

Understanding Public Charging Preferences of Potential and Existing Electric Vehicle Users in Great Britain

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- Potoglou, D., **Song, R.** and Santos, G. 2023. Transportation Research Part D: Transport and Environment 121, article number: 103824. (10.1016/j.trd.2023.103824)
- **Song, R.** and Potoglou, D. 2020. Are existing battery electric vehicles adoption studies able to inform policy? A review for policymakers. *Sustainability* 12(16), article number: 6494.

Conference proceedings:

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Book sections:

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Abstract

Understanding the factors influencing an individual's choice for public-charging infrastructure is important to facilitate Electric Vehicle (EV) adoption and support the development of on-demand public charging networks. In this thesis, a survey containing a stated preference discrete choice experiment was conducted with a total of 588 potential and existing EV users in Great Britain. The aim was to explore what features of public charging points are perceived as important for existing and potential EV (non-EV) users. This was achieved through a thoughtful synthesis of a literature review on all relevant indicators, followed by the design of a discrete stated preference choice experiment focused on public charging, whose reliability was then validated by conducting cognitive interviews. Through choice modelling, significant disparities in preferences between EV users and potential users were identified. Both EV and non-EV users preferred lower charging prices, shorter waiting times, a higher percentage of renewable energy sources at public charging stations, automatic verification by just plugging in the charger, and nearby facilities such as small stores, cafes, or shopping centres to be built around the charging station and five-star charging stations. In addition, they were indifferent to varying payment methods and the number of charging points available at the public charging station. However, non-EV users specifically valued fast charging availability while EV users did not perceive this as important. The latent class logit model succeeds in classifying two distinct groups among EV and non-EV users, revealing important preferences and different socio-demographic and attitudinal characteristics. Their preferences towards charging prices were associated with income level, while their preferences towards charging locations were found to interact with gender differences. Finally, the attitudinal variables (e.g., environmental cognition, risk aversion, technophilia) had significant impacts on the EV user segment's public charging preference, the effect on non-EV users was not substantial. These findings have important implications for policymakers and public charging service providers to help identify potential early adopters and consumer segments of public charging users, and to help shape the desired public charging infrastructure.

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List of Abbreviations

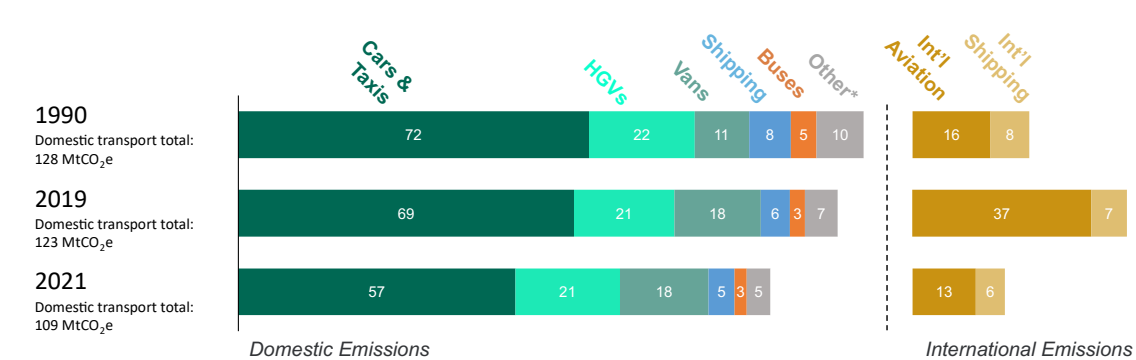
EV	Electric Vehicle
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
GHG	Greenhouse Gas Emissions
IEA	International Energy Agency
OLEV	Office for Low Emission Vehicles
EVHS	Electric Vehicle Home Charge Scheme
WCS	Workplace Chargepoint Scheme
ORCS	On-Street Residential Charge Point Scheme
DC charger	Direct Current Charger
AC charger	Alternating Current Charger
SPDCE	Stated Discrete Choice Experiment
RFID-card	Radio Frequency Identity Card
SOC	State of Charge
DCE	Discrete Choice Experiment
MNL	Multinomial Logit Models
MXL	Mixed Logit Models
LCL	Latent Class Logit Models
WTP	Willingness to Pay

Chapter 1 Introduction

1.1 Climate change and road decarbonisation challenges

Climate change has caused serious problems, such as rising sea levels, increasing surface temperatures, and extreme weather events, endangering humans and millions of species worldwide. The [Six Assessment Report of the Intergovernmental Panel on Climate Change](#) concluded that industrial activities such as burning fossil fuels for electricity, heat, and transportation are the main culprits of almost all the increases in greenhouse gas emissions over the past 50 years (IPCC 2023). To slow down the process of climate change and alleviate its related influences, it is necessary to reduce greenhouse gas emissions substantially (White and Sintov 2017).

In the UK, the transport sector has emerged as the leading contributor to greenhouse gas emissions among all industries. Recent data from 2021, as reported by the Department for Transport (2023), highlights that transportation accounts for 26% of the country's total emissions. Specifically, within the broader transport sector, Figure 1-1 illustrates the breakdown of greenhouse gas emissions by various modes of transportation, revealing that road transport stands out as the primary source of these emissions.



