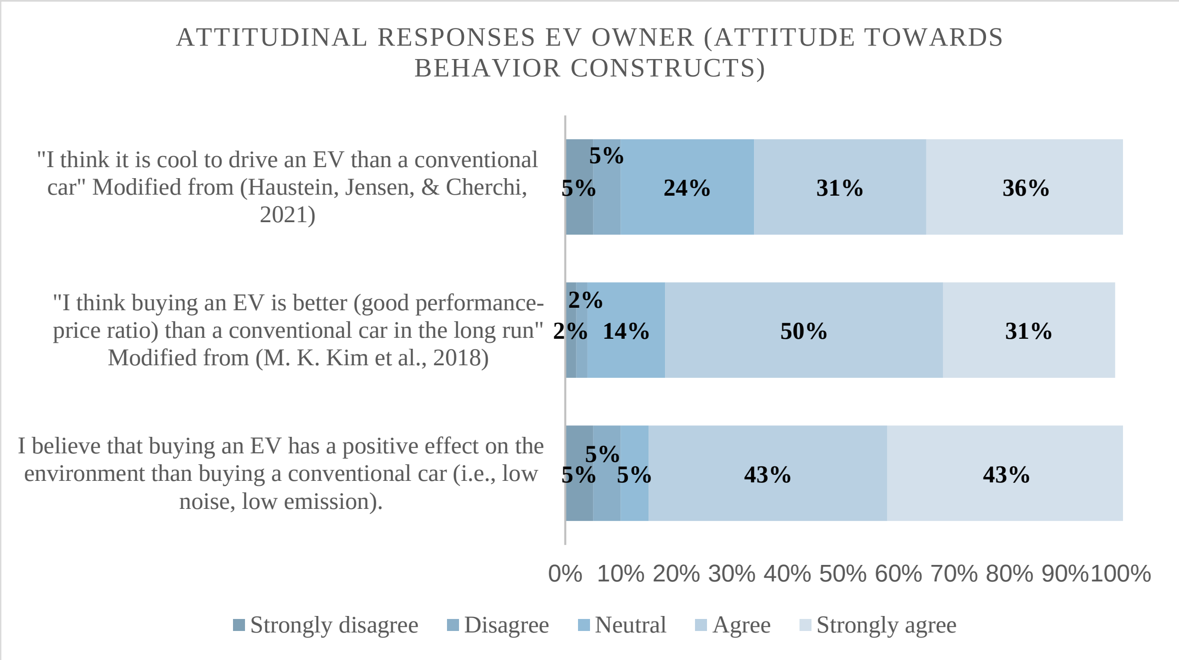


Figure 22: Likert plot of attitudinal statements responses of the EV owner (ATB)

While regarding the environmental concern statement, over 80% of the EV owner voted agreed to the positive side of environmental concern while a very few percentages of 5% people disagree with the statements of the environmental concern (fig 23).

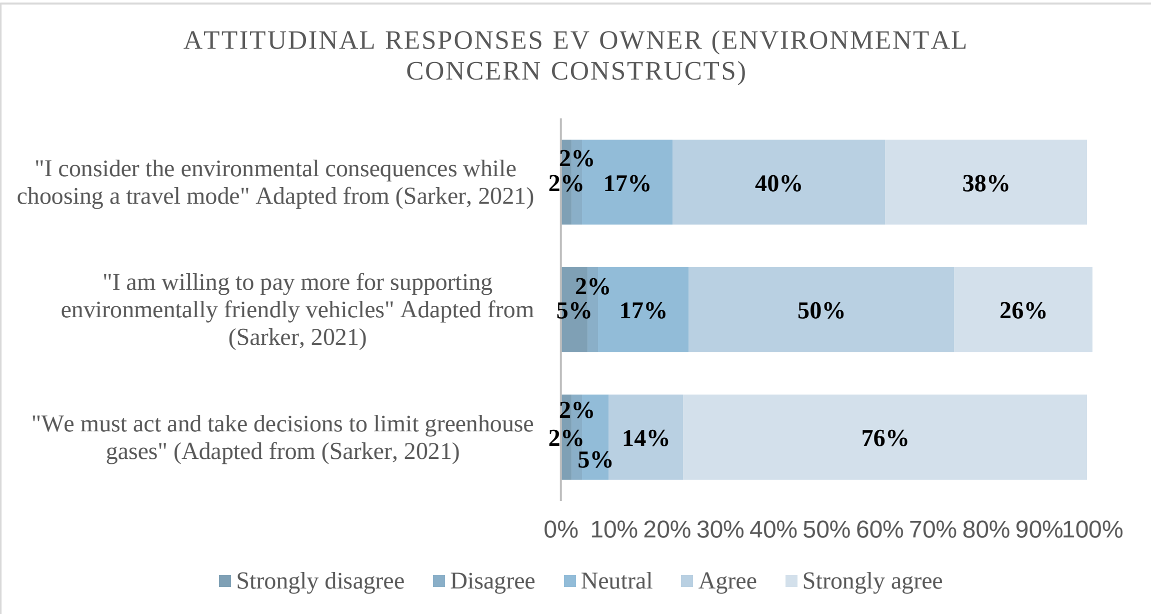


Figure 23.Likert plot of attitudinal statements responses of the EV owner (EC)

Lastly, the survey asked about the statements regarding the subjective norms that includes the items such as “people’s opinion , advertising by media for EV positivity , promotion of EV being influenced for buying EV” have scored high as the percentage vary for different items. Nevertheless, a large neutral vote of around 43% can be observed among the EV owner regarding the statement of the advertising of EV in media (SN4, fig 24).

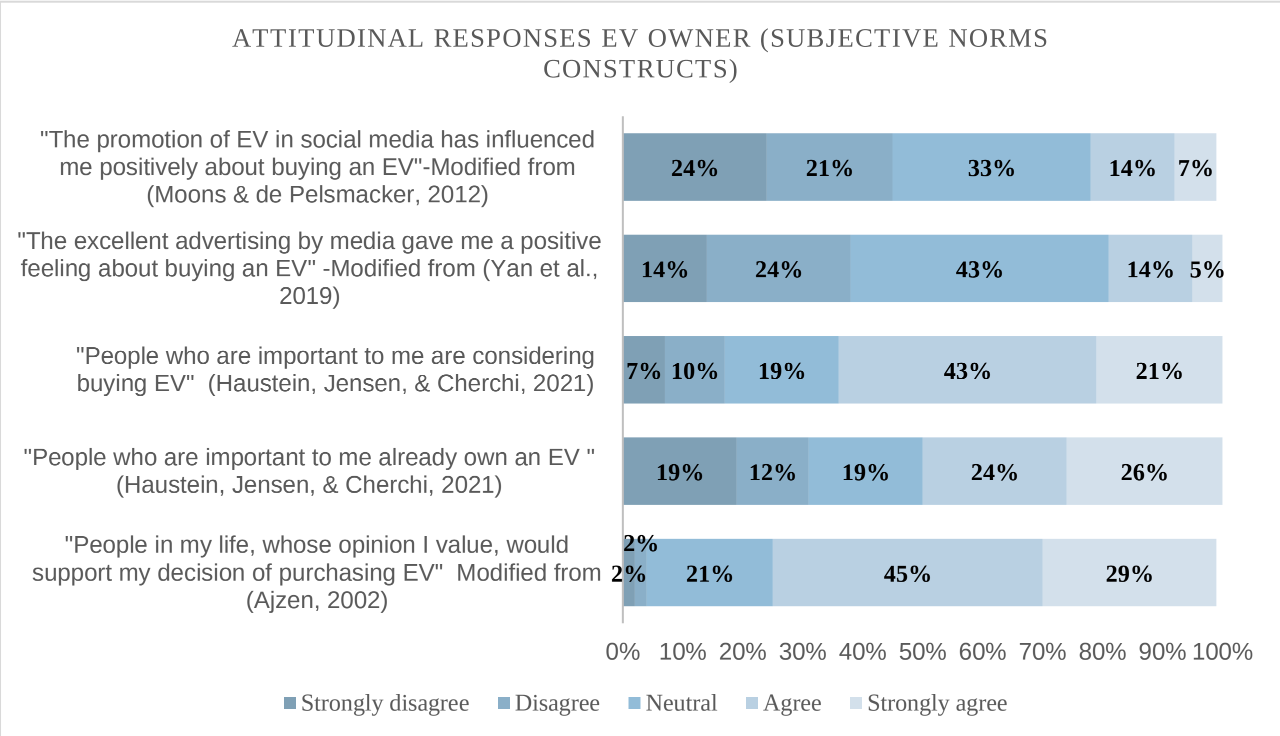


Figure 24:Likert plot of attitudinal statements responses of the EV owner (SN)

4.5.2. Non EV owner :

Comparing the situation with EV owner for the perceive behavioral control items such as the purchase subsidies and tax exemption by the Government, more than 50% of the sample population of the non EV owner disagrees with statements. Moreover, the range of EV, insufficient charging infrastructures, and battery life of EV are of great concern to the non EV owners compared to the EV owner (PBC2, PBC3, PBC 5) items. Considering the resale value of EV, (PBC6) item non EV owners (fig 25) are not greater concern.

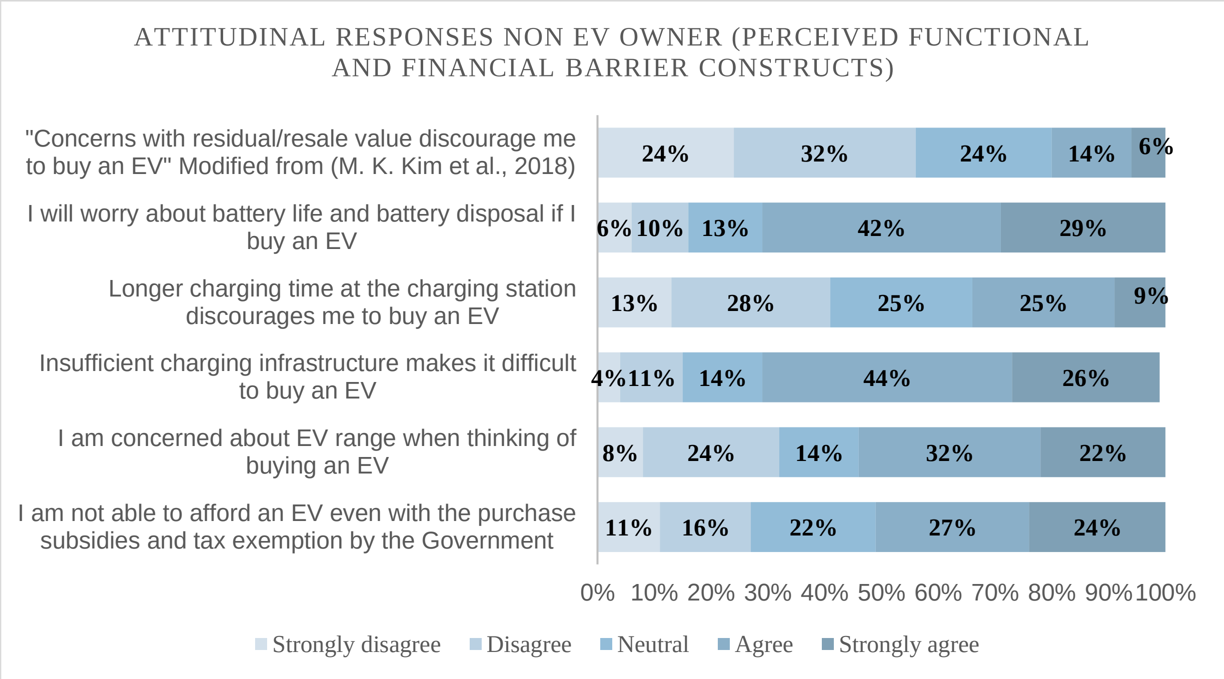


Figure 25.Likert plot of attitudinal statements responses of the non-EV owner (PBC)

Similarly, the construct of "General Attitude towards EV adoption behavior", non EV owners, shows a similar trend as well for considering EV as a better replacement for conventional car. Moreover, for non EV owners, 41% agree with the statement that they believe on the positive effect of EV on environment by purchasing EV (fig 26).

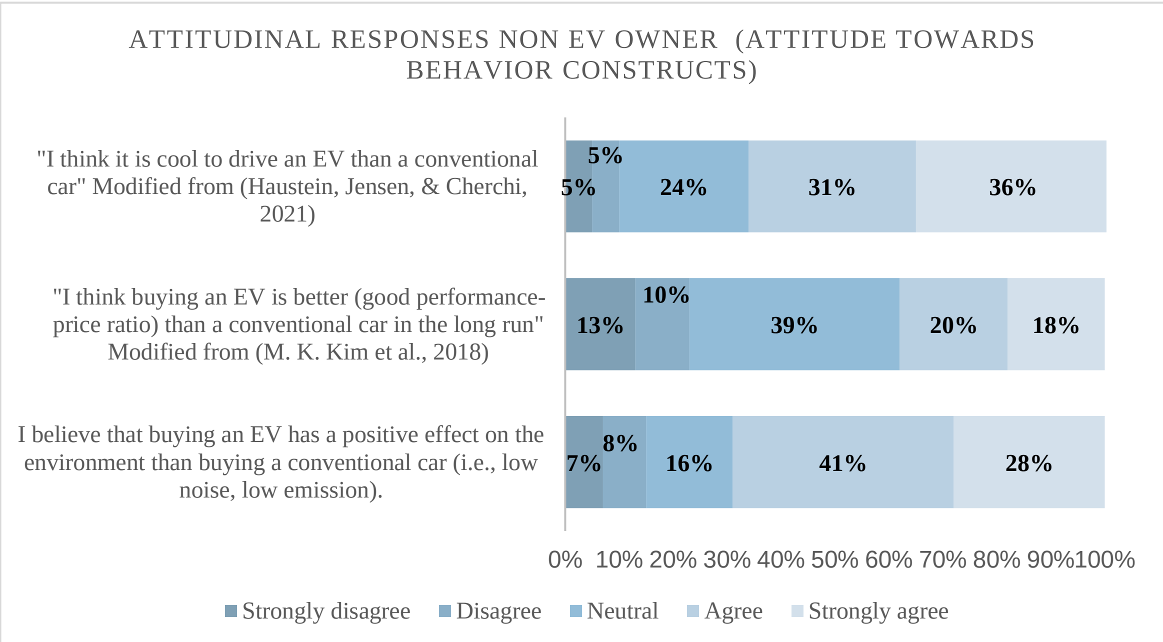


Figure 26:Likert plot of attitudinal statements responses of the non-EV owner (ATB)

When asked regarding the 'Subjective norms' a contradictory trend can be observed from the non EV owners compared to the EV owners . The subjective norms constructs include the items such as people's opinion, advertising by media, promotion of EV in social media has a distinct perspective compared to EV owners (fig 27).

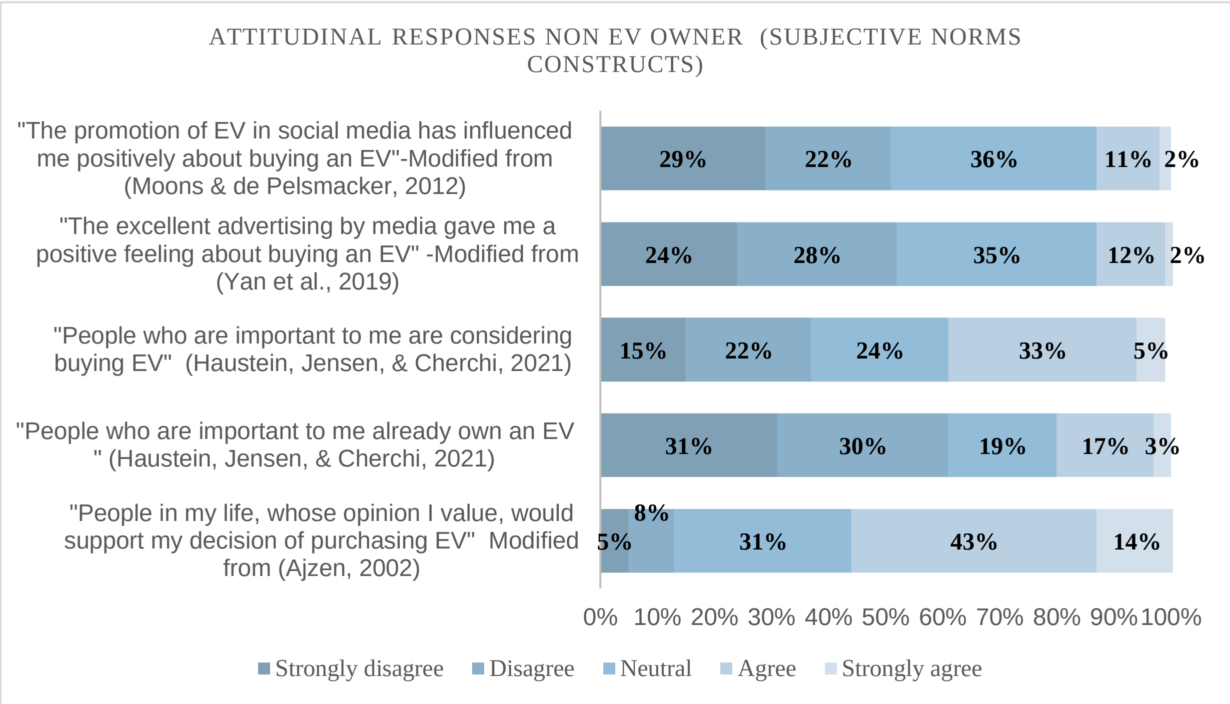


Figure 27: Likert plot of attitudinal statements responses of the non EV owner (SN)

Regarding the environmental concerns, both the focused group having a similar positive trend of paying more attention towards environment friendly vehicles (fig 28).