*Comprises, in 2021: Rail, 1.6; Domestic Aviation, 0.7; Motorcycles and mopeds, 0.5; other transport, 1.7; other road transport, 0.6

Figure 1-1: Breakdown of greenhouse gas emissions by various modes of transportation in 1990, 2019, and 2021

Source: Department for Transport (2023)

Based on data provided by the Department of Transportation (shown in Figure 1-2), a comparison was conducted to compare the percentage of miles travelled by road vehicles with

their GHG emissions by these modes of transportation. The results show that cars have the largest share of miles travelled among all road vehicles and produce the highest GHG emissions.

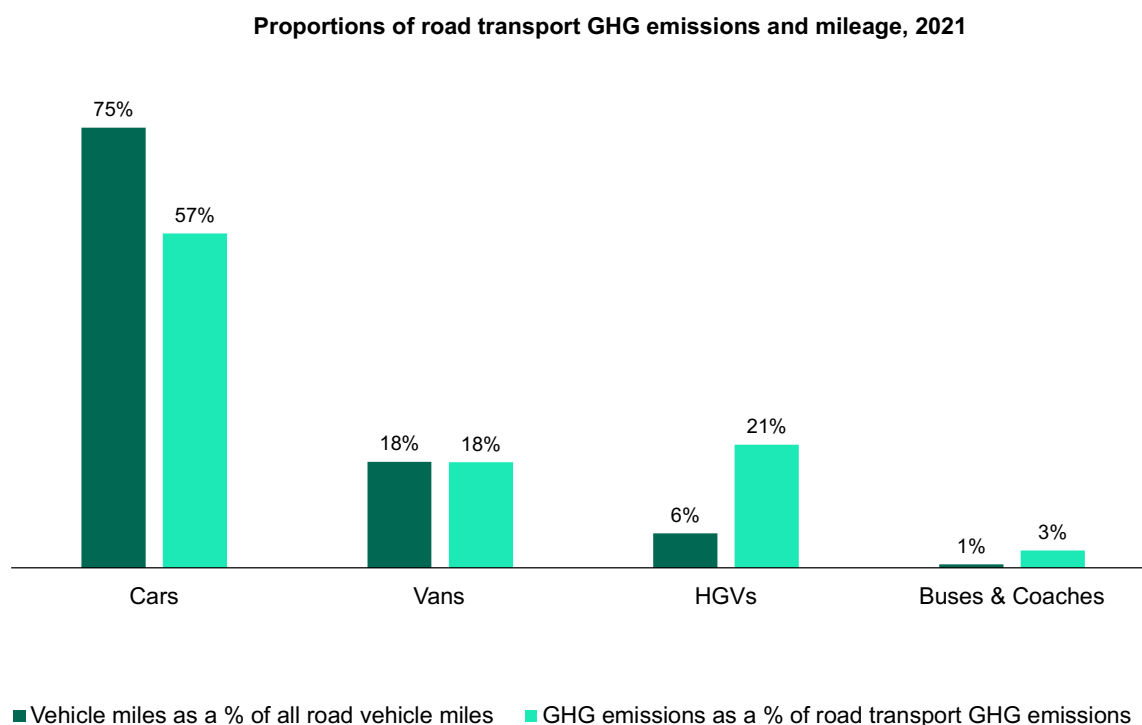


Figure 1-2: Proportions of road transport GHG emissions and mileage, 2021

Source: Department for Transport (2023)

Not only do greenhouse gas emissions from the transport sector have a significant influence on global warming, but they also pose a significant threat to air quality and people's physical health. According to the World Health Organisation, diesel transport can cause air pollution, and the Oxides of nitrogen (NO_x) generated by vehicle engines can contribute to chronic respiratory diseases indirectly, especially childhood asthma (World Health Organization 2020). Meanwhile, too much road traffic also causes severe noise pollution. According to the World Health Organization (2020), noise can cause short- and long-term health problems, including sleep disturbance, cardiovascular effects, poorer work and school performance, hearing loss, etc. The 2012 data from the European Environment Agency (2017) showed that road traffic noise makes around 100 million people exposed to traffic noise above 55 dB L_{den} and 32 million of them are exposed to very high noise levels above 65 dB L_{den} . Thus, all the problems listed above from the transport sector suggest that it is urgent to decarbonise road transport and find a more sustainable way for people to travel around.

1.2 Electric vehicles, electric-vehicle-related policies and adoption

As an emerging and promising technology, electric vehicles (EVs) are currently viewed as [a potential solution to addressing](#) the problems mentioned above in the transport sector. Electric vehicles (EVs) are all types of cars that can be fuelled fully or partly by electricity (Rezvani et al. 2015). Because of this characteristic, EVs usually emit less or no air pollution without burning fossil fuel. They also generally reduce less noise compared to conventional cars.