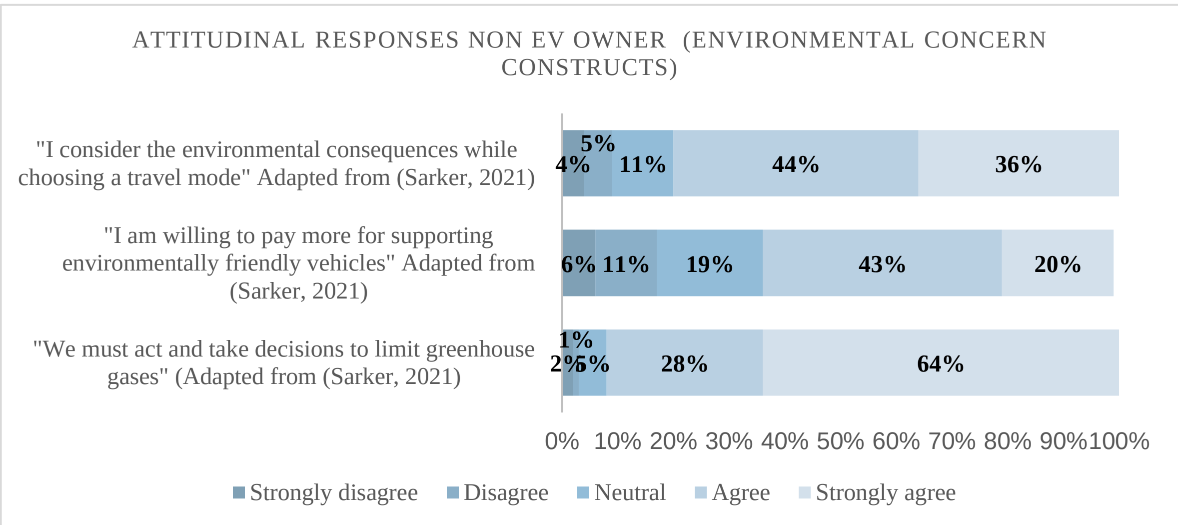


Figure 28:Likert plot of attitudinal statements responses of the non EV owner (EC)

4.6. Behavioral intentions of the focused group

4.6.1. Repurchase intentions for EV owner:

When EV owners asked about their repurchase intentions for electric vehicles, around 85% (36 respondents out of 42) are satisfied with their current electric vehicle and will purchase EV again if necessary (fig 29).

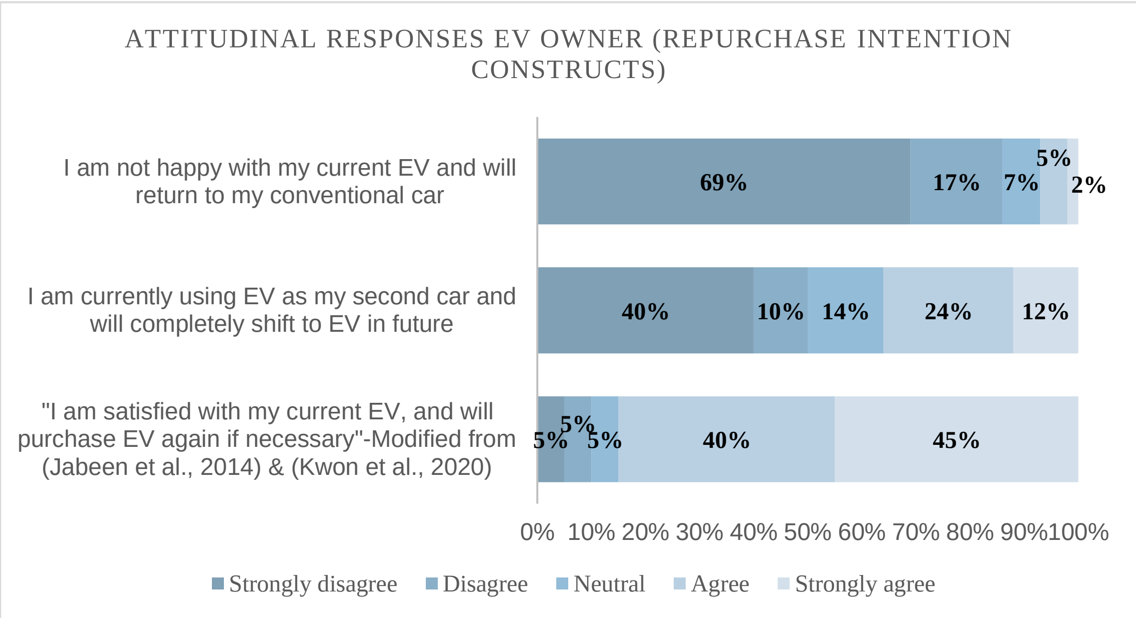


Figure 29: Likert Plot-EV repurchase intention attitudinal construct for EV owner

Around 12% of the EV respondents currently using EV as the second car and will shift to EV in near future, however 50% of them disagree with the statement. When asked regarding returning to conventional car, 69% disagree with the statement while only 7% agree with the statement (fig 28). Moreover, when EV owners asked about the degree of satisfaction with current EV and will purchase EV in case of necessity, 85% agree with the statement while 10% disagree with the term. From this attitudinal construct, however based on a sample size of 42 which is relatively very small to access regarding EV repurchase intentions, the EV owners are satisfied with their current EV.

4.6.2. Non EV owner Adoption Intentions:

Similarly, the non EV owners have also been asked regarding the adoption of electric vehicle. When asked about the willingness to buy electric car in future, around 52% agree with the statement, 17% possess a neutral statement and the rest 31% does not agree with the statement. To explore more about the EV adoption intentions the additional construct such as ‘EVNU2’ and ‘EVNU3’ which focuses on willing to forgo some advantages of conventional vehicles and willing to spend more money to buy EV. In the statement of 'EVNU2' around 71% of the respondents agree with the fact of willing to forgo some advantages of conventional car while 14% possess a neutral statement and the rest 17% chooses to disagree with the statement. Moreover, non EV owner population are willing to spend more money to buy an EV which constitutes to 40% of the overall population and 22% of the population possess a neutral statement while 38% of the non EV owner population disagree with the statement (fig 30).

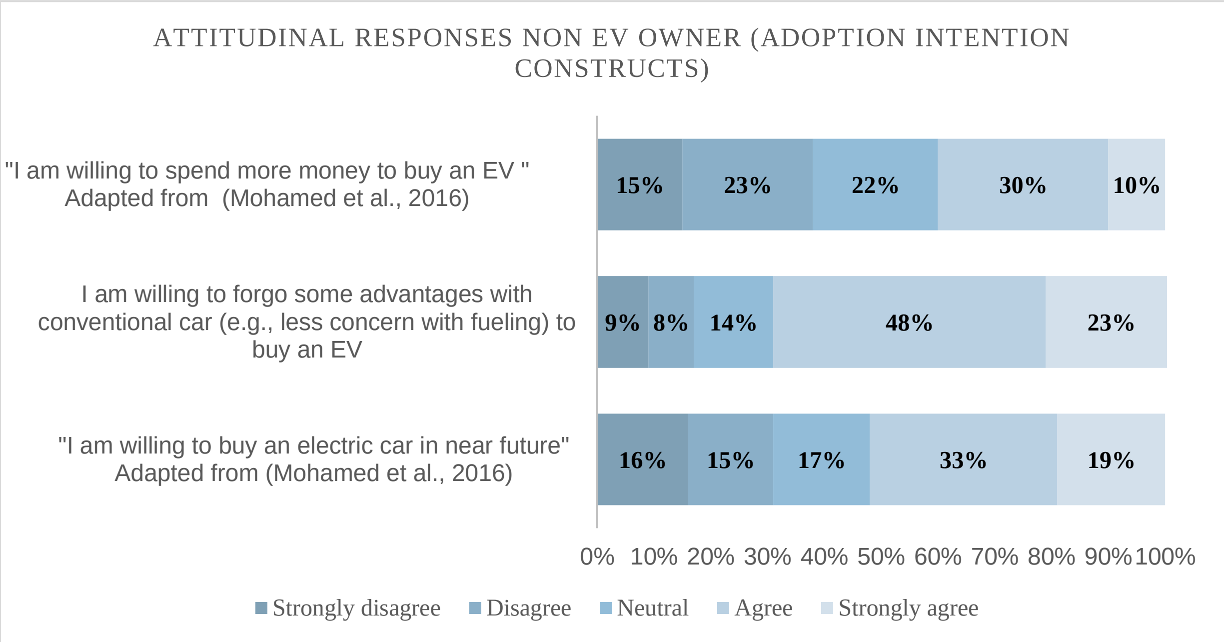


Figure 30:Likert Plot-EV adoption intention attitudinal construct for non-EV owner

4.6.3. Exploratory factor analysis:

For the dimension's reduction, first of all an exploratory factor analysis has been conducted which is required to establish in order to understand the latent behavior of the focused groups. The latent variables that include in the part of the exploratory factor analysis as a measured variables are- General Attitude towards behavior (ATB), Subjective Norms (SN), Environmental Concern (EC), and Perceived behavioral control (PBC). Each of this variable contains 3, 5, 3, 3 items respectively. In order to measure the sampling adequacy, KMO criteria has been checked for factor analysis. The overall KMO is 0.86, which measures as "Meritorious" according to kaiser's criterion (Kaiser, 1974). In addition to this, to understand the intentional behavior of EV adoption to the focused group (EV owners and non EV owners) , additional measured variables have been included such as EV repurchase intention (RPI) for EV owners and EV adoption (non-owners, EVNO) for the factor analysis of SEM path models in later section. Upon deciding the framework of the latent variable, the next step includes the factor extraction. Factor extraction is done based on the parallel analysis and scree plot (see appendix **A9** for figure). Apart from the other techniques of the factor extraction such as the (ML) Maximum likelihood (data is relatively normally distributed), un-weighted least square, factor extraction is done by Maximum likelihood that considers normally distributed data (Osborne, 2014). According to the extraction method of 'ML' with varimax (orthogonal) rotation considering the uncorrelated factors, firstly the parallel analysis and scree plot suggest that the number of factors to retain is 6. In order to clarify the factor structure and making EFA more interpretable, the factor rotation technique that has been finally chosen is the 'oblique' rotation by retaining 5 factors (allowing factors to be correlated) (Osborne, 2014).

The items with factor loading greater or equal to 0.6 (cut off value) considered and retain for further analysis in HCM (hybrid choice model) and Structural equation modeling (SEM). The below tabular format (Table 4) dictates all the possible factoring of the items in the framework of the exploratory factor analysis. The factors which are latent and unobserved for EV adoption and behavioral intentions are of greater interest in SEM path models.

Items Coded	Description	Factor Loadings Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
PBC1	Not able to afford					
PBC2	Range concern of EV			**0.65**		
PBC3	Charging infrastructure insufficient			**0.63**		
PBC4	Longer charging time			**0.72**		
PBC5	Battery life					
PBC6	Resale/residual value of EV					
EC1	Limit GHG		**0.70**			
EC2	Environmentally friendly vehicle		**0.65**			
EC3	Environmental consequences		**0.78**			
ATB1	Positive effect on environment	**0.76**				
ATB2	Performance/Price ratio	**0.69**				
ATB3	Cool to drive EV	**0.60**				
SN1	Opinion value					
SN2	People important					**0.61**
SN3	Consideration of buying EV					**0.76**
SN4	Advertising by media				**0.86**	
SN5	Promotion of EV in social media				**0.79**	

Table 4: Factor Loadings (Results from factor extraction)

Moreover, these factors help to determine the model which in turn would be included as the latent explanatory variable as the underlying factors for EV adoption intention and also relevant for policy making viewpoint. The loadings with and greater than equal to 0.6 has been shown in the table 4 above and table 5 below shows the SS loadings which indicates, factors with greater than 1 are worth retaining:

Loadings	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SS loadings	2.11	1.77	1.70	1.53	1.33
Proportion Var	0.12	0.10	0.10	0.09	0.08
Cumulative Var	0.12	0.23	0.33	0.42	0.5
Proportion Explained	0.25	0.21	0.20	0.18	0.16
Cumulative Proportion	0.25	0.46	0.66	0.84	1

Table 5: Sum of Squared Loading, SS Loadings (<1)

5. Model Development

5.1. Baseline MNL model:

At first a simple Multinomial logistics regression model has been developed using the R software of Apollo package for choice modelling. With the attributes that were present in the choice settings, a baseline model has been established. At first, the model has been developed excluding the alternative specific constants. The estimated signs are as expected while developing the priors (**Table 6**).

In the next model (**Table 7**), alternative specific constant has been included. This has been done because, the alternative specific constants capture the facts that are unobserved by the analyst in the survey task or capturing the effect of left to right survey response bias. Moreover, without ASC the model assumes that the mean of the error terms is equal and hence inclusion of these constants captures the mean impact of all factors that are not included in the deterministic utility function. Keeping the ASC_1(reference level) value fixed and estimating the other ASC's shows that all else being equal the respondents tend to prefer the second unlabelled option more likely than the third unlabelled option. The third unlabelled option has a negative estimate which shows that respondents is less likely to prefer. As expected, the baseline model accurately predicts the expected signs of the different attributes such as the charging speed, reservation time, distance to the charging stations, and monthly price of the package etc. According to the baseline MNL model, the attribute, charging speed (ß_cspeed) shows a positive estimated coefficient which means that the respondents are likely to prefer higher charging speed rather than the lower ones.

Similarly, the estimated coefficient of distance, reservation, and price (ß_dist, ß_resv, ß_price) are respectively negative, positive, negative etc. From this it can be said that the respondents likely to prefer having the distance of the charging station near and prefer having the higher reservation time. Nevertheless, the respondents negatively perceive the price of the different cost associated with the charging distance, which indicates a higher price in unlikely to be preferred by the respondents (refer to MNL baseline model- **table 6** -Tabular format). Hence from this model it can be understood from both the existing and potential users' perspective is that the expectations relating to the adoption of EV's includes the higher reservation time, less price package , higher charging speed, nearby distances of EV charging stations.

Next for the development of higher models, the trial-and-error analysis method has been obtained by adding and dropping of variables. Since the experimental design is generic hence to specify more advance MNL model, the main effects of the socio-demographics, travel pattern, mobility behaviour variables cannot be ascertained directly in the utility functions. The only way to make a meaningful interaction of the socio demographics variable and other explanatory variable with the attributes of the experimental design to develop an interpretable model. Otherwise, these utility functions are meaningless in an unlabeled experiment with generic alternatives.

In an unlabeled experiment, all utility functions need to be the same as otherwise the model cannot be interpreted. Hence in the further section, MNL model has been developed based on the interaction term with socio demographics or other explanatory variables. The trial and error method ends until a satisfied interpretable model is developed that describes the best of the data collected from the sample population with significant parameter estimates and better statistical fit results.