In general, EVs are divided into two categories (as shown in Figure 1-3), including hybrid electric vehicles (HEVs) and plug-in electric vehicles (PEVs) (Liao et al. 2017). Hybrid electric vehicles (HEVs) are usually powered by an internal combustion engine (ICE) and a battery powertrain, which can be recharged through the energy lost during the breaking of cars. Comparably, plug-in electric vehicles can solely be powered through electricity plugged into a power outlet. Plug-ins then can be further divided into plug-in hybrids (PHEVs, which can be powered both by a rechargeable battery and an internal combustion engine) or full-battery electric vehicles (BEVs, which can only be powered by a rechargeable battery).

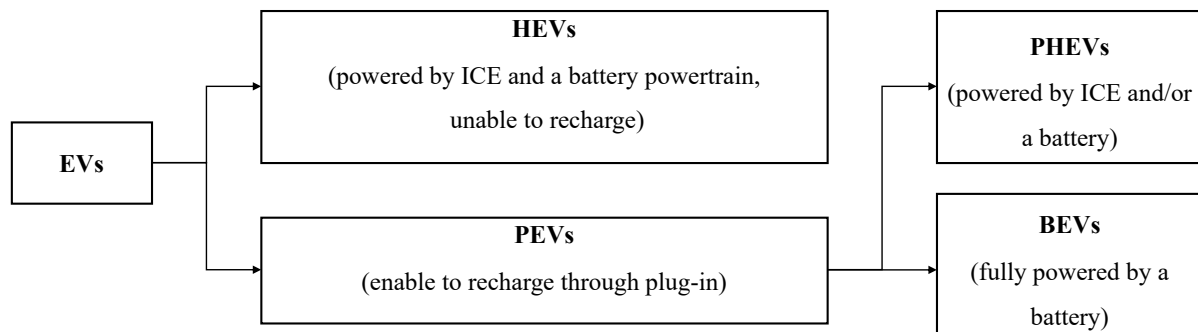


Figure 1-3: Classification of different kinds of EVs

[As EVs can benefit the environment and society](#), different countries have proposed and implemented many related policies to encourage uptake (Table 1-1). Four types of policy interventions are generally employed in various countries, including monetary incentives, non-monetary incentives, targets, and regulations. Monetary measures usually incorporate tax exemption, subsidies, and other non-monetary measures such as travel priority (e.g., access to bus lanes, and car license plate priority).

Norway has played a leading role in implementing EV policies and set a good example to the world by successfully opening up a big domestic EV market. According to the Global EV Outlook 2019 report, the market share of electric cars in Norway reached 46% in 2018, while other countries' figures were all below 8% simultaneously (Till Bunsen et al. 2019). [Table A1 in the Appendix](#) summarises different measures and national plans for promoting EV uptake in various countries and regions. As this table shows, the Norway Government has published a lot of policy incentives for encouraging EV uptake since 1990, including financial benefits such as tax benefits (purchase/operation/VAT) and free parking, and non-financial policies such as access to bus lanes (Norsk elbilforening 2020).

According to data from IEA in 2019 (Till Bunsen et al. 2019), [the global EV fleet](#) exceeded 5.1 million in 2018, which doubled compared to the number in 2017, and China contributed the largest new electric car sales among them. Different from financial incentive policies in common within other countries' choices, China had implemented a strong national regulation – zero-emission vehicles (ZEVs)/new energy vehicle (NEV) mandate since 2016 (Till Bunsen et al. 2019). This regulation requires manufacturers to produce EVs to accelerate their rate of deployment, thus credit can be accumulated through the production of EVs, and also credit trading between car manufacturers is allowed as well. The Chinese government set annual minimum requirements for the number of credits that manufacturers need to earn, and the target is to achieve 12% NEV credit sales in passenger cars by 2020 (Futurefuel Strategies 2019). Till now, only China, several states of the US, and the Quebec province of Canada have adopted ZEVs ([please see Table A1 in the Appendix](#)).

[In 2019](#), the European Commission (2019) launched many programmes to urge member countries' participation in EV public procurement and provide guidance on technologies related to EVs, including the Clean Vehicles Directive, the Energy Performance Buildings Directive, the Clean Power for Transport, the European Clean Bus Deployment Initiative, etc.

UK has published a series of clear and consistent policies to boost the market. The Office for Low Emission Vehicles (OLEV) is a specified team set that enables cross-government work to support the emerging market for ultra-low emission vehicles (ULEV). [The government announced that £900 million will be invested in ULEV development, manufacture, and use](#) (Office of Low Emission Vehicles 2020). The ambitions of OLEV (2018) are 50% to 70% of new car sales and 40% of new van sales to be [ultra-low](#) emission by 2030; all new cars and

vans to be effectively zero emission by 2040, and sale of new conventional petrol and diesel cars and vans will end at the same time; eventually, by 2050, all vehicles on the roads are expected to be zero emission cars. (Balzhauser 2019). Meanwhile, the UK government released the Plug-in Car Grant, Electric Vehicle Home Charge Scheme (EVHS), Workplace Chargepoint Scheme (WCS), and On-Street Residential Charge Point Scheme (ORCS) to provide grants to EV buyers and charging infrastructure.