Model information: Basic MNL Model (Forced DCE) > Generic Parameters (Excluding ASC)						
Estimates	**Signs**	**Design Type**	**Overview of choices for Basic MNL components**	**Option 1**	**Option 2**	**Option 3**
Speed	+	Generic Attribute	Times available	2976	2976	2976
Distance	-		Times chosen	886	1087	1003
Reservation	+		Percentage chosen overall (%)	30%	37%	34%
Cost	-		Percentage chosen when available (%)	0.30	0.37	0.34
Model Estimates						
Items	**Estimates**	**||t.ratio||**	**P _value**	**Significance level (95% CI)**		
Beta Charging Speed	0.638659	11.969	0.0000	****		
Beta Reservation time	0.021624	19.726	0.0000	****		
Beta Distance	-0.001719	8.83	0.0000	****		
Beta Cost	-0.053604	17.358	0.0000	****		
Model Estimates						
Sample Size			496			
No. Of Observations			2976			
No. of Estimated Parameters			4			
LL(start)			-3269			
LL(0)			-3269			
LL(C)			-3259			
LL(final)			-1641			
Rho-square (0)			0.4979			
Adj.Rho-square (0)			0.4966			
Rho-square (C)			0.4963			
Adj.Rho-square (C)			0.49			
AIC			**3291**			

Table 6: MNL model excluding ASC

Note: [a] Evaluated at 90% CI (t >1.65), [b] Evaluated at 95% CI (t >1.96) *p value: < 0.01 ***, < 0.05 ** , <0.1**

Model information : Basic MNL model (Forced DCE) > Generic Parameters (Including ASC)						
Estimates	**Signs**	**Design Type**	**Overview of choices for Basic MNL components**	**Option 1**	**Option 2**	**Option 3**
Speed	+	Generic Attribute	Times available	2976	2976	2976
Distance	-		Times chosen	886	1087	1003
Reservation	+		Percentage chosen overall (%)	30%	37%	34%
Cost	-		Percentage chosen when available (%)	0.30	0.37	0.34
Model Estimates						
Items	**Estimates**	**||t.ratio||**	**Value**	**Significance level (95% CI)**		
ASC_1 (reference level)	0	N/A	N/A	**N/A**		
ASC_2	0.192776	2.964	0.0015	****		
ASC_3	-0.20612	2.795	0.00259	**		
Beta Charging Speed	0.63547	11.368	0.0000	****		
Beta Reservation time	0.021905	8.611	0.0000	****		
Beta Distance	-0.001636	18.663	0.0000	****		
Beta Cost	-0.054559	17.002	0.0000	****		
Model Information						
Sample Size			496			
No. of Observations			2976			
No. of Estimated Parameters			6			
LL(start)			-3269.47			
LL(0)			-3269.47			
LL(C)			-3259.12			
LL(final)			-1624.9			
Rho-square (0)			0.503			
Adj.Rho-square (0)			0.5012			
Rho-square (C)			0.5014			
Adj.Rho-square (C)			0.50			
AIC			**3261**			

Table 7: MNL model including ASC

Note: [a] Evaluated at 90% CI (t >1.65), [b] Evaluated at 95% CI (t >1.96) *p value: < 0.01 ***, < 0.05 ** , <0.1**

5.1.1. MNL model with Socio demographics & travel behavior characteristics:

In this section, after the development of baseline model and in order to investigate more deeper insights about the respondents' choices, the socio demographics variables have been incorporated with the base line model (Table 8). Since the experimental design is generic, the model is restricted to determine the main effects of the socio-demographics variable. Hence, the inclusion of the socio demographics variables to the baseline model only makes sense where the variables differ across the alternatives. That means, the socio-demographic variables require to be interacted with the attributes of the alternatives to make a meaningfully interpretable model (Table 8) (for further details readers are requested to refer to the 'unlabeled choice alternatives' section 2.7 of the literature review). Hence, in this case the 'price' and 'distance' attribute has been selected from the attributes of the alternatives to be interacted with chosen socio-demographic (through trial and error method) with other explanatory variables.

In this model **the base** MNL model with covariates, has been developed further by incorporating the travel behavior and other socio demographics criteria of the respondents in the utility functions (table 6). After several attempts of trial and error, the inclusion of the explanatory variables with the base MNL model has become a better fit based on the 'Akaike information criterion' and rho squared value. In this model 3, at first different explanatory variables have been added to investigate more deeper the effects of socio demographics variables. From model 3 (table 6), the interaction with working full time professionals and self-employed people with price shows a positive estimate which interprets that relative to the student and holding the price constant the full time working professionals and self-employed people are likely to be less sensitive with price of charging EV at EVCS whereas the situation is reversed in case of the part time working professionals, all else being equal. The interaction term is statistically significant at 95% CI suggesting that shows: coefficient is statistically significant different from 0.

However, the interaction term with household sizes (here, Household Size = 1 , 2, 3 ,4 etc.) with price attribute reveals a negative estimate. Although the household sizes do not show any statistically significant result. Similarly, no significant relationship has been found with the educational status of the sample population, associated with the cost of charging EV in EV charging station (EVCS).

Furthermore, EV ownership experience has been interacted with price to investigate sensitive towards the cost of EV charging at charging station. The model reveals that, the respondents having the experience of EV as their own car or company car tends to less sensitive towards the cost associated for EV charging. However, when the variables are interacted with distance attribute, they are statistically significant at lower alpha values, where the non-EV owners are sensitive to the distance of the charging infrastructure. The explanatory variable ‘age’ and income does not show any significant results. Model 3 has also studied frequency of travel behavior of the respondents and its relationship with the different attributes of the MNL model. Respondents who answered, using ‘Car as a driver’, ‘Car Sharing’ , ‘bicycle’ as their travel modes (1-3 days / month), the positive interaction between them with price shows that holding the price constant the respondents tend to be less sensitive to the cost of charging EV at public stations relative to the people using public transportation as their mode for travel (1-3 days / month- indicates less frequency of respective travel modes).

Those interactions with the price attribute show significance in terms of p value and model fit. The reported model provides the best model fit in terms of the lower AIC value evaluation and hypotheses driven utility functions.

Model no. 3 (MNL with SP Covariates)		
Parameters/ Variables (reference level/ordered)	**Estimates**	**||t.ratio||**
ASC_1 (reference level)	0	N/A
ASC_2	0.224***	3.37[b]
ASC_3	-0.21***	2.8[b]
Beta speed	0.623***	10.96[b]
Beta reservation time	0.024***	9.2[b]
Beta distance	-0.0016***	15.46[b]
Beta cost	-0.047***	3.52[b]
Interaction with monthly cost at charging station		
Employment Status (Student)	-	-
Full time x Price	0.016**	9.2[b]
Part Time x Price	-0.012*	2.4[b]
Self Employed x Price	0.0317**	2.04[b]
Retired x Price	0.015	0.78
Others x Price	-0.0032	0.24
Household size (HHsize1)	-	-
Household size 2 x Price	-0.00082	0.13
Household size 3 x Price	0.005	0.77
Household size 4 x Price	0.007	1.13
Education level (Compulsory School)	-	-
Middle School x Price	-0.0149	0.88
Secondary School/Matura x Price	-0.019	1.56
Technical College /University x Price	-0.016	1.45
EV ownership experience (Continuous)	-	-
EV (as own Car) x Price	0.016**	2.32[b]
EV (as Company car) x Price	0.018**	1.98[b]
Age (Ranked [18 -25])	-	-
Age [26 -35] x Price	-0.004	0.94
Age [46 -55] x Price	-0.0114	1.56
Household Income (below average)	-	-
Household Income (average) x Price	-0.0016	0.27
Household Income (above average) x Price	-0.009	1.27
Household Income (other) x Price	-0.0037	0.52
Travel behavior frequency [(PuT) > 1-3 days /month]	-	-
Car as driver x Price	0.008**	1.9[a]
Car as passenger x Price	-0.0155***	3.7[b]
Car Sharing x Price	0.039***	4.89[b]
Bicycle x Price (find their main mode of transport)	0.017***	3.38[b]

Interaction with Distance of Charging Station/ Infrastructure		
No. of Cars in Household (Car == 1)	-	-
Car 2 x Distance	-0.000361**	2.24[b]
EV (as own Car) x Distance	0.000451*	1.8[a]
EV (as Company car) x Distance	-0.000615*	1.7[a]

Note: [a] Evaluated at 90% CI, (t >1.65), [b] Evaluated at 95% CI, (t >1.96) *p value: < 0.01 ***, < 0.05 ** , <0.1**

Model fit statistics (Model no. 3)	
Sample Size	496
No. of observations	2976
No. of Estimated Parameters	31
LL(start)	-3269
LL(C)	-3259
LL(final)	-1563
Rho-square (0)	0.52
Adj.Rho-square (0)	0.51
Rho-square (C)	0.5204
Adj.Rho-square (C)	0.52
AIC	**3188**

Table 8: MNL model with SP Covariates

5.1.2. Model accuracy (Model fit statistics for MNL models):

The model diagnostics and fit statistics has been associated with different models in the subsequent tables. Comparing the Akaike information criteria (AIC) between the subsequent models gives the model improvement result. Hence, the model with the lower AIC is regarded as the best model. Moreover, the incremental value of adjusted rho square also shows that the final model has been improved from the baseline model. A likelihood ratios test is only applicable to compare between the generic and alternate specific models. Since the design is generic and hence the test of likelihood ratio becomes obsolete. Note that, with the increase in the complexity of the model BIC value tend to penalize the parameters and as such the value increases which happened in this case.

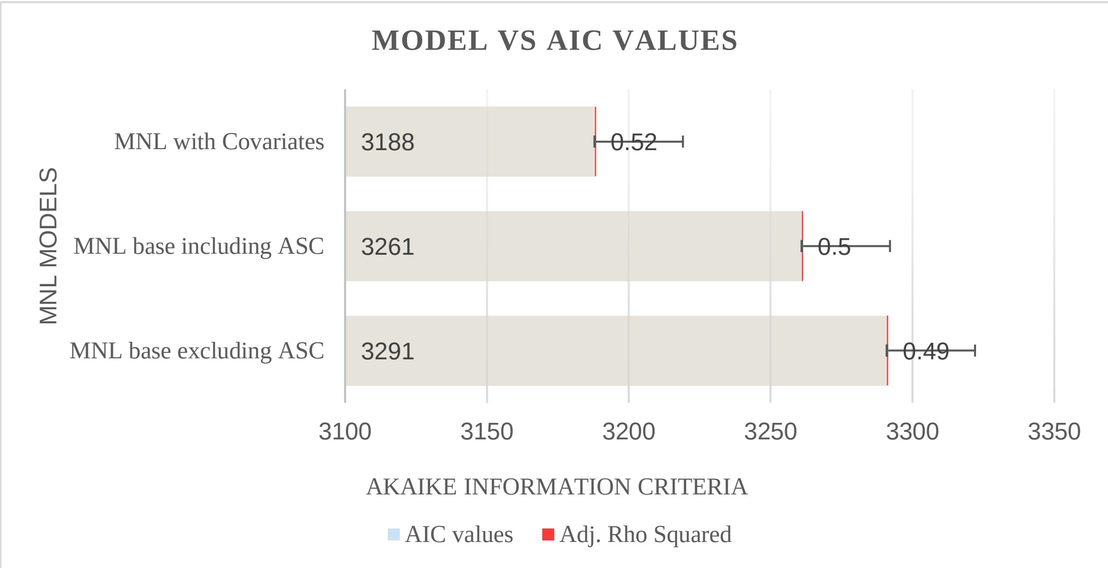


Figure 31: Model fit test with AIC values

The next section deals with more complex and advance model by inclusion of the latent variables, which are always unobserved by the analyst such as the attitudinal constructs asked in the survey regarding the perceptions, attitudes, subjective norms, and environmental awareness etc. of the respondents and this is measured through the psychometric indicators with the five scale level of agreement or so called Likert scale. The inclusion of this unobserved latent variable, into the utility function of the choice model is complex but useful to interpret by linking the underlying latent factors with the respondents' characteristics.

5.2. Hybrid choice model (inclusion of Latent constructs) with ordered logit:

Following the MNL model with SP covariates, an HCM model with different settings (trial and error attempts) has been explored in order to understand the latent factors of the focused group (fig 32). The HCM model is comprised of 2 different models namely the structural model, measurement model which enters into the utility function along with the explanatory variables and attitudinal indicators. For the measurement pat of the model, the chosen indicators are the results of the exploratory factor analysis conducted earlier in section (4.6.3). For the random coefficient parameter, finally with 500 inter-individual draws (normally distributed) have been considered in this framework to represent as final model. Albeit Halton draws with 150,200,300 resulted in lower model fit compared to 500 draws (see appendix-A5). This estimation of the whole process occurs simultaneously, and the results of Hybrid choice model with ordered logit is described in different parts of the table in the next section.

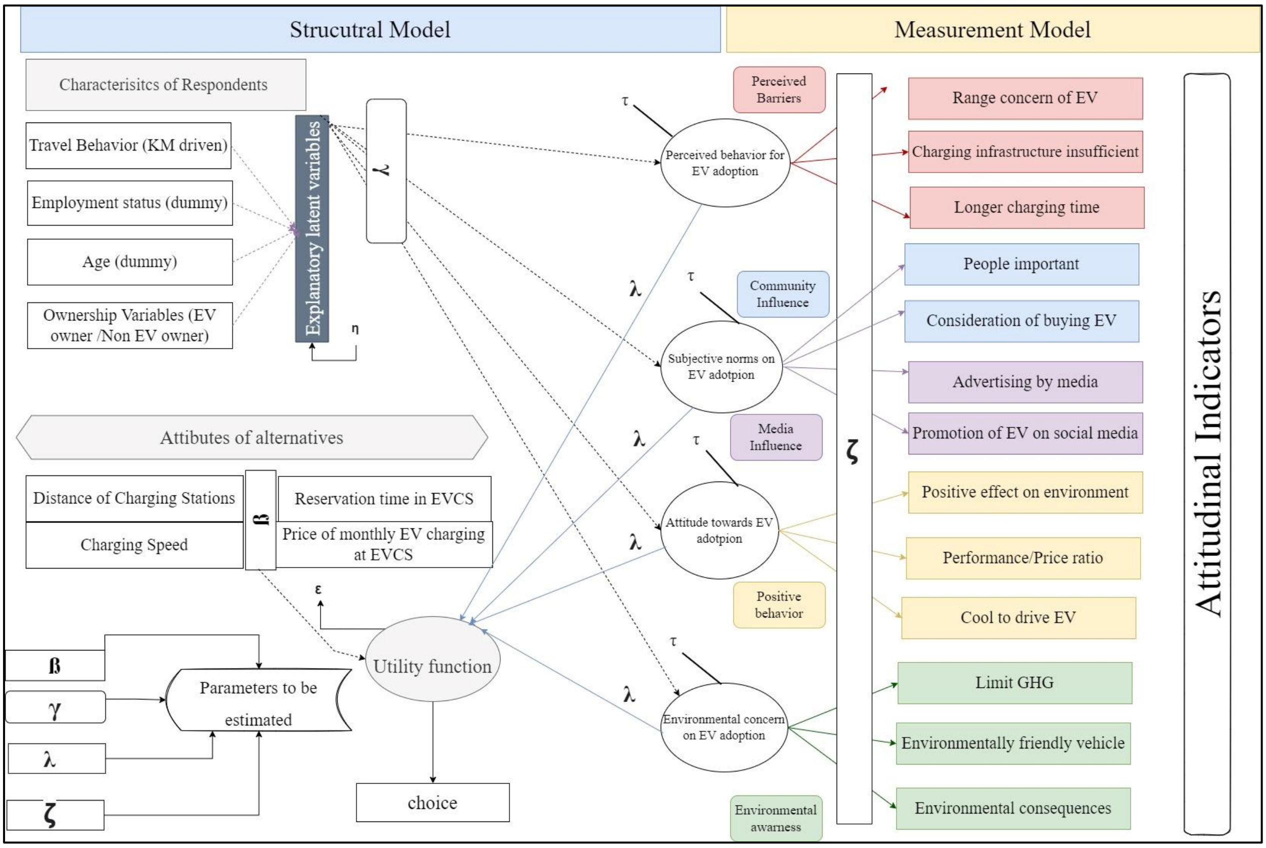


Figure 32: HCM framework settings for EV adoption-own illustration based on (Bolduc & Alvarez-Daziano, 2010)

Utility specification for HCM & OL: The utility specification of the generic design of HCM with ordered logit is measured by lambda (λ) which captures the impact of the latent variable on the utility function. Since, the design is generic, hence lambda (λ) is added in only two alternatives ('option 1' & 'option 2'); i.e., lambda (λ) has been applied to the j = 2 alternatives i.e., first and second option of the utility function. The utility specification is shown below in a tabular form 9:

Utility specification	Hybrid Choice model with Ordered Logit	
items	estimates	t-ratio
ASC_1	0	-
ASC_2	0.19	3.02
ASC_3	-0.26	3.07
Beta Charging speed	0.63***	11.38
Beta Distance	-0.001***	18.64
Beta Reservation time	0.021***	8.59
Beta Cost	-0.05***	17.06
Latent variables		
Lambda (PBC) on option 1 &2	0.0014	0.019
Lambda (SN) on option 1 &2	0.094	1.26
Lambda (EC) on option 1 &2	0.11**	1.65
Lambda (ATB) on option 1 &2	0.063	0.76
Model information		
Number of individuals		496
AIC		19697
BIC		20376
Number of Halton draws (Inter individual)		500

Table 9: Utility specification of HCM with OL

The parameters that were involved in the estimation of the MNL model have the same sign of the estimates. The coefficient to the four latent variables (PBC, SN, EC, and ATB) entered positively in the HCM model for the options (alternative) 1 & 2, which indicates that the latent variables have a positive impact on the alternative 1 & 2 of the choice probabilities (table 9). The only latent variable (EC), Environmental concern is statistically significant, which interprets that environmental awareness is a great concern when respondents choosing options (alternative) 1 & 2 relative to option 3.