Table 1-1: EV Policy measures across countries by the end of 2019

Policy Incentives	European Union	Norway	Netherlands	Sweden	UK	Germany	France	China	Japan	Korea	Canada	US
Monetary incentives	Tax benefits											
	Purchase subsidies											
	Charging subsidies											
	Industrial subsidies											
	Free tolls, parking, ferries											
Non-monetary incentives	Travel priority											
	Parking priority											
Target	Target for vehicles											
	Target for chargers											
Regulations	ZEV mandate											
	Fuel economy standards											
	Buildings											
	Public procurement											

SOURCE: IEA, policy database [7]; International Energy Agency (2019) [6]; Norsk elbilforening (2020) [11]; BALZHÄUSER (2019) [12]; Office for Low Emission Vehicles (2016)[13]; European Commission (2019) [14]; Columbia University (2020)[15]; Ministry of Finance of the People's Republic of China (2020) [16]; Hybrid & Electric Vehicle Technology Collaboration Programme (2012)[17]; Balzer (2020) [18]; International Energy Agency (2016) [8]; International Energy Agency (2017) [9]; International Energy Agency (2018)[10].

Notes: Dark green means national policies, light green means local policies.

With numerous policies being proposed and implemented in various countries, Figure 1-4 below shows the share of EV sales in some of the major countries around the world from 2019 to 2022. Notably, Norway, Sweden, the Netherlands, and Germany had the top four highest sales shares in 2022. Additionally, China saw a significant increase in EV sales, which grew by approximately 30% in the same year. However, the United States had the lowest share of EV sales among the regions. In Europe (including the United Kingdom), the share of EV sales remains relatively stable, hovering around 20% in both 2021 and 2022.

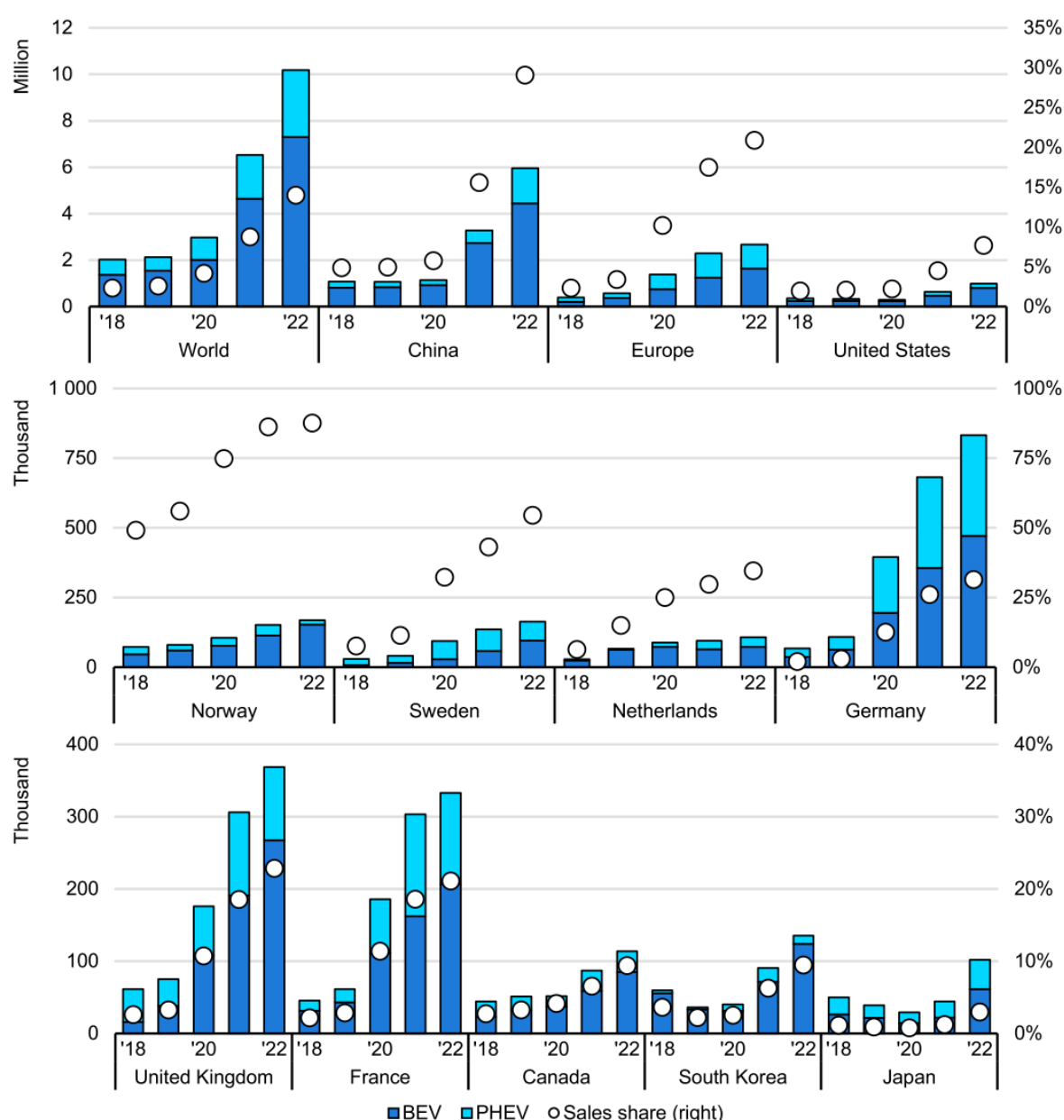


Figure 1-4: Electric car registrations and sales across countries and regions, 2018-2022

Source: International Energy Agency (2023)

As seen from Table 1-1, the policy interventions proposed by different countries were very similar. They were expected to be very successful, but in reality, they proved to be not as successful as Nordic countries. This phenomenon prompts us to think about and examine the reasons behind it. For example, the availability of charging infrastructure can also play an important role in consumer acceptance of electric vehicles.

1.3 Electric-vehicle charging infrastructure

The surge in global EV penetration highlights the urgent need for expanded charging infrastructure. With the rise in EV sales, developing a robust charging network has become critical to driving EVs' continued growth and widespread acceptance. EV charging infrastructure can be categorised into private charging (home/workplace) and public charging based on differences in charging locations. Public charging can then be further divided into public slow charging and fast charging according to the speed of charging (as shown in Figure 1-5).

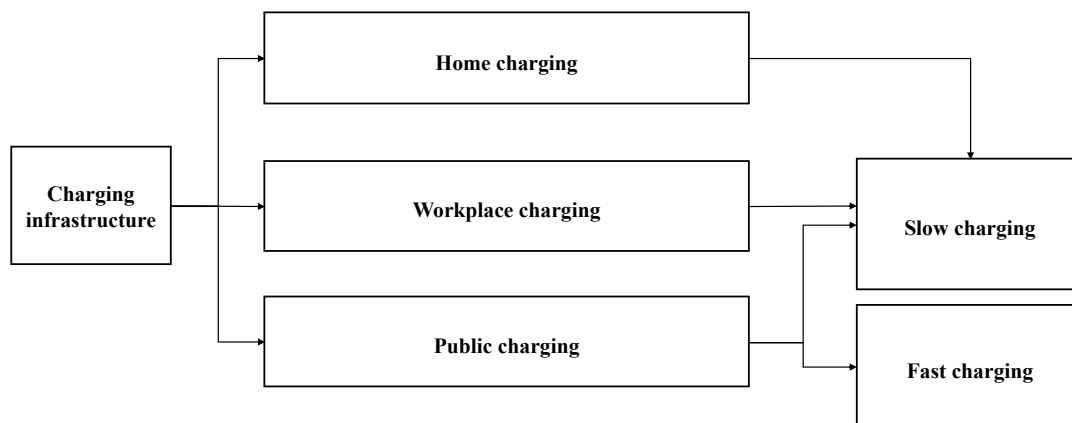


Figure 1-5: Classification of charging infrastructure by charging locations and speeds

The existing charging infrastructure of PEVs is installed with different types of chargers, and this causes long or short charging speeds or durations (as shown in Table 1-2). According to the international standard of IEC 61851-1, charging infrastructures can be divided into four charging modes based on the power of chargers (IEC 2003). Mode 1 allows vehicles to charge using common household sockets and cables with a typical power level of 2.3 kW; Mode 2 charging requires a specialised cable equipped with a control box, though it is acceptable to

use a standard electrical socket; Mode 3 requires a special plug socket and a dedicated circuit to charge EVs at a higher power level at about 20 kW; and Mode 4 provides direct current (DC) at a power level higher than 50 kW. However, the Global EV Outlook 2016 gives slightly different definitions of slow and fast charging (International Energy Agency 2016). Slow charging units (SCUs) include alternating current (AC) level 1 and AC level 2 charging units. The slowest charge is from level 1 chargers, which use standard plug sockets and charge PEVs with 100 miles of range in around 24 hours and are mostly used for overnight charging at home. Level 2 (208–240 V) charging has a wide range of charging speeds based on the charging equipment used and the vehicle's capability. Level 2 infrastructure can charge a PEV with 100 miles of range in 4–12 hours. Level 2 chargers are often installed at homes, workplaces, and public locations. Level 3 is the fast charging units (FCUs) including AC 43 kW charging units, direct current charging units, Tesla Supercharging units and inductive charging units (Zhang et al. 2018). DC fast chargers charge PEVs in the fastest possible time. They are also considerably more expensive than level 2 chargers.

Table 1-2: Different modes and levels of charging

Type	Mode [IEC 61851]	Levels	Power [KW]	Possibility to control charging	Typical location	Time to charge 100 miles
Slow charging	Mode 1	Level 1	≤ 3.7 kW	No	Home	24 h
	Mode 2	Level 2	> 3.7 kW and	Yes	Home, work, public	4-12 h
	Mode 3		≤ 22 kW			
Fast charging	Mode 4	Level 3	AC 43 kW, currently 50-150 (<400 kW)	Yes	Corridor	<15 min

Source: (Hardman et al. 2018a; International Energy Agency 2018)

1.4 Public charging infrastructure

Increasing the market share of EVs is a potentially effective route to decarbonise road transport and improve air quality in cities (European Environment Agency 2022). To successfully achieve this, reliable and sufficient charging infrastructure needs to be developed (Coffman et al. 2017; Liao et al. 2017). Charging points and associated services are currently divided into home, work, and public charging, with home charging being the most popular worldwide

(Hardman et al. 2018b; Baresch and Moser 2019; Chakraborty et al. 2019; Delmonte et al. 2020). In 2018, for example, private chargers accounted for over 90% of global charging points (International Energy Agency, IEA, 2019). Although home and workplace charging play a fundamental role in fulfilling most potential and existing EV users' charging requirements, this does not mean public charging is not important.