Structural Part of HCM & OL: This part of the model focuses on the relationship between the explanatory latent variable and the latent constructs involved in the estimation process. The explanatory latent variable that are considered in this part of the models are the ownership variables (as own car vs no experience), Age as a (dummy coded variables), respondents travel characteristics (dummy coded variables) and respondents employment status as a dummy coded variable (full time vs others). The following table describe the impact of these latent construct on the explanatory latent variable and how respondents likely to be responding on the latent constructs that were chosen from the exploratory factor analysis. *Note: Higher value means agree in accordance with the Likert scale arguments (1-5).*

Latent variable vs Explanatory latent variable	Perceived functional barrier on EV adoption		General Attitude towards EV adoption		Environmental concern on EV adoption		Subjective norms on EV adoption	
	PBC		ATB		EC		SN	
	est	t-ratio	est	t-ratio	est	t-ratio	est	t-ratio
EV owner (as own car)	-0.82***	4.54	0.48***	3.12	-0.016	0.08	0.5***	2.18
Non EV owner (no exp)	0.46***	3.42	-0.24***	2.22	-0.19**	1.73	-0.029	0.27
Travel more than 10 km vs (Less than 10km)	0.31***	2.86	-0.38***	3.96	-0.41***	3.98	-0.16**	1.57
Age over 25 vs (under 25)	-0.17	1.36	-0.03	0.03	0.29***	2.39	-0.2**	1.72
Full time vs (others)	-0.06	0.5	-0.89	0.89	-0.04	0.34	-0.11**	1.74

Table 10: Structural part of HCM - OL

From the above table 10, it can be seen that the EV owner disagrees with the functional barrier of the EV whereas the non EV owner address positively the functional barrier for EV adoption. Respondents who travel longer distance for instance here (more than 10km), agree with the functional barrier of the EV relative to the respondents who travel less kilometers. This can be explained as the EV's are best with short range and the fear of anxiety or so called 'range anxiety' is a great concern for the people traveling longer distances. 'Age' and 'occupation status' are seemed to be non-significant in case of the functional barrier for EV adoption. Similarly, EV owners agree to the positive attitude towards EV adoption whereas the non EV owners disagree. Respondents who travel, less than 10km likely to have a positive attitude towards EV adoption relative to the respondents traveling more than 10 km. This can be explained as electric vehicles have good performance to price ratio for shorter range. Likewise, respondents under age 25 are more likely to have a positive attitude towards EV adoption relative to age over 25 but this is not statistically significant. Respondents with full time employment status does not have any significant relation with the attitude towards EV adoption compared to the other profession. Non EV owners are seemed to be less likely to agree with the environmental awareness associated with EV adoption relative to EV owners (EV owners being negative and not statistically significant).

Albeit respondents who travel less than 10km, agree with the environmental concern associated with EV adoption with respect to the respondents traveling longer distances. In addition to this, these respondents are likely to be greater than age 25 and involved in other different profession rather than full time profession (although employment status is not statistically significant). Subjective norms have a positive influence on EV owners rather than non EV owners. Subjective norm has a positive impact on most of the respondents which are likely to be travelling less than 10km, age is under 25 and involved in other profession rather than full time profession.

Measurement Part of HCM & OL: This part of the model (Table 11) focuses on the relationship between the latent constructs and the measurement indicators involved in the estimation process. The measured items of the attitudinal questions are the results of earlier exploratory factor analysis. The measurement model is shown below in the following table:

Measurement part of the model		
Perceived functional barrier	est	t-ratio
I am concerned about EV range when thinking of buying an EV (PBC2)	1.91***	8.91
Insufficient charging infrastructure makes it difficult to buy an EV(PBC3)	1.27***	9.16
Longer charging time at the charging station discourages me to buy an EV(PBC4)	2.24***	8.41
General Attitude towards EV adoption	est	t-ratio
I believe that buying an EV has a positive effect on the environment than buying a conventional car (i.e., low noise, low emission) (ATB1)	2.75***	9.02
"I think buying an EV is better (good performance-price ratio) than a conventional car in the long run" (ATB2)	2.69***	9.27
"I think it is cool to drive an EV than a conventional car" (ATB3)	1.98***	10.57
Environmental concern on EV adoption	est	t-ratio
"We must act and take decisions to limit greenhouse gases"(EC1)	2.98***	7.34
"I am willing to pay more for supporting environmentally friendly vehicles" (EC2)	1.82***	9.73
"I consider the environmental consequences while choosing a travel mode"(EC3)	2.79***	7.95
Subjective norms on EV adoption	est	t-ratio
"People who are important to me already own an EV" (SN2)	0.50***	4.94
"People who are important to me are considering buying EV" (SN3)	0.88***	7.67
"The excellent advertising by media gave me a positive feeling about buying an EV" (SN4)	3.24***	6.88
"The promotion of EV in social media has influenced me positively about buying an EV"(SN5)	3.43***	6.42

Table 11: Measurement model of HCM & OL

From the above table it can be seen that; all the measurement indicators are statistically significant and positively impact on EV adoption. For instance, the functional barrier for EV adoption, respondents agree positively (positive estimated sign) with the functional barriers related to electric vehicles. Similarly, the environmental concern on EV adoption has also positive effect since the estimates are positive sign that reveals that respondents are aware of the environmentally friendly vehicles. Thus, the benefit of using the HCM is that it links latent constructs with the respondent's characteristics and establish the connection or relations that gives better interpretation and insights which is not possible with simple models.

5.3. Validation of the Modeling Framework (Extended theory of Planned Behavior)

This section validates the use of the Extended theory of planned behavior for EV adoption study to what extent, both of the focused group varies in the latent behavioral constructs as shown in the conceptual model below. Essentially, in this section two different ownership classes have been considered such as EV owners (that includes EV as own car), non EV owner (includes the respondents that do not own EV but have other form of experience with EV such as the company car, rental car, car sharing or no experience at all etc.) which drives further for the filtration of the data into two different sets, resulting in further exploratory factor analysis.

Figure 33: Conceptual Path model for the focused group

As such, the different items of ETPB constructs have been considered as the different predictors and the intentions (adoption intention vs repurchase intentions) of both the ownership classes has been considered as the regressors. Furthermore, the path analysis is done using the Structural equation modeling considering a linear equation between the different latent variables and to observe their effects on the intentions of the focused groups. A set of models have been explored that describes the best latent intentions for both the user group. The final path model has been selected based on the Chi squared test, RMSEA (absolute fit index), CFI (Comparative Fit index) and TLI (Tucker Lewis index). Before proceeding for the path model, it is also necessary to check the internal consistency of the items of latent constructs known as the Cronbach's alpha that describes how closed the set of items are related in a group of items and 'Kaiser Meyer Olkin' (KMO) for sampling adequacy of two different filtered datasets.

5.3.1. Path model for non EV owner group

Two path analysis structure will be developed, one is for EV owners and other is for the respondents belonging to the group of non EV owners. The development of 2 different SEM models is necessary in this case since both of the focused group attended the common ETPB constructs but however, each of the focused group has additionally respondent to an additional attitudinal statement that depicts the 'Repurchase Intention' (only valid for EV owners) and 'Adoption Intention' (only valid for non EV owners). Hence, the decision was made to introduce two different path models to understand collectively the intentions of the consumer for electric vehicles. Note that, the items that have been consider for path models of both focused groups are the results of exploratory factor analysis items with factor loading greater or equal to 0.5 (cut off value) has been retained. Moreover, both of the SEM path models consist of the variables in form of Likert scale which is ordered categorical data with the level of argument staring from 1 to 5. Hence, the decision was taken to use "DWLS", (diagonal weighted least square) method for the estimation procedure instead of "ML" (maximum likelihood), thereby providing unbiased results (Xia & Yang, 2019).

After the suggested procedure of estimation, the model fit becomes better which is indicated by the model fit indices. Following the several trial and error method, the constructs 'SN2' and 'SN3' has been excluded in SEM analysis for 'EV owner' group as indicated by the model fit indices & RMSEA values. The following table 12 gives the description of the model estimates for non EV owners:

Model Estimates	Estimates	Z- value	P-value	Cronbach's Alpha (α)	KMO (overall Sampling adequacy)
Perceived barriers (PBC)					
Measurement Model					
PBC->PBC2R	fixed	-	-		
PBC->PBC3R	0.414***	8.69	0.00		
PBC->PBC4R	0.975***	10.60	0.00		
Subjective Norms (SN)					
SN->SN3	fixed	-	-		
SN->SN2	0.434***	7.65	0.00		
Environmental Concern (EC)					
EC -> EC1	fixed	-			
EC-> EC2	1.369***	9.53	0.00	0.86	0.86
General Attitude towards EV adoption behavior (ATB)					
ATB->ATB1	fixed	-	-		
ATB->ATB2	0.892***	14.67	0.00		
ATB->ATB3	0.898***	14.39	0.00		
Adoption Intention (AI)					
AI->EVNO1	fixed	-	-		
AI->EVNO2	1.149***	14.29	0.00		
Structural Model					
PBC->EVNOI (DE)	0.19***	3.13	0.00		
SN->EVNOI (DE)	0.139***	0.758	0.03		
EC -> EVNOI (DE)	0.22	2.13	0.712		
ATB->EVNOI (DE)	0.64***	0.37	0.00		

Table 12: Estimated SEM path model (non-EV owners/users)

**DE= direct effects on latent construct EVNOI*

From the above table 12, it is seen that all constructs of ETPB (Perceived behavior, General attitude towards behavior, subjective norms, and environmental concern) are significant in terms of the measurement model and are related to the adoption intention of EV. The direct effects of four different latent constructs on adoption intention of non EV owner (EVNOI) are statically significant except the Environmental concern. The path model has a chi-squared test statistics value of 50.91 which is less than the chi-squared critical value and P value of 0.22 > 0.05 suggesting that the model is interpretable, and hence the hypothesis is supported. Thus, it validates that the constructs from the ETPB point of view is relevant for EV adoption. The measurement of the internal consistency i.e., Cronbach's alpha is 0.86, which is a good measure of internal consistency and KMO (MSA) which measures the sampling adequacy is 0.86. Since SEM is a nested CFA, hence these tests are mandatory to check for further analysis. For the structural part of the model, all of the ETPB factors are regressed on the adoption intention of the non EV owners. The results indicates that, PBC, SN and ATB are statistically significant, making a positive relation for EV adoption intention except the 'EC'. This findings is consistent with study that is relevant to EV adoption by authors (S. Wang, Fan, Zhao, Yang, & Fu, 2016), (Shalender & Sharma, 2021) except the 'EC' construct. Hence, the path diagram for adoption intention using the 'lavaan' package in 'R' is depicted below.

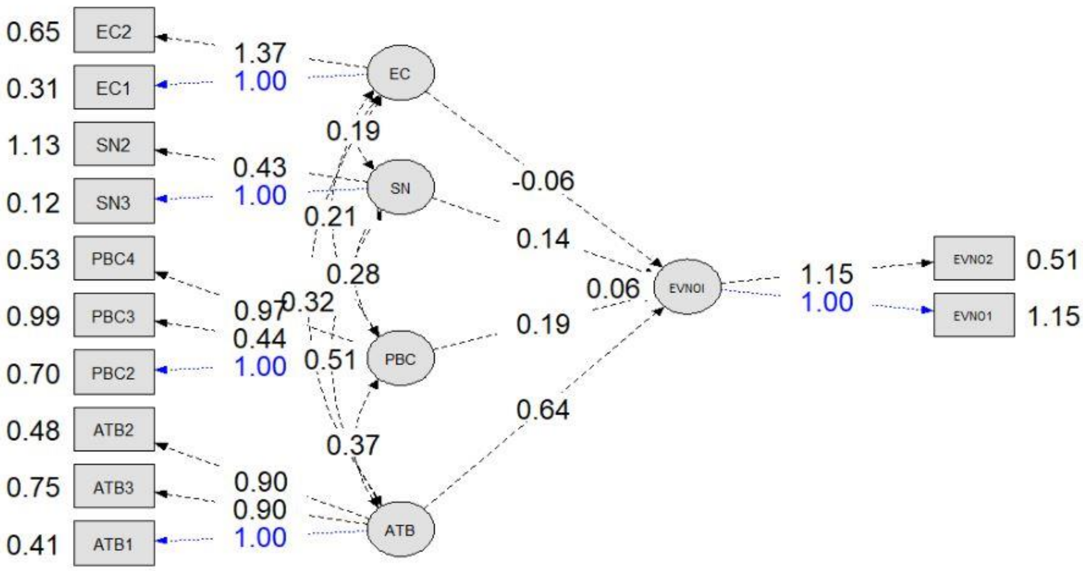


Figure 34:Path diagram for Adoption Intention (non EV owner)

5.3.2. Path model for EV owner group

Similarly, the path model for the focused group of EV owner has also been developed. The model is affected due to the lack of the sample size. The sample size for EV owners is very small,(N=42, KMO =0.5). At first the model does not converges using the ‘lavaan’ package in R (Rosseel, 2012). There after a different approach has been implied so that the model converges yielding a reasonable fit. Different approaches have been suggested for the non-convergence of the model by authors Jonckere & Roseel (2022) such as the penalized likelihood methods or Bayesian estimation procedure. Hence, in order to converge the model a ‘Bounded Estimation’ procedure has been applied, as an effective alternative approach and simple solution (Jonckere & Roseel, 2022). After several trial and error procedure the path model that has been selected here provides the best fit according to the Chi-squared P value test (0.1 > 0.05), RMSEA value and other incremental fit indices. Due to the lack of the sample size, the interpretation of the model likely to be highly skeptical in this case. The direct effects of four different latent constructs on repurchase intention of non EV owner (EVO) are not statically significant except the subjective norm (Z > 1.65). However, the reasonable assumption that can be made from the part of structural model is that the Subjective norm is related to the electric vehicle repurchase intentions (Z>1.65) at 90% CI and also this is in consistent with the literature where subjective norm is relevant for EV repurchase intentions (Hasan, 2021).

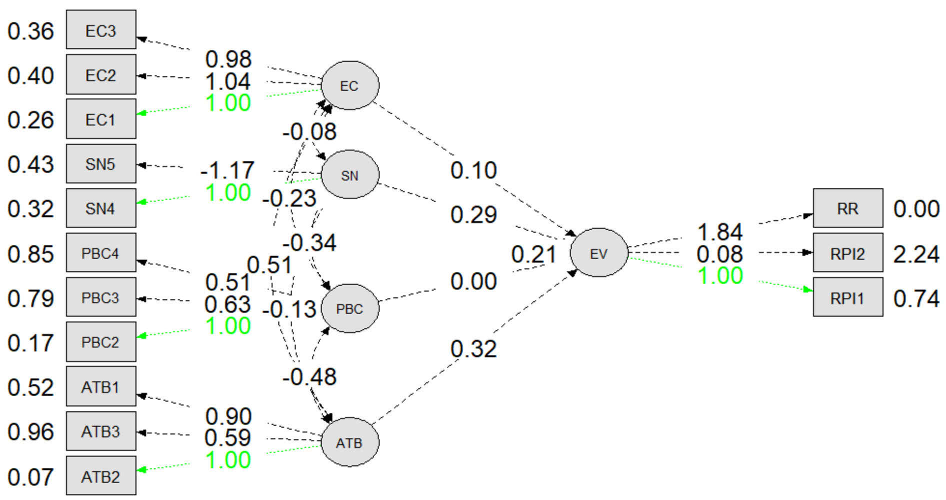


Figure 35:Path diagram for Repurchase Intention (EV owner)

Model Estimates	Estimates	Z- value	P-value	Cronbach's Alpha (α)	KMO (overall Sampling adequacy)
Perceived barriers (PBC)					
Measurement Model					
PBC->PBC2	fixed	-	0.00		
PBC->PBC3	0.63***	4.22	0.00		
PBC->PBC4	0.51***	3.64	0.00		
Subjective Norms (SN)					
SN->SN4	fixed	-	-		
SN->SN5	-1.2***	4.045	0.00		
Environmental Concern (EC)					
EC -> EC1	fixed	-			
EC-> EC2	1.043***	5.20	00.00		
EC-> EC3	0.98***	5.17	0.00	0.74	0.5 (Miserable)
General Attitude towards EV adoption behavior (ATB)					
ATB->ATB2	fixed	17.55	0.00		
ATB->ATB1	0.90***	5.599	0.00		
ATB->ATB3	0.58***	2.997	0.00		
Repurchase Intention (AI)					
RI->RRI1	fixed	-			
RI->RPI2	0.084	0.21	0.829		
RI->RRI3	1.845*	2.635	0.008		
Structural Model					
PBC->EVO (DE)	0.003	0.032	0.98		
SN->EVO (DE)	0.321*	1.65	0.09		
EC -> EVO (DE)	0.102	0.245	0.806		
ATB->EVO (DE)	0.321	0.747	0.455		

Table 13. Estimated SEM path model (EV owners/users)

**DE= direct effects on latent construct (EVO)*

Hence, the model fit indices path model of two different focused group is summarized in the following table:

SL No.	SEM Path model	Sample Size (N)	Comparative Fit Index (CFI)	Threshold range	Tucker Lewis Fit Index (TLI)	Threshold Range	RMSEA	Cronbach's Alpha (α)	KMO (MSA)	Sources
1	Path model for non EV owner (DWLS estimation procedure)	454	0.99	> 0.95	0.99	>0.95	0.02	0.86 (Good)	0.86 (Meritorious)	(Hu & Bentler, 1999) (Xia & Yang, 2019)
2	Path model for EV owner (bounded estimation procedure)	42	0.94	> 0.95	0.92	>0.95	0.06	0.74 (Acceptable)	0.5 (Miserable)	(Kaiser, 1974) (Taber, 2018) (Hooper, Coughlan, & Mullen, 2008),