While home charging can provide most of the charging demand of EV users, the need for public charging stations is growing to ensure that EVs offer the same convenience and accessibility as conventional vehicles when refuelling. This requirement is particularly acute in densely populated urban centres, where home charging options are limited, making public charging infrastructure critical in facilitating the widespread adoption of EVs. According to data from the EV outlook 2023 (International Energy Agency 2023) (in Figure 1-6), the number of public charging points will reach 2.7 million globally by 2022, with more than 900,000 installed in that year alone, a significant 55% increase from the previous year.

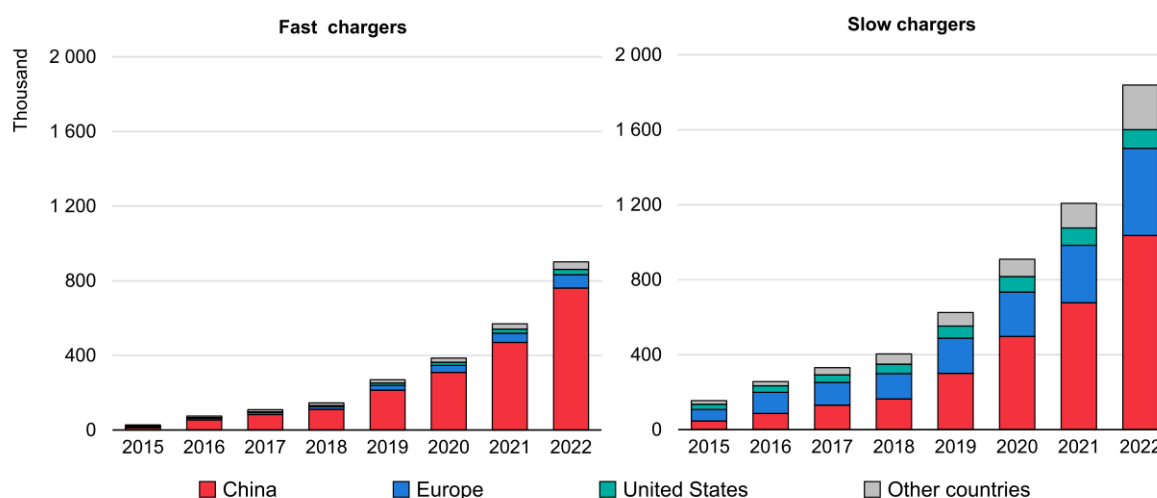


Figure 1-6: Installed publicly accessible light-duty vehicle charging points by power rating and region, 2015-2022

Source: International Energy Agency (2023)

According to the latest figures from the UK, at the end of February 2024 (zapmap 2024), the country had a network of 57,290 EV charging points spread across 32,575 charging locations, which showed a large 47% increase in the total number of charging points compared to February 2023 data. Based on data from the UK Department for Transport (2024) (shown in

Figures 1-7), it is possible to get a general idea of the current distribution of public charging infrastructure in the UK. As can be seen from the figure, the distribution of charging resources is unbalanced, mainly in London, Scotland, England, and Wales. At the same time, the density of public charging facilities in Northern Ireland is relatively low.