Table 14. Fit indices for SEM path models

5.4. Willingness to pay (WTP) estimates

Based on the MNL model, where the parameters are statistically significant the willingness to pay for the short and long term charging facility is obtained by simply diving the estimated coefficient of the monetary value. That means, WTP is calculated as the ratio of the two marginal utility parameters. In this regard, however for the calculation of the short time (>75 KW) and long- time charging facilities (11-22KW), attribute of charging time is required which has been associated in the survey choice task in the 'remark' section for each of the alternative 'Option' in the choice experimental section. These values of the charging time are being associated with the charging speed (with higher charging speed means lower charging time and vice versa) and have been replaced respectively maintaining the similar design of the choice experiment. Furthermore, for the calculation of such ratio of the coefficients which are derived from the choice model, including the standard errors of the estimates of the coefficient is done by delta method in 'Apollo' package in 'R' (Hess & Palma, 2019) (see appendix section A4). The function of the delta method has been described much by the authors Daly, Hess, & de Jong (2012). The below figure depicts the scenarios of the WTP for charging EV in public charging station for different Geographical regions:

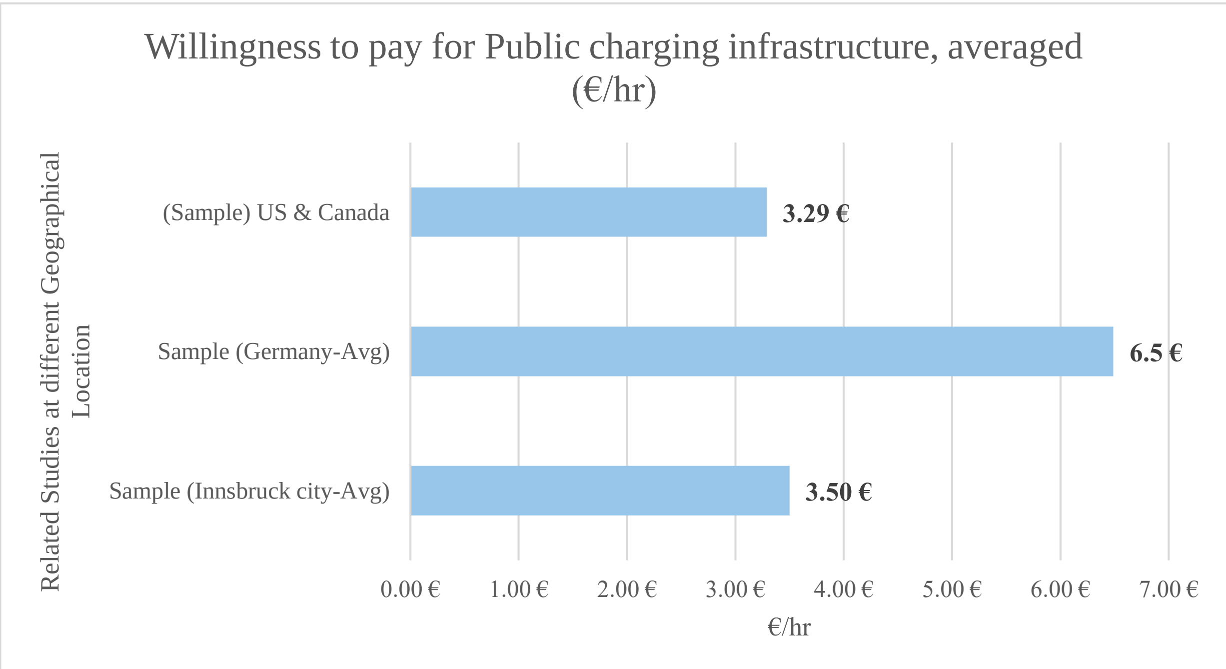


Figure 36:WTP estimates for charging EV in public charging infrastructure

Previous study by (Plenter et al., 2018) for quantifying the WTP for EV charging has been depicted in the above mentioned (fig 36). Although the authors (Plenter et al., 2018) quantified the WTP estimates for different areas including the parking fees, and also recommended further price for charging service per hour, in different locations such as the city center, sub-urban areas ad city. The recommend price suggested by the author (Plenter et al., 2018) in the city areas, per hour ranges from 4.99€ to 7.99€ and it's subjected to the power modality of 11 KW to 22KW.The result obtained from this study is varied due to difference in sample population associated with different demographic backgrounds, different power modalities and different geographical locations. Furthermore from the case study of Germany, the authors (Ensslen et al., 2016) have found that the respondents are willing to pay up to 3.95€ (for > 3.3 KW power modality) per hour of charging at public infrastructure within the regional charging network. Similarly, a recent report from (Bill LeBlanc, 2022) mentioned regarding WTP, that ranges from $3-$4 which is equivalent to 3.29€ (Note: using the conversion rate for US$ to Euro € (1$ = 0.94€) : 1st June 15:15 UTC) for one hour charging in public charging station from the online survey based on respondents of USA and Canada.

5.5. Acceptance/Rejection of Hypotheses:

The below table provides the hypotheses testing results in a summarized form that were involved for different models:

SL No.	Hypotheses	Status
	MNL models	
1	O	Retain
2	X	Reject
3	-	neither reject nor retain
4	-	neither reject nor retain
5	X	Reject
6	X	Reject
7	O	Retain
8	O	Retain
9	-	neither reject nor retain
10	O	Retain
11	-	neither reject nor retain
12	X	Reject
13a	X	Reject
13b	X	Reject
	HCM Models	
14	X	Reject
15	X	Reject
16	X	Reject
17	-	neither reject nor retain
	SEM Path models	
18	O	Supported
19	O	Supported

Table 15: Summarized hypotheses table

6. Discussion

6.1. Discussion on Main Findings:

This section of the research includes the main finds of the result obtained through the Stated preference (SP) survey including a valid and complete response of 496 respondents of the alpine city Innsbruck, Austria. The descriptive statistics between the focused group indicates that the non EV owners are not able to afford EV even with the purchase subsidies and tax benefits provided from the Government. Furthermore, more than 50% of the non EV owner’s population are concerned with the EV range when buying EV. This creates a distinction of preference heterogeneity in the sample population of the focused group. In order to understand the expectations and challenges to different barriers for both of the focused group that includes the EV owner and non-EV owner, a three stage modeling process has been adopted. This is done by starting with the base simple model and gradually moving towards the more complex models by the inclusion of the latent constructs and socio-demographics variables. The simple MNL model gives the result of the different attributes that has been considered in the choice experiment process for SP survey. The base model reveals that, the respondents are willing to prefer a greater utility for having reservation time in EV charging station. The distances of the charging infrastructure are preferred to be near for the respondents since there exists an inverse relation between the distance of the charging points and choice preferences of the respondents. Furthermore, one of the most and commonly cited barrier for the electric vehicle adoption is the charging time with different power modalities. The base MNL model reveals that the respondents giving much more importance to higher charging speed i.e., to have lower charging time. This is true in case of both focused groups. Additionally this is as well consistent with the literature from the authors, Illmann & Kluge (2020). Lastly, the base MNL model also gives insights regarding the price attribute that has been considered in the choice experiment. As the monthly cost with respect to the distance of EV charging infrastructure increases and available power modality with a maximum possible charging state is 80%, respondents are sensitive and have a greater disutility with the increase of the cost associated for charging EV in public charging infrastructure.

The MNL model with SP covariates gives further insights regarding the effect of socio demographics in the sample population and their inclusion interprets a broader meaning of the attributes of the alternatives. These are discussed below:

- *Employment Status:* The MNL model with SP covariates (model 3) reveals that, relative to the student, the part-time working professionals are sensitive to the cost of charging EV at public charging station compared to the full time working professional. This indicates a barrier to the part time working professionals (15%, N=80) for EV adoption. Hence this outcome supports the hypothesis #1. No significant relationship has been observed with respect to the distance attribute and employment status. On the other hand, full time working professional tend to be less sensitive with the cost of the charging plans in public charging infrastructure. This indicates the employment status and its effect on EV charging at public charging stations which in turn related to EV adoption. This is consistent with the study from the authors Tiwari, Aditjandra, & Dissanayake (2020). People who are self-employed seem to be less price sensitive to the cost of EV charging at public charging station. But the outcome of the MNL model with SP covariates rejects this hypothesis #2.

- *Household size :* The monthly cost associated with charging EV at public charging station has also negative effect on the household size. With the increase in household size the sensitivity towards the cost also rises. But again, the variables are not statistically significant to support or reject the null hypothesis #3.

- *Educational status:* No significant relationship has been found with the educational status of the sample population, associated with the cost of charging EV in EV charging station. Due to non-significance evidence from statistical point of view (hypothesis #4), is neither retained nor rejected.

- *Ownership experience:* Interestingly it is found that the respondents who have experience of having EV as their own car are less sensitive towards the monthly cost of charging their EV's at charging stations. Thus, the outcome of the model, rejects the hypothesis #5. Furthermore, it is found that, non-EV owners (using EV as company car) are less sensitive towards the monthly cost of charging their EV's at charging stations. The outcome of the results rejects hypothesis #6. However, findings from (L-Charge, 2021), has mixed results where it depicts that 34% if the EV owners are satisfied while 56% of the EV owners are not satisfied with cost involved in EV charging at public stations. The resulting behavior changes with respect to the distance of the charging station in case of respondents using EV as the company car. This indicates the expectation of the respondents using EV as company car to have more denser charging infrastructure. Thus, the outcome of the result supports in retaining the hypothesis #7 and #8.

- *Age /Number of cars in household / Income:* With middle age category and higher age category tend to be sensitive to the cost of charging EV at EVCS with respect to the younger age group of 18-25. But no significant relation has been observed from the outcome of the model. Thus, hypothesis #9 is neither retained nor accepted. Moreover, number of cars in the household has a significant association with the distance of the charging station. Higher number of cars in household are more sensitive to the distance of the charging station with respect to the household that have one car. The outcome supports the hypothesis #10. Lastly, no significant relation has been observed between respondents' income and cost of charging EV at charging station. Hence, the outcome of the result, neither supports nor rejected hypothesis #11.

- *Mobility pattern of respondents:* Mobility pattern has a significant relation with the cost of charging EV at the charging stations. Respondents who use (1-3days/month) on different mobility has different sensitivity to the cost of charging at the public stations. Respondents who use 'car as driver' relative to public transport users, are less sensitive to the cost of charging their cars at EVCS relative to public transport users. The outcome rejects the hypothesis #12. Furthermore, respondents who uses 'Car Sharing' as travel modes (1-3days/month) are less sensitive to price of charging EV at charging station relative to public transport users. The outcome of the MNL model rejects the hypothesis #13a. From this it indicates the 'Car sharing' users have a positive mindset for EV adoption. Findings from (Clewlow, 2016), found a significant correlation between car sharing adoption and purchase of EV. Moreover, respondents who uses bicycle as travel modes with a very low frequency (1-3days/month), relative to public transport users are also less sensitive to price of charging EV at charging station. The outcome of the MNL model rejects the hypothesis #13b. This might be the fact that low frequency 'bicycle' users are being more environmentally aware and hence is likely to adopt EV early.

Finally, in order to understand the effect of the latent constructs of both potential consumers, a hybrid choice model has been explored that includes the socio demographics and latent constructs such as the perceived functional barriers, attitude towards EV adoption, subjective norms, and environmental awareness for both of the focused group. From the HCM model, which links the consumer characteristics with the latent constructs reveals the insights of the sample data. From the sample data the main findings suggest that the non EV owner agree with the functional barrier of EV which is a barrier for EV adoption as well and the case is opposite in case of non-EV owner. Thus hypothesis #14 is rejected. Respondents who travel longer distance for instance here (more than 10km), agree with the functional barrier of the EV relative to the respondents who travel less kilometers. This is consistent with the findings in a systematic literature reviews by the authors Stockkamp, Schäfer, Millemann, & Heidenreich (2021), and Rezvani, Jansson, & Bodin (2015). ‘Age’ and ‘occupation status‘ are seemed to be non-significant in case of the functional barrier for EV adoption. EV owners agree to the positive attitude towards EV adoption and non EV owners disagree to the positive attitude of EV. Thus hypothesis #15 is rejected. In line with this, non EV owner (with no experience of driving EV at all) found to be less concern about the environment than EV owners. Thus hypothesis #16 is neither retained nor accepted. Respondents traveling for shorter distances also have an environmental awareness. Lastly, the societal influence (Subjective Norms) for EV adoption has a positive impact on EV owners rather than non EV owners. This is consistent with the literature by the authors Jansson, Pettersson, Mannberg, Brännlund, & Lindgren (2017) conducted for their study for adoption of AFV. Thus hypothesis #17 is neither retained nor rejected.

Moreover, the descriptive statistics shows that most of the trip made by the sample respondents (70%) are within the range of 20km, and hence no preference of the highway charging facilities have been observed while selecting the location preference for both of the focused group within this sample size. This is in turn a crucial fact behind the choice modeling part of the survey, since the perception of the respondents for choosing the location of the charging infrastructure, is closely related to the choice tasks presented to them. Both of the focused group have a similar trend while choosing the location preferences. This is in fact also observed from the choice models (MNL models), where the consumers have greater disutility with the increase in the distance of the charging stations. Furthermore, reservation time has a significant association at charging infrastructure. Respondents prefer having a reservation time which ensures a reservation spot in charging the EV as can be seen from the MNL models. Since, parking fees are not included by the service provider (IKB), benefit of inclusion of the reservation time ensures the reserving a spot for EV which is in fact a crucial factor for wider EV adoption. With the increases in the charging infrastructure, the range anxiety of the EV will be reduced. The inhabitants of the Innsbruck city need to understand the investing on EV is more profitable than CGV due to the lower operational cost in long run.

Lastly, willingness to pay measures have also been explored to understand consumers behaviour for short- and long-term charging facilities. Consumers are willing to pay almost double (2.8 €/hr to 4.2 €/hr) for additional hour of charging EV at fast/ rapid public charging stations considering the factors that the charging stations are within the nearby distances with inclusion of reservation time.

6.2. Limitation of the Study:

This study has some limitations and several assumptions while carrying out the research. Firstly, the choice experiment settings, different prohibitions have to be introduced in order to mitigate the problem of dominant alternatives and to provide a meaningful choice experiment. In doing so, it compromises the design strength of the efficient designs of the choice experiments but has been done within the threshold range prescribed by the sawtooth software (such as the two way frequency test, and standard errors). Because of the prohibitions, the different combination of the attribute's levels is missing from the choice experiment and hence which cannot be explored in the choice models. Although, the outcome of the 'a-priori' estimates for the efficient designs yields expected signs (positive / negative signs) for the estimates of the attributes.

Secondly, in order to reduce the cognitive burden of the respondents, the survey questionnaire has been restricted to six choice scenarios (minimum number of choice tasks has been calculated before). Moreover, the experimental design has been developed based on the generic parameters with unlabeled choice alternatives along with forced discrete choice experiment. As such, the only way to include the sociodemographic effects in the choice model is to make a meaningful interaction between attributes of the alternatives. Since all of the explanatory variables are constant across the alternatives. Alternatively, alternate specific parameters with the inclusion of the 'none' alternative could have been developed in order to explore main effects of the variables as well as the interaction effects. Pilot survey has not been involved in this study.

Thirdly, the sample size of the survey with only 496 valid responses, allowing 2976 observation points. Although around 105 invalid responses have not been considered for the sake of simplicity, a proper way of handling those invalid responses (by optimal imputation method) would provide more insights from the choice model. Out of 496 respondents, 454 (91.5%) respondents are the non EV owners and only 42 (8.46 %) sample size consists of the EV owner. Although the number of EV population in Innsbruck is very low compared to the other federal states of Austria. As such, the study has suffered from different potential sample bias along with other socio demographic profiles. The different choice models (MNL, HCM) had to explored in order to answer the different perspective of the biased sample characteristics.

Due to the possible sample bias, Mixed logit model has not been explored, which might explain different taste heterogeneity across the respondents. In line with the preference heterogeneity, the Latent class model for the class segmentation has not been explored due to smaller sample size of one group. Furthermore, the analysis of the structural equation modeling especially the path models for the validation of the ETPB constructs, suffers some limitations. Hence, the interpretation of the path model might be highly skeptical in this case (for EV owners).

Lastly, while developing the hybrid choice model, an assumption has been made regarding the attitudinal constructs. Apart from the constructs of the extended theory of planned behavior, there are two additional constructs for the group specific which have been focused to understand the latent intentions such as, repurchase intention (construct for EV owners) and adoption intention (construct for the non EV owners). A decision was made to incorporate only the latent constructs of ETPB in HCM model. Finally, HCM model (HCM framework presented in this study) with 500 Halton draws has been developed as the final result, obviously with more Halton draws and exploring different HCM framework settings, the results would become much better provided the AIC and BIC model fits but again this requires much more computational and time effort which was uncertain due to logistic support.

7. Conclusion and Further development

7.1. Conclusion:

This study uses the theory of planned behavior in an extended version by the inclusion of the construct ‘Environmental Concern’ from the point of view of the two different focused group namely EV owners and non EV owners to understand the latent intentions of these focused groups. The findings of MNL model with SP covariates of the consumer characteristics shows that the full time working professionals are less sensitive compared to the part time working professionals where self-employed respondents also shows less sensitive with the cost of charging EV in charging stations. Within this sample size, no significant effect has been observed with respect to age, gender, and income. Respondent’s mobility behavior has shown a significant relation with the price associated to charge EV in charging stations. In conclusion from the MNL model, it can be said that both of the focused group prefer nearby charging distances, inclusion of the reservation time in charging station, and faster charging speed along with additional services in EVCS. From the findings it is found that, the barrier for the adoption intentions of the non EV owner group are the functional barriers of the electric vehicles such as the longer charging time, cruising range, insufficient charging infrastructure. Although, with the technological advancement, different range extended EV’s offers promising cruising range with good battery backups. In case of the EV owner group, repurchase intentions of electric vehicles primarily driven by the subjective norms, or the societal influence. These adoption barriers need to be mitigated since future of the mobility is electric, and Innsbruck goal of sustainable mobility for smart city initiative requires an early adoption of EV in a wider range to achieve the target of *‘Sustainable Development Goals #11 (Sustainable cities and communities)*’. The different purchase subsidies and tax benefits from the central Government is an effective way for EV promotion. But even still, with purchase subsidies and tax benefits, the purchasing cost of EV’s are still way too high for different socio-demographic backgrounds. Furthermore, the density of the fast charging stations is centered around only in the inner city (from the heatmap visualization). For more wider network of the EV, the charging stations more specifically faster charging speeds needs to be scattered to the different location based on the demand of the EV. Respondents are willing to pay additionally 4.2€ per hour for charging in fast charging stations (short term charging facilities) with certain amenities as beneficial factors. A robust planning for the installation of fast charging infrastructure, inclusion of the reservation time and different amenities surrounding EVCS must be considered for widespread EV adoption including more balanced support and close cooperation from the Government, automotive industries, stakeholder associations, city authorities, and charging service providers. This study further provides the policy implication in the framework of consumer's intention and location of the public charging stations in Innsbruck city.

7.2. Policy Implications:

Installation of the charging infrastructure is necessary for wider EV adoption. At the same time, focusing only on charging stations with less attractive EV purchase price will lead to unbalanced growth. Rather than installing various charging infrastructure at different locations, an integrated charging location with different household could be implemented. Hence, some of the different measures that can be considered in the policy implication scenarios are discussed shortly:

Different cities in Austria have developed the concept called 'Model Region' that focused on electric mobility. This enables vehicle to grid integration so called 'Smart Grid Model' that consists of different household or even a community. As the electricity produced through the renewable energies, the same energy can be restored to the grid supply. This allows for optimum use of the energy being generated and thereby optimizing the utilization rate of EVCS. A flagship project is being tested in the neighboring state in Salzburg (köstendorf community) integrating different households with electric cars (Klimafonds.gv.at, 2015). Furthermore, to mitigate the commonly cited factors that are barriers for EV penetration such as the range anxiety, longer charging time at EVCS, a wireless charging or inductive charging technologies can be adopted in near future for more wider EV penetration and adoption. From the findings of hybrid choice model, it is found that the non EV owner are less concern with the environment consequences associated with gasoline vehicles. In this case, stringent policy for banning of the commercial gasoline vehicle inside the city might be another way to combat with the barriers for EV adoption. In light of this statement, many countries have pure electrification targets by banning of the commercial gasoline vehicle at different timelines (International energy agency, 2021). With the growth of fast charging infrastructures, the location of the fast charging should contain different amenities surrounding it, which would be able to trigger the wider acceptance of charging EV in charging stations**.** Although excessive installation of the fast charging infrastructure will result in less utilization rate. Hence in order to have a systematic growth between charging points and registered electric vehicles, a well-balanced 'demand and supply interactions' should be considered at first. Benefits of having the fast chargers is required which might have a positive social outcome with wide visibility of the EV charging stations in Innsbruck city. A reliable coverage of the EV charging station is required for large scale EV uptake. A study by Bahamonde-Birke & Hanappi (2016) in Austria, have suggested in their findings for a reliable coverage of charging station.

7.3. Further development / Recommendation:

The study can further be developed by exploring from different periphery of the study area and these are mentioned below shortly:

I. The choice experiment part of the study can be improved by involving more choice tasks or scenarios and inclusion of alternative specific design such as the station based and inclusion of the non-alternative. Such design allows to investigate main effects as well as interaction effects in the model development. The aspects of the discrete choice experiment can further be developed considering the 'best' & 'worst' choice experiment. Increasing the number of sample size or considering invalid responses by different imputation methods within this experimental design can be considered for further developments.

II. In order to study, the latent intentions of the EV owners revealed preference survey can be considered to closely monitor or observe the travel behaviors. The study can be taken further by integrating revealed and stated preference together.

III. Further approach can be ascertained in the stated preference survey such as inclusion of the gamified survey to understand the response behavior from the sample population. A notable example in this area done by the authors Dorcec, Pevec, Vdovie, Babic, & Podobnik (2018) to explore the willingness to pay for EV charging.

IV. SP survey can be improved by including the 'choice scenarios' in form of animation clips or video graphics. This might be able to attract more respondents as the repeated choice task or scenarios becomes cognitive burden to the respondents and sometimes subjected to the potential bias, due to conventional repeated text based surveys.

V. Since the study consists of two different focused group, Mixed logit models could have been implemented or else a special example of hybrid choice model, inclusion of the latent classes with integrated choices (ICLV) model can be explored to understand the preference heterogeneity of the different classes or group in the sample population.

VI. Lastly, in order to understand the location of the charging infrastructure, the demand for the electric vehicles in particular area or zones is required or the OD data from EV is required. With suitable available data, a notable example in this research plethora by the authors Efthymiou, Chrysostomou, Morfoulaki, & Aifantopoulou (2017) can be carried out using the genetic algorithm approach to investigate the deployment of optimal number of charging infrastructure for an area or zone.

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Declaration

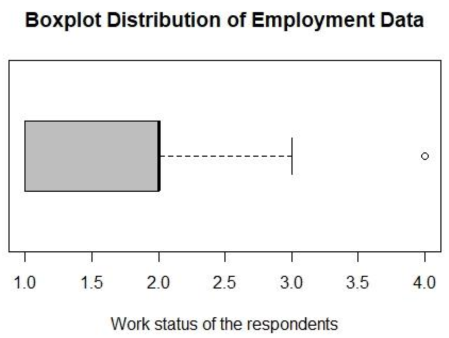
I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

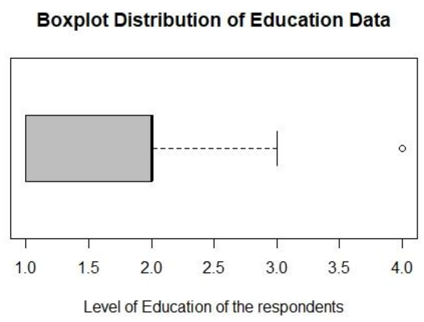
Munich, 15.06.2022, Yashin Abdullah Ali

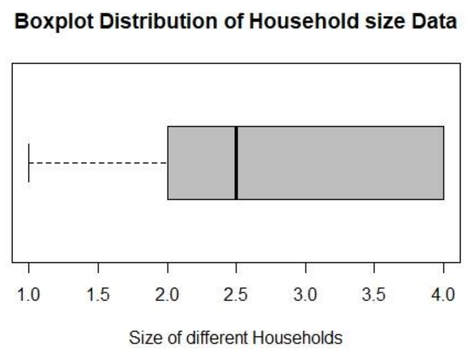
Place, Date, Signature

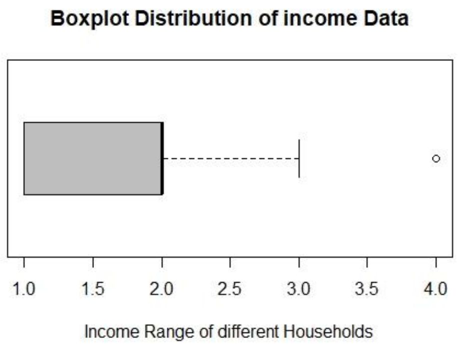
8. Appendix

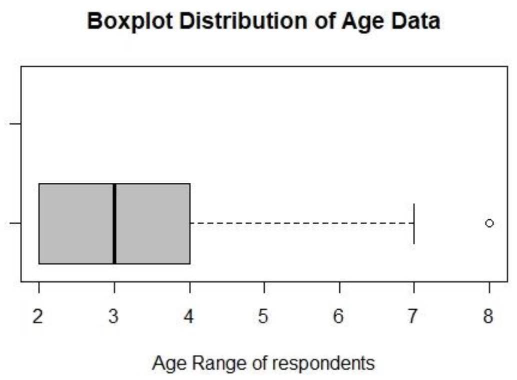
Appendix (A1): Box plot distribution of socio demographic variables

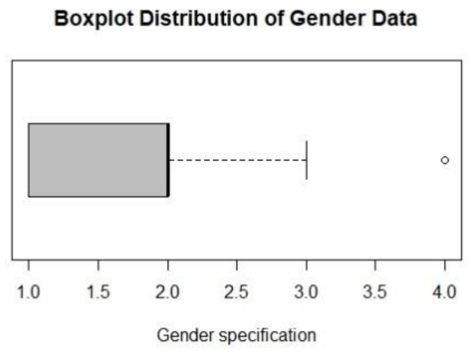












Appendix (A2): Experimental Design and Prohibition Matrix

Version	Task	Concept	Att 1 - Charging station distance	Att 2 - Reservation	Att 3 - Charging Speed	Att 4 - Monthly Price
1	1	1	1	3	2	2
1	1	2	2	2	1	3
1	1	3	3	1	3	1
1	2	1	3	3	1	3
1	2	2	2	1	2	2
1	2	3	1	2	3	1
1	3	1	1	1	2	3
1	3	2	3	2	1	2
1	3	3	2	3	3	1
1	4	1	2	3	3	1
1	4	2	1	1	1	2
1	4	3	3	2	2	3
1	5	1	3	1	3	1
1	5	2	2	2	3	2
1	5	3	1	3	1	3
1	6	1	2	1	1	3
1	6	2	1	2	3	1
1	6	3	3	3	2	2

Table 16: Experimental design (1st block)

Prohibition Matrix	A4L1 (Price=55)	A4L2 (Price=75)	A4L3 (Price=95)
A3L1 (Moderate)	**X**	**ok**	**ok**
A3L2 (Fast)	**X**	**ok**	**ok**
A3L3 (Rapid)	**ok**	**ok**	**X**

Table 17: Prohibition Matrix (Price & Charging Speed)

Attributes	Levels	Level 1 (L1)	Level 2 (L2)	Level 3 (L3)
Charging station distance (m) (A1)	3	500	1000	1500
Reservation Time (A2)	3	No	15 min	30 min
Charging Power (KW) (A3)	3	Moderate (11-22) KW	Fast (50-75)KW	Rapid (>75)KW
Price (€) (A5)	3	55	75	95

Table 18: Attributes and Levels of experimental design

Appendix (A3): Word Cloud Text (used in the questionnaire survey from the project report of IKB (Sarker & Morshed, 2020)

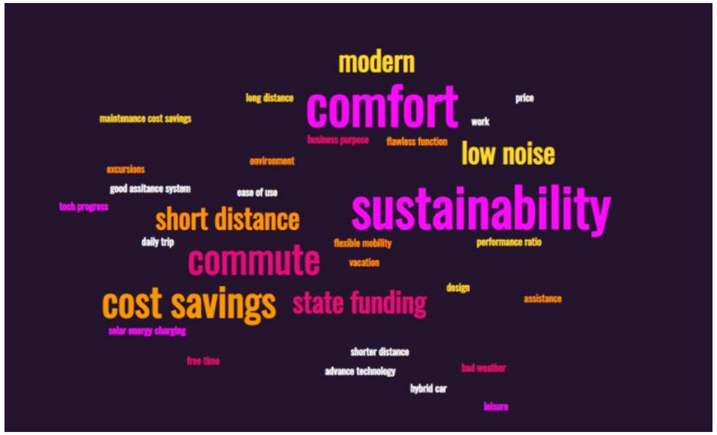


Figure 38: Benefits of EV (Respondents with age group from 25-50 & up

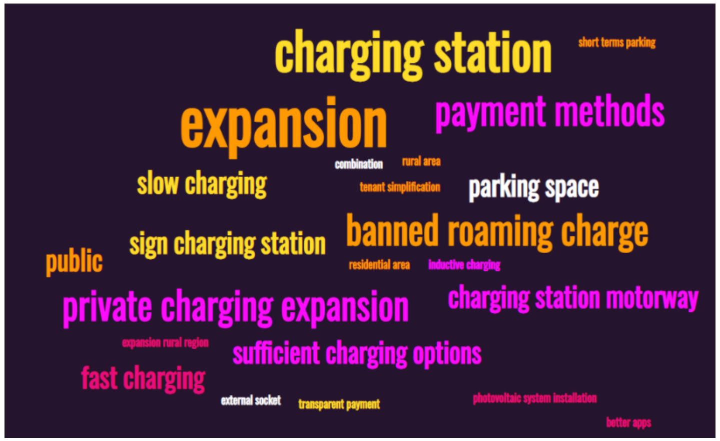


Figure 37: Problems with EV (Respondents with age group from 25-50 & up)

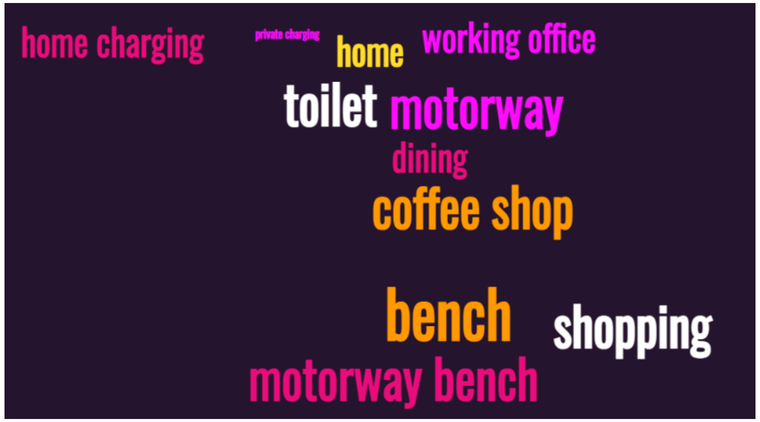


Figure 39: Amenities in Charging Stations (Respondents with age group from 25-50 & up)

Appendix (A4): Apollo ‘R’ Model scripts (Hess & Palma, 2022) & WTP standard errors

MNL models excluding’ ASC’- Utility specifications

V [['Option_1']] = b_dist * Distance_1 +b_resv * Reservation_1 +

b_cost * Price_1 + b_cspeed * Charging_Speed_1

V [['Option_2']] = b_dist * Distance_2 +b_resv * Reservation_2 +

b_cost * Price_2 + b_cspeed * Charging_Speed_2

V [['Option_3']] = b_dist * Distance_3 +b_resv * Reservation_3 +

b_cost * Price_3 + b_cspeed * Charging_Speed_3

MNL models including’ ASC’- Utility specifications

V [['Option_1']] = ASC_1 + b_dist * Distance_1 +b_resv * Reservation_1 +

b_cost * Price_1 + b_cspeed * Charging_Speed_1

V [['Option_2']] = ASC_2 + b_dist * Distance_2 +b_resv * Reservation_2 +

b_cost * Price_2 + b_cspeed * Charging_Speed_2

V [['Option_3']] = ASC_3+ b_dist * Distance_3 +b_resv * Reservation_3 +

b_cost * Price_3 + b_cspeed * Charging_Speed_3

WTP estimates with standard error

Items	€/min	€/hr.	Robust s.e	Rob t-ratio
WTP=(Beta Charging time/Beta Cost)-> Long term Charging (11-22KW)	0.05	2.8	0.006	7.733***
WTP=(Beta Charging time/Beta Cost)-> Short term Charging (>75KW)	0.07	4.2	0.009	7.712***

MNL-SP models including' ASC'- Utility specifications

V[['Option_1']] = asc_1 +b_resv * Reservation_1 +b_cpeed * Charging_Speed_1 +b_dist*Distance_1+b_cost*Price_1+b_ft*(workstatus==1)*Price_1+b_pt*(workstatus==2)*Price_1+b_student*(workstatus==3)*Price_1+b_student*(workstatus==3)*Price_1+b_ret*(workstatus==6)*Price_1+b_selfemp*(workstatus==7)*Price_1+b_other*(workstatus==8)*Price_1+ b_hh1*(HHsize==1)*Price_1+b_hh2*(HHsize==2)*Price_1+b_hh3*(HHsize==3)*Price_1+b_hh4*(HHsize==4)*Price_1+ b_ca1*(CarAvail==2)*Distance_1+b_ca2*(CarAvail==3)*Distance_1+b_TR1*(Travelmodes_r1==1)*Price_1+b_TR2*(Travelmodes_r2==1)*Price_1+ b_TR3*(Travelmodes_r3==1)*Price_1+b_TR4*(Travelmodes_r4==1)*Price_1+b_TR5*(Travelmodes_r5==1)*Price_1+b_age2*(Age==2)*Price_1+b_age3*(Age==3)*Price_1+b_age5*(Age==5)* Price_1+b_st*(Edu==4)*Price_1+b_mschl*(Edu==2)*Price_1+b_sschl*(Edu==3)*Price_1+b_cschl* (Edu==1)*Price_1+b_EVO_OC*(ECar==1)*Price_1+b_EVNO_CC*(ECar==3)*Price_1+b_EVO_OCD*(ECar==1)*Distance_1+b_EVNO_CCD*(ECar==3)*Distance_1+ b_binc*(income==1)*Price_1+b_ainc*(income==2)*Price_1+ b_aainc*(income==3)*Price_1+b_nts*(income==4)*Price_1