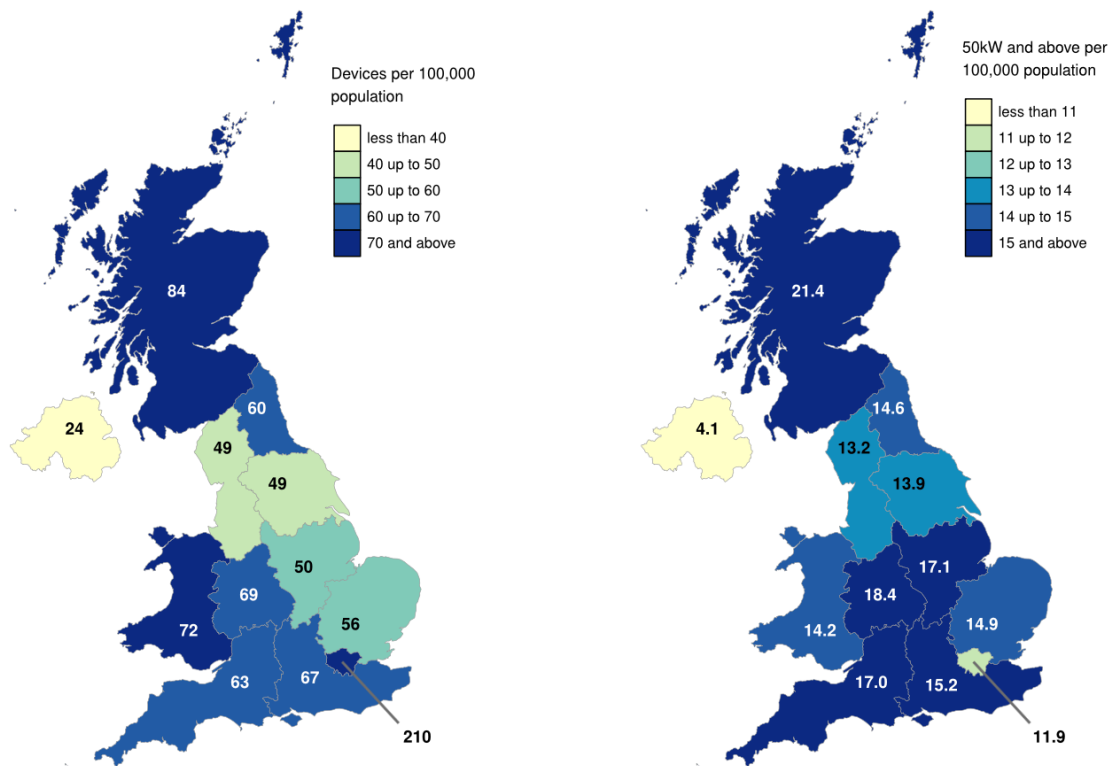


Figure 1-7: Total and 50kW and above public charging infrastructure distribution in the UK by 1 Jan 2024

Source: Department for Transport (2024)

The imbalanced distribution of public charging infrastructure in the UK requires research to focus on how to invest in and distribute EV charging systems in a scientifically rational way, based on consumers' demand in the country. Therefore, a study is needed to understand public charging preferences. It can not only build confidence in future EV purchases and in terms of addressing range anxiety and thus facilitate faster transition to electric vehicle adoption (Kester et al. 2018; Greene et al. 2020; Santos and Davies 2020). It is also crucial to examine consumers' public charging preferences, which is valuable for infrastructure planning to accommodate the existing and future public charging demand.

The inadequate provision of public EV charging infrastructure is a pressing problem, especially in light of the announcements by several governments to bring forward more stringent CO₂

emission targets and restrictions on conventional petrol and diesel vehicles in urban areas. For example, the UK Government plans for at least 50% of new registrations to be low-emission vehicles by 2030 (please see Table A1 in the Appendix). This target requires the number of charging points to increase tenfold – i.e., from 25,000 public charging points currently available to 280,000 by 2030 (Competition & Markets Authority, CMA, 2021). This is an emerging challenge, particularly for high-density urban areas. For example, nearly half of households in Europe are unable to install a charging point due to the type of dwelling they live in (Azarova et al. 2020). For these households, workplace and public charging would be their only options, and public charging could become essential under such circumstances. As a result of all this, the coverage of public charging infrastructure must be maximised.

A better understanding of the public charging preferences of potential and existing EV users is of utmost importance for: the deployment of public chargers, such as where they should be placed; what charging speeds and public infrastructure designs would be required; how they should be priced; how many and when they should be deployed; and what public charging information system should be made available to customers. Such knowledge would greatly benefit government decision-makers to tailor policies to regulate and support the deployment of public charging infrastructure, vehicle manufacturers to design and produce EV models that meet customers' preferences and maximise the efficiency of charging infrastructure, and public charging providers to plan future infrastructure and make related investment decisions. All of these together will support the development of an adequate public charging infrastructure for the future.

1.5 Research questions and objectives

The objective of this study is to explore potential and existing users' preferences for public charging by placing emphasis on 'what configurations' and 'which locations' would be more attractive for public charging, particularly in terms of:

- (a) Identifying specific aspects or characteristics of public charging infrastructure that users may consider important and the extent to which these factors are associated with their preferences for public charging.
- (b) Identifying the heterogeneity of public charging preferences among people with different attitudes (e.g., environmental cognition, technophilia, risk-aversion) and socio-demographic characteristics.