V[['Option_2']] = asc_2 +b_resv * Reservation_2 +b_cpeed * Charging_Speed_2 +b_dist*Distance_2+b_cost*Price_2+b_ft*(workstatus==1)*Price_2+b_pt*(workstatus==2)*Price_2+b_student*(workstatus==3)*Price_2+b_student*(workstatus==3)*Price_2+b_ret*(workstatus==6)*Price_2+b_selfemp*(workstatus==7)*Price_2+b_other*(workstatus==8)*Price_2+ b_hh1*(HHsize==1)*Price_2+b_hh2*(HHsize==2)*Price_2+b_hh3*(HHsize==3)*Price_2+b_hh4*(HHsize==4)*Price_2+ b_ca1*(CarAvail==2)*Distance_2+b_ca2*(CarAvail==3)*Distance_2+b_TR1*(Travelmodes_r1==1)*Price_2+b_TR2*(Travelmodes_r2==1)*Price_2+ b_TR3*(Travelmodes_r3==1)*Price_2+b_TR4*(Travelmodes_r4==1)*Price_2+b_TR5*(Travelmodes_r5==1)*Price_2+b_age2*(Age==2)*Price_2+b_age3*(Age==3)*Price_2+b_age5*(Age==5)* Price_2+b_st*(Edu==4)*Price_2+b_mschl*(Edu==2)*Price_2+b_sschl*(Edu==3)*Price_2+b_cschl* (Edu==1)*Price_2+b_EVO_OC*(ECar==1)*Price_2+b_EVNO_CC*(ECar==3)*Price_2+b_EVO_OCD*(ECar==1)*Distance_2+b_EVNO_CCD*(ECar==3)*Distance_2+ b_binc*(income==1)*Price_2+b_ainc*(income==2)*Price_2+ b_aainc*(income==3)*Price_2+b_nts*(income==4)*Price_2

V[['Option_3']] = asc_3 +b_resv * Reservation_3 +b_cpeed * Charging_Speed_3 +b_dist*Distance_3+b_cost*Price_3+b_ft*(workstatus==1)*Price_3+b_pt*(workstatus==2)*Price_3+b_student*(workstatus==3)*Price_3+b_student*(workstatus==3)*Price_3+b_ret*(workstatus==6)*Price_3+b_selfemp*(workstatus==7)*Price_3+b_other*(workstatus==8)*Price_3+ b_hh1*(HHsize==1)*Price_3+b_hh2*(HHsize==2)*Price_3+b_hh3*(HHsize==3)*Price_3+b_hh4*(HHsize==4)*Price_3+ b_ca1*(CarAvail==2)*Distance_3+b_ca2*(CarAvail==3)*Distance_3+b_TR1*(Travelmodes_r1==1)*Price_3+b_TR2*(Travelmodes_r2==1)*Price_3+ b_TR3*(Travelmodes_r3==1)*Price_3+b_TR4*(Travelmodes_r4==1)*Price_3+b_TR5*(Travelmodes_r5==1)*Price_3+b_age2*(Age==2)*Price_3+b_age3*(Age==3)*Price_3+b_age5*(Age==5)* Price_3+b_st*(Edu==4)*Price_3+b_mschl*(Edu==2)*Price_3+b_sschl*(Edu==3)*Price_3+b_cschl* (Edu==1)*Price_3+b_EVO_OC*(ECar==1)*Price_3+b_EVNO_CC*(ECar==3)*Price_3+b_EVO_OCD*(ECar==1)*Distance_3+b_EVNO_CCD*(ECar==3)*Distance_3+ b_binc*(income==1)*Price_3+b_ainc*(income==2)*Price_3+ b_aainc*(income==3)*Price_3+b_nts*(income==4)*Price_3

Appendix (A5): HCM model & OL(ordered logit) – Utility specification:

Ordered logit settings measurement model

ol_settings1 = list(outcomeOrdered = PBC2, V = zeta_perceive_2*LV_PBC, tau = list(tau_perceive2_1, tau_perceive2_2, tau_perceive2_3, tau_peceive2_4),rows = (Task==1), componentName = "PBC_2")

ol_settings2 = list(outcomeOrdered = PBC3, V = zeta_perceive_3*LV_PBC, tau= list(tau_perceive3_1, tau_perceive3_2, tau_perceive3_3, tau_perceive3_4),rows = (Task==1), componentName = "PBC_3")

ol_settings3 = list(outcomeOrdered = PBC4, V = zeta_perceive_4*LV_PBC, tau = list(tau_perceive4_1, tau_perceive4_2, tau_perceive4_3, tau_perceive4_4),rows = (Task==1), componentName = "PBC_4")

ol_settings4= list(outcomeOrdered = SN2, V = zeta_SN_2*LV_SN, tau = list(tau_SN2_1, tau_SN2_2, tau_SN2_3, tau_SN2_4),rows = (Task==1),componentName = "SN_2")

ol_settings5 = list(outcomeOrdered = SN3, V= zeta_SN_3*LV_SN, tau = list(tau_SN3_1, tau_SN3_2, tau_SN3_3, tau_SN3_4),rows = (Task==1),componentName = "SN_3")

ol_settings6= list(outcomeOrdered = SN4, V = zeta_SN_4*LV_SN, tau = list(tau_SN4_1, tau_SN4_2, tau_SN4_3, tau_SN4_4), rows = (Task==1), componentName = "SN_4")

ol_settings7 = list(outcomeOrdered = SN5, V = zeta_SN_5*LV_SN, tau = list(tau_SN5_1, tau_SN5_2, tau_SN5_3, tau_SN5_4), rows = (Task==1), componentName = "SN_5")

ol_settings8 = list(outcomeOrdered = EC1, V= zeta_EC_1*LV_EC, tau = list(tau_EC1_1, tau_EC1_2,tau_EC1_3,tau_EC1_4), rows = (Task==1), componentName = "EC_1")

ol_settings9 = list(outcomeOrdered = EC2, V = zeta_EC_2*LV_EC, tau = list(tau_EC2_1, tau_EC2_2, tau_EC2_3, tau_EC2_4), rows = (Task==1), componentName = "EC_2")

ol_settings10 = list(outcomeOrdered = EC3, V = zeta_EC_3*LV_EC, tau = list(tau_EC3_1, tau_EC3_2,tau_EC3_3,tau_EC3_4), rows = (Task==1),componentName = "EC_3")

ol_settings11 = list(outcomeOrdered = ATB1, V= zeta_ATB_1*LV_ATB, tau = list(tau_ATB1_1, tau_ATB1_2,tau_ATB1_3,tau_ATB1_4), rows = (Task==1),componentName = "ATB_1")

ol_settings12 = list(outcomeOrdered = ATB2, V = zeta_ATB_2*LV_ATB, tau = list(tau_ATB2_1, tau_ATB2_2, tau_ATB2_3, tau_ATB2_4), rows = (Task==1),componentName = "ATB_2")

ol_settings13 = list(outcomeOrdered = ATB3, V = zeta_ATB_3*LV_ATB, tau = list(tau_ATB3_1, tau_ATB3_2,tau_ATB3_3,tau_ATB3_4), rows = (Task==1),componentName = "ATB_3")

HCM settings for structural model

V [['Option_1']] = ASC_1 + b_dist * Distance_1 +b_resv * Reservation_1 + b_cost * Price_1 + b_cspeed * Charging_Speed_1+ lambda2_1*LV_PBC +lambda2_2*LV_SN+lambda2_3*LV_EC +lambda2_4*LV_ATB

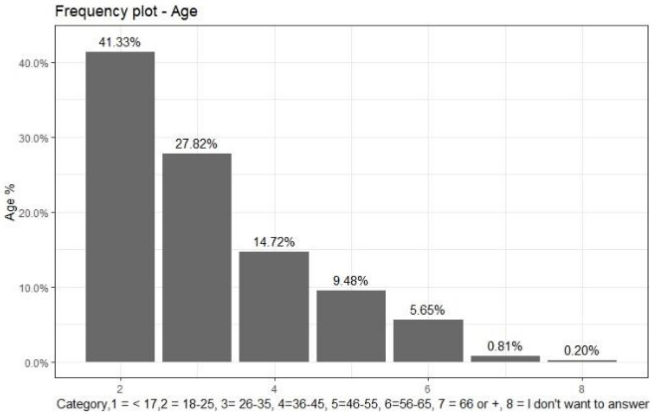
V [['Option_2']] = ASC_2 + b_dist * Distance_2 +b_resv * Reservation_2 +b_cost * Price_2 + b_cspeed * Charging_Speed_2+ lambda2_1*LV_PBC +lambda2_2*LV_SN+lambda2_3*LV_EC +lambda2_4*LV_ATB

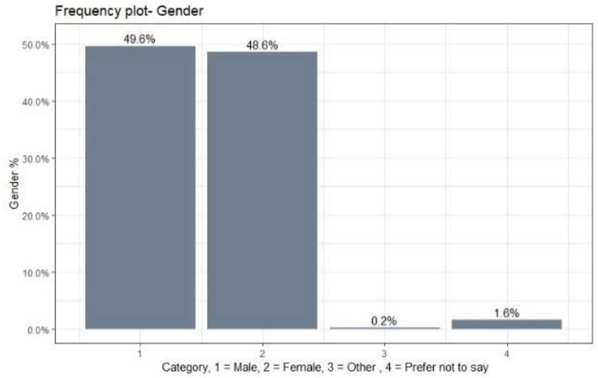
V [['Option_3']] = ASC_3+ b_dist * Distance_3 +b_resv * Reservation_3 +b_cost * Price_3 + b_cspeed * Charging_Speed_3

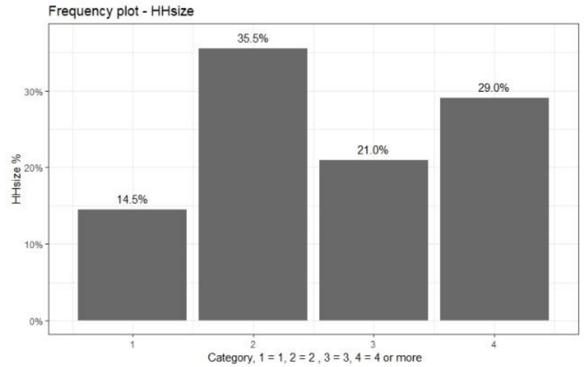
Halton draws vs (AIC & BIC)

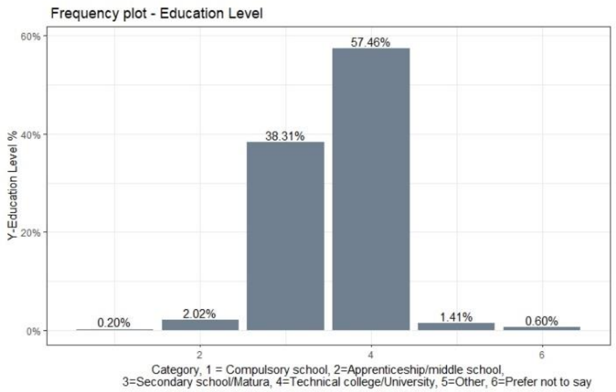
HCM +OL models		
Halton draws	AIC	BIC
150	19752	20431
200	19773	20453
300	19721	20401
500	**19697**	**20376**

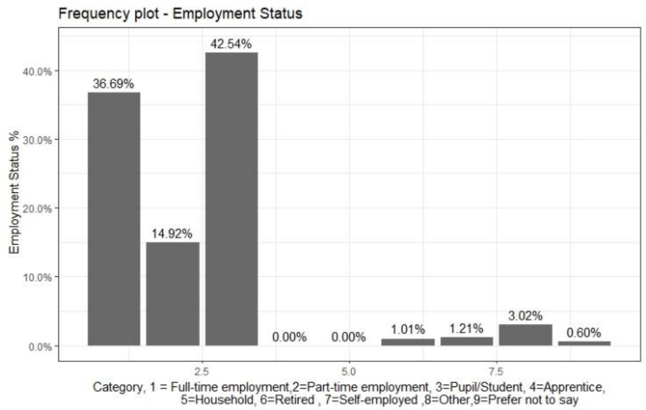
Appendix (A6): Descriptive statistics of the Socio-demographic variables from the responses of the sample population

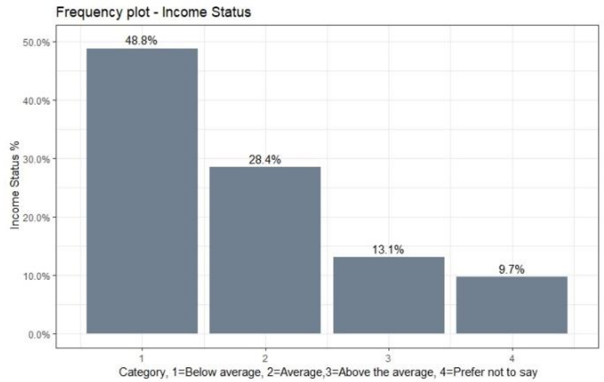




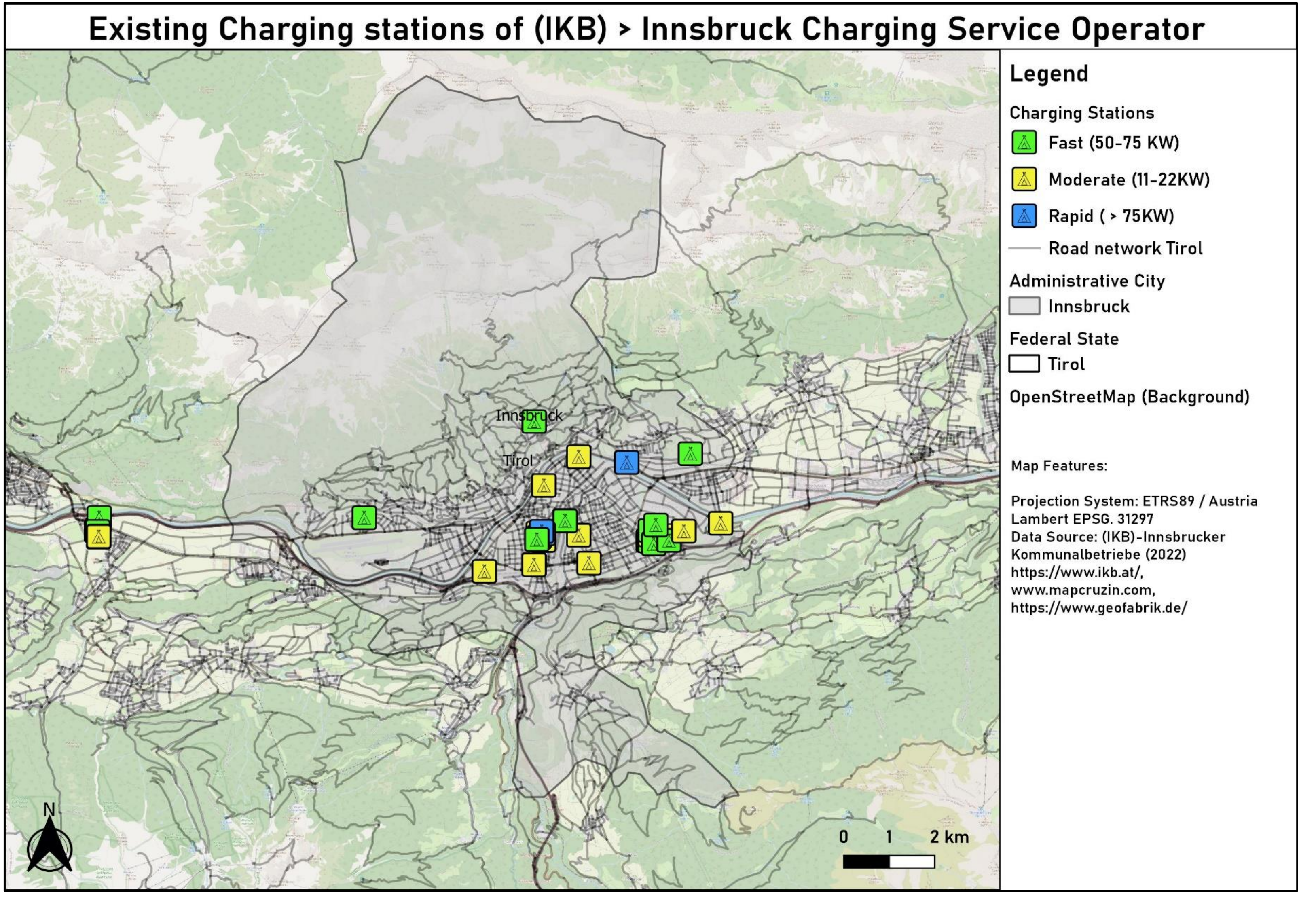








Appendix (A7): Distribution of the existing charging system



Appendix (A8): List of Attitudinal Constructs with sources-ETPB

SL No.	Attitudinal Statements	Attitudinal factor	Description/Title	Mean	Std Dev	Remarks/ Source	Items Coded
1	*I am not able to afford an EV even with the purchase subsidies and tax exemption by the Government*	Perceived behavioral control (PBC)	Not able to afford	3.2	1.32	Created for this study	PBC1
2	*I am concerned about EV range when thinking of buying an EV*		Concern EV	3.3	1.29	Created for this study	PBC2
3	*Insufficient charging infrastructure makes it difficult to buy an EV*		Charging infrastructure insufficient	3.7	1.11	Created for this study	PBC3
4	*Longer charging time at the charging station discourages me to buy an EV*		Longer Charging time	2.8	1.208	Created for this study	PBC4
5	*I will worry about battery life and battery disposal if I buy an EV*		Battery life Concern	3.6	1.208	Created for this study	PBC5
6	*Concerns with residual/resale value discourage me to buy an EV*		Resale/residual value of EV	2.44	1.15	Modified from (M. K. Kim et al., 2018))	PBC6
7	*I believe that buying an EV has a positive effect on the environment than buying a conventional car (i.e., low noise, low emission).*	General Attitude towards EV adoption (ATB)	Positive effect on environment	3.77	1.14	Created for this study	ATB1
8	*I think buying an EV is better (good performance-price ratio) than a conventional car in the long run*		Performance/Price ratio	3.45	1.1	Modified from (M. K. Kim et al., 2018)	ATB2
9	*I think it is cool to drive an EV than a conventional car*		Cool to Drive EV	3.25	1.23	Modified from (Haustein, Jensen, & Cherchi, 2021)	ATB3
10	*"People in my life, whose opinion I value, would support my decision of purchasing EV"*	Subjective Norms (SN)	Opinion value	3.55	0.99	Created for this study and modified from (Ajzen, 2002)	SN1
11	*"People who are important to me already own an EV"*		People important	2.39	1.22	Adapted from (Haustein et al., 2021)	SN2
12	*"People who are important to me are considering buying EV"*		Consideration of buying EV	2.97	1.17	Adapted from (Haustein et al., 2021)	SN3

13	*The excellent advertising by media gave me a positive feeling about buying an EV*	Subjective Norms (SN)	Advertising by media	2.43	1.02	Modified from (Yan et al., 2019)	SN4
14	*The promotion of EV in social media has influenced me positively about buying an EV*		Promotion of EV	2.35	1.07	Modified from (Moons & de Pelsmacker, 2012)	SN5
15	*"We must act and take decisions to limit greenhouse gases"*	Environmental Concern (EC)	Limit GHG	4.52	0.79	Adapted from (Sarker, 2021)	EC1
16	*"I am willing to pay more for supporting environmentally friendly vehicles"*		Environmentally friendly vehicle	3.62	1.1	Adapted from (Sarker, 2021)	EC2
17	*"I consider the environmental consequences while choosing a travel mode"*		Environmental consequences	4.04	0.99	Adapted from (Sarker, 2021)	EC3
18	*"I am willing to buy an electric car in near future"*	EV adoption intention (non-user, n = 454)	Willing to buy EV	3.24	1.57	Adapted from (Mohamed, Higgins, Ferguson, & Kanaroglou, 2016)	EVNOI1
19	*I am willing to forgo some advantages with conventional car (e.g., less concern with fueling) to buy an EV*		Forgo advantage of CGV	3.65	1.51	Created for this study	EVNOI2
20	*"I am willing to spend more money to buy an EV"*		Spend more money	2.97	1.44	Adapted from (Mohamed et al., 2016)	EVNOI3
21	*I am satisfied with my current EV, and will purchase EV again if necessary*	EV repurchase intention, (EV Owners, n=42)	Satisfaction of EV	2.57	1.2	Modified from (Jabeen, Olaru, Smith, Braunl, & Speidel, 2014) & (Kwon, Son, & Jang, 2020)	RPI1
22	*I am currently using EV as my second car and will completely shift to EV in future*		Second car as EV	1.54	0.83	Created for this study	RPI2
23	*I am not happy with my current EV and will return to my conventional car*		Unhappy with EV	3.24	0.52	Created for this study	RPI3

Appendix (A9): Parallel analysis and Scree Plot

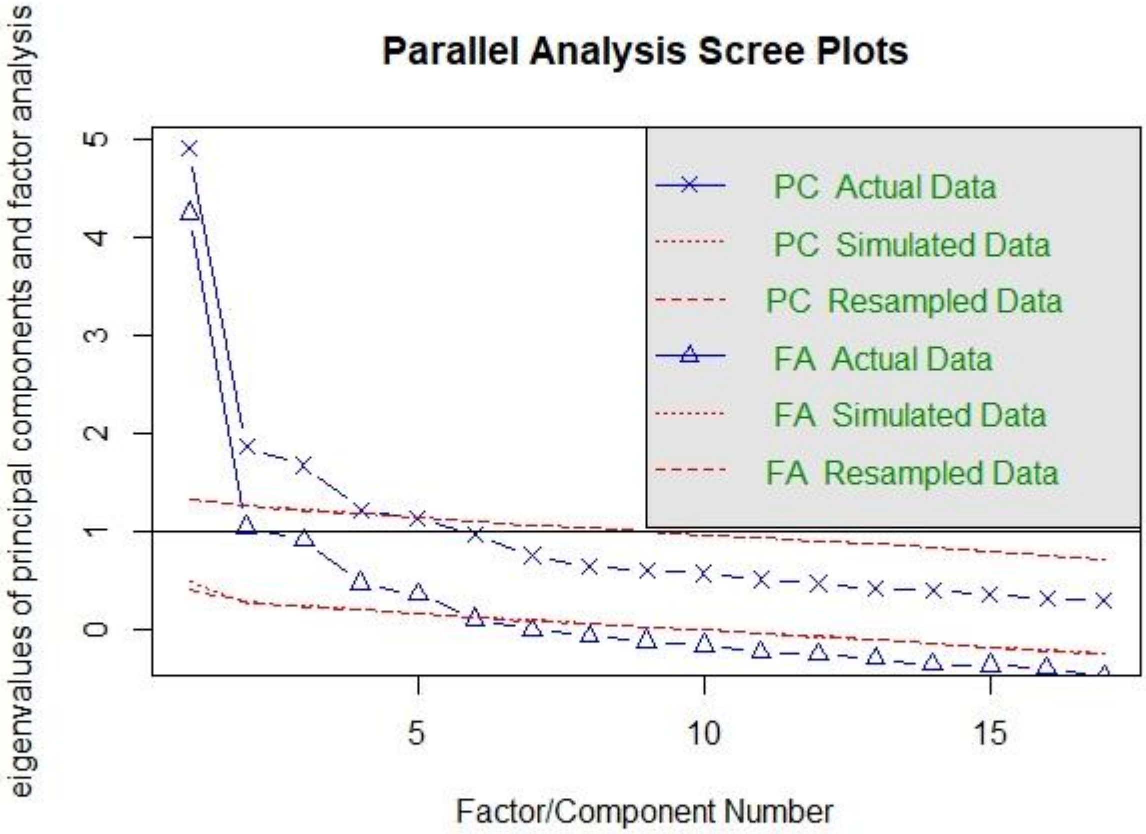


Figure 40: Factor extraction (Parallel Analysis)

Appendix (A10): Questionnaire Survey:

Welcome to the Survey

Dear respondents,

We would like to invite you to participate in a study in which we are conducting a research survey to investigate consumers' intentions for electric vehicle (EV) adoption and other relevant factors in the context of Innsbruck city, Austria.

Credit: hydrogenfuelnews.com

This is part of a research of my Master's thesis, which is being funded by Innsbrucker Kommunalbetrieb AG (IKB), the currently one of the charging service providers in Innsbruck city.

The **aim** **of this survey** is to identify the main factors influencing the users' decision for EV adoption and **outcome of the survey** will help the researcher to determine the existing barriers for EV adoption and other relevant factors.

The **questionnaire consists of 4 sections** **(i)** Travel habits, **(ii)** Attitudinal questionnaires, **(iii)** Choice preferences based on hypothetical scenarios , **(iv)** Questions on socio-demographic characteristics.

The survey will take about **20-25 minutes** of your time. You can only fill up the survey once and you can edit your responses before submission.
Participation in this study is completely voluntary & anonymous and can be withdrawn entirely at any time. In case of any concerns, please do not hesitate to contact me via email: *yashin.ali@tum.de*

Regards,
Yashin Ali
If you understand the above mentioned information, please click the **Next button** to participate in the survey.

Note: ***There are 30 questions in total. All the information will be kept confidential and will be handled anonymously. The data collected from the survey will only be used for the research purpose.***

Q. Do you live in Innsbruck ?

◯ Yes

◯ No

Back Next

0% 100%

Q. In which part of the Innsbruck city do you live?

List of districts ▼

Back Next

0% 100%

Q. Do you commute to Innsbruck?

◯ Yes

◯ No

Back Next

0% 100%

Q. Please provide your postal code

Back Next

0% 100%

Q. Which one of the following describes the current status of your driver's license ?

- Yes, I have a valid driver's license
- I am currently learning
- No, I don't have a driver's license

Back Next

0% 100%

Q. For how many years have you had your driver's license?

Back Next

0% 100%

Q. For how many years have you had your driver's license?

Back Next

0% 100%

Q. How many cars do you have in your household?

Back Next

0% 100%

Q. In which form do you have experience of driving an electric car mostly? (please select one option that apply)

- Own car
- Corporate service
- I do not have any experience
- Car-sharing
- Rent-a-car

Back Next

0% 100%

Q. *How much do you agree or disagree with each of the following statements?*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am satisfied with my current EV, and will purchase EV again if necessary	○	○	○	○	○
I am currently using EV as my second car and will completely shift to EV in future	○	○	○	○	○
I am not happy with my current EV and will return to my conventional car	○	○	○	○	○

Remarks:
***EV = Electric Vehicle**

Back Next

Q. *How much do you agree or disagree with each of the following statements?*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am willing to buy an electric car in near future	◯	◯	◯	◯	◯
I am willing to forgo some advantages with conventional car (e.g., less concern with fueling) to buy an EV	◯	◯	◯	◯	◯
I am willing to spend more money to buy an EV	◯	◯	◯	◯	◯

Remarks:
***EV = Electric Vehicle**

Back Next

0% 100%

Q. Please choose your **preferred location** of charging stations (please select one option that apply):

- ◯ Public places (e.g. shopping malls, tiefgarage)
- ◯ Private place (near home)
- ◯ Within neighbourhood block
- ◯ Near highways/ motorways
- ◯ Near working places

Back | **Next**

0% 100%

(1 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1000m	1500m	500m
Reservation time	For 15 Minutes	Not possible	For 30 Minutes
Charging speed	Fast	Moderate	Rapid
Monthly price	95€	75€	55€
	Select	Select	Select

***Reservation "not possible" means**that no free space for your electric car can be guaranteed.
***Charging speed "moderate" means 11 - 22 KW** , this charging capacity takes about**4 - 6 hours**to recharge 80% of the battery.
***Charging speed "Fast" means 50 – 75 KW,** this charging capacity takes about **1 – 1.5 hours**to recharge 80% of the battery.
***Charging speed "very fast" means > 75 KW,** this charging capacity takes about **45 minutes - 1 hour**to recharge 80% of the battery.

(2 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1500m	1000m	500m
Reservation time	For 30 Minutes	Not possible	For 15 Minutes
Charging speed	Moderate	Fast	Rapid
Monthly price	95€	75€	55€
	Select	Select	Select

(3 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	500m	1500m	1000m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Fast	Moderate	Rapid
Monthly price	95€	75€	55€
	Select	Select	Select

(4 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1000m	500m	1500m
Reservation time	For 30 Minutes	Not possible	For 15 Minutes
Charging speed	Rapid	Moderate	Fast
Monthly price	55€	75€	95€
	Select	Select	Select

(5 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1500m	1000m	500m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Rapid	Rapid	Moderate
Monthly price	55€	75€	95€
	Select	Select	Select

(6 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1000m	500m	1500m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Moderate	Rapid	Fast
Monthly price	95€	55€	75€
	Select	Select	Select

Block 2 design

(1 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	500m	1000m	1500m
Reservation time	For 30 Minutes	For 15 Minutes	Not possible
Charging speed	Fast	Moderate	Rapid
Monthly price	75€	95€	55€
	Select	Select	Select

(2 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1500m	1000m	500m
Reservation time	For 30 Minutes	Not possible	For 15 Minutes
Charging speed	Moderate	Fast	Rapid
Monthly price	95€	75€	55€
	Select	Select	Select

(3 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	500m	1500m	1000m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Fast	Moderate	Rapid
Monthly price	95€	75€	55€
	Select	Select	Select

(4 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1000m	500m	1500m
Reservation time	For 30 Minutes	Not possible	For 15 Minutes
Charging speed	Rapid	Moderate	Fast
Monthly price	55€	75€	95€
	Select	Select	Select

(5 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1500m	1000m	500m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Rapid	Rapid	Moderate
Monthly price	55€	75€	95€
	Select	Select	Select

(6 von 6)

	Option 1	Option 2	Option 3
Distance of charging station	1000m	500m	1500m
Reservation time	Not possible	For 15 Minutes	For 30 Minutes
Charging speed	Moderate	Rapid	Fast
Monthly price	95€	55€	75€
	Select	Select	Select

How often do you use the following modes of transport?

	1-3 times a month	1-3 times a week	4-7 times a week	Rarely/Never
car (as driver)	◯	◯	◯	◯
car (as passenger)	◯	◯	◯	◯
On-demand services (e.g. car sharing)	◯	◯	◯	◯
Local public transport	◯	◯	◯	◯
bicycle	◯	◯	◯	◯

How many kilometers do you cover on average in a day?

- ◯ Less than 10km
- ◯ Between 11-20km
- ◯ Between 21-30km
- ◯ More than 30km

← →

Q. ***How much do you agree or disagree with each of the following statements?***

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am not able to afford an EV even with the purchase subsidies and tax exemption by the Government	○	○	○	○	○
I am concerned about EV range when thinking of buying an EV	○	○	○	○	○
Insufficient charging infrastructure makes it difficult to buy an EV	○	○	○	○	○
Longer charging time at the charging station discourages me to buy an EV	○	○	○	○	○
I will worry about battery life and battery disposal if I buy an EV	○	○	○	○	○
Concerns with residual/resale value discourage me to buy an EV	○	○	○	○	○

Remarks:
***EV = Electric Vehicle**

Q. *How much do you agree or disagree with each of the following statements?*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I believe that buying an EV has a positive effect on the environment than buying a conventional car (i.e., low noise, low emission).	○	○	○	○	○
I think buying an EV is better (good performance-price ratio) than a conventional car in the long run.	○	○	○	○	○
I think it is cool to drive an EV than a conventional car	○	○	○	○	○

Remarks:
***EV = Electric Vehicle**

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0% 100%

Q. *How much do you agree or disagree with each of the following statements?*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
People in my life, whose opinion I value, would support my decision of purchasing EV	○	○	○	○	○
People who are important to me already own an EV	○	○	○	○	○
People who are important to me are considering buying EV	○	○	○	○	○
The excellent advertising by media gave me a positive feeling about buying an EV	○	○	○	○	○
The promotion of EV in social media has influenced me positively about buying an EV	○	○	○	○	○

Remarks:
***EV = Electric Vehicle**

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Q. *How much do you agree or disagree with each of the following statements?*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
We must act and take decisions to limit greenhouse gases	○	○	○	○	○
I am willing to pay more for supporting environmentally friendly vehicles	○	○	○	○	○
I consider the environmental consequences while choosing a travel mode	○	○	○	○	○

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Q. The average income in Austria is 2000-3000€. What is your income?

- ○ Below average
- ○ Above average
- ○ Average
- ○ I prefer not to answer

Q. What is your current work status?

- ○ Full time working
- ○ Apprentice
- ○ Self-employed
- ○ Part time working
- ○ Housekeeping
- ○ Other
- ○ Pupil/Student
- ○ Retired

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0% 100%

Q. What is your age?

Q. What is your Gender?

Q. What is the highest level of education you have completed?

- ◯ Primary or Secondary school
- ◯ High school
- ◯ Bachelor's degree
- ◯ Master's degree or Diploma
- ◯ Doctorate
- ◯ Prefer not to answer

Q. How many people currently live in your household including yourself?

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 3+

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Q. What additional services would you like to have in an EV charging stations ?
(Please rank 3 most preferred services from the list)

Ranking of Items (Choose any 3)

- **Coffee shop**
- **Fitness center/gym**
- **Hotels/Waiting room**
- **WLAN hotspot**
- **Supermarket**
- **Shopping facilities**
- **Public toilets**

Most Preferred

Least Preferred

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Submit Survey

0% 100%