1.6 Outline of the thesis

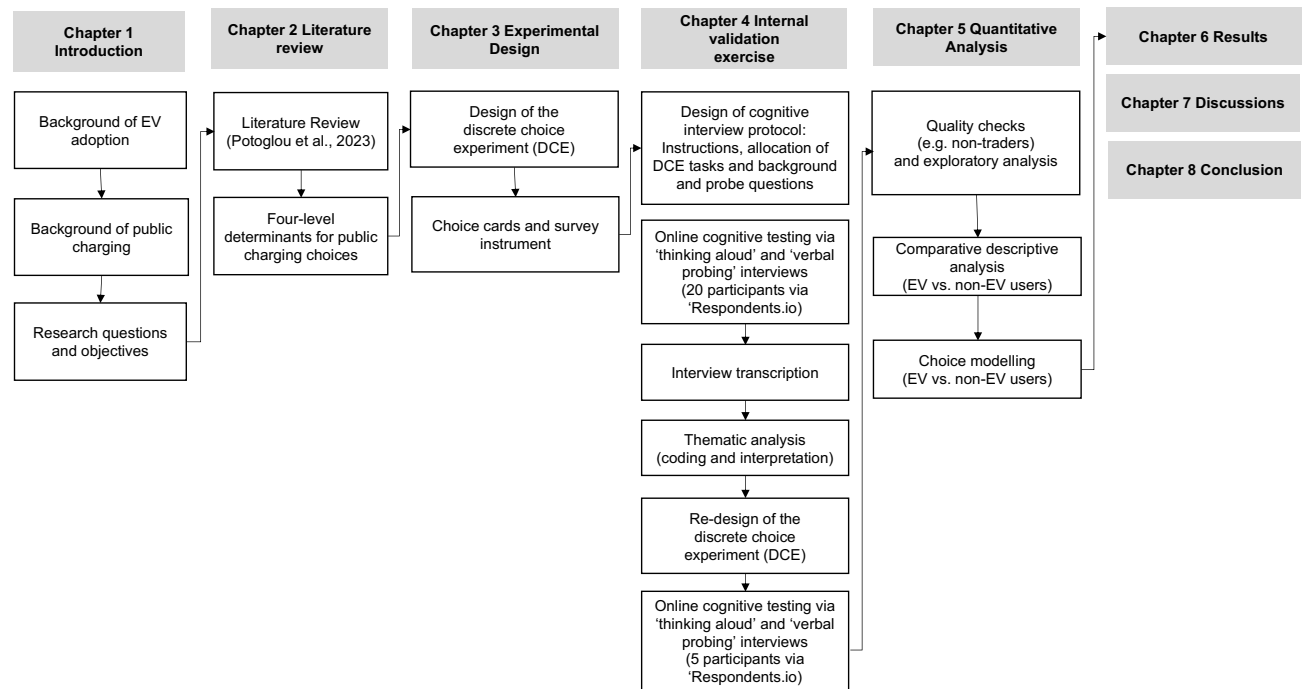


Figure 1-8: Outline of the thesis

To address the above-mentioned objectives, this study used several methods to explore the answers. First, a comprehensive literature review (Potoglou et al. 2023) was conducted to synthesise the factors from previous studies that have a significant impact on public charging preferences of EV and non-EV users, and all the results are presented in Chapter 2. Discrete choice experiments were then crafted based on the factors identified in the literature review. All the processes involved in the experimental design are described in Chapter 3. The study subsequently conducted two phases of cognitive testing with 25 participants in the UK as part of an internal validation exercise (See, Song & Potoglou, 2023), whilst gaining an understanding of the reasons why existing and potential EV users choose public charging. Based on the results of these qualitative cognitive interviews, the choice experiment and the overall survey questions were refined for later quantitative analysis. All of these processes and results are described in Chapter 4. Chapter 5 presents discrete choice modelling for a sample of EV and non-EV users ($N = 588$) in the UK. Descriptive analyses are conducted in this chapter and choice models such as Multinomial Logit Models (MNL), Mixed Logit Models (MXL) and Latent Class Logit Models (LCL) are developed in order to explore the specific effects of different characteristics of public charging stations on EV and non-EV users, as well

as the heterogeneity of preferences at the level of the individual and small groups. Discussions on the results of cognitive interviews and choice modelling were summarised in Chapter 6, with a comparison with previous relevant studies. Also, the future research direction, advances and limitations, and policy suggestions were provided in this chapter. Finally, the main findings are summarised in Chapter 7, which is the conclusion.

Chapter 2 Literature review

2.1 Introduction

The literature on public charging choices has now reached a level of maturity with a lot of empirical evidence being published in the academic and grey literature (see, Tables B1 and B2 in the Appendix). This literature review is designed to provide a synthesis of the current state-of-knowledge and do so beyond anecdotal evidence or an unstructured pull of references. The synthesis generated in this study provides solid evidence for researchers entering this field of study and would benefit charging point operators, vehicle manufacturers and decision-makers to help them plan, design and supply public charging. Better knowledge of public charging choices in turn will: (a) attract potential EV users who have less knowledge about EV and EV charging, (b) attract existing and potential EV users who are risk-averse towards range, and (c) attract potential EV users who would never be able to charge their vehicles at home because of the type of their dwelling.

Table 2-1 summarises previous literature reviews on charging infrastructure focused on the comparison of infrastructure across countries (Funke et al. 2019), system architecture and international standards (Rajendran et al. 2021), players of infrastructure provision (LaMonaca and Ryan 2022), models of optimal charging locations (Kchaou-Boujelben 2021; Metais et al. 2022), infrastructure and grid integration (Das et al. 2020), and charging strategy for freight (Teoh 2021).

Table 2-1: Review articles related to electric vehicle charging infrastructure

Topic	Reference
The comparison of infrastructure among countries	Funke et al. (2019)
System architecture and international standards	Rajendran et al. (2021)
Players of infrastructure provision	LaMonaca and Ryan (2022)
Models of optimal charging locations	Kchaou-Boujelben (2021); Metais et al. (2022)
Infrastructure and grid integration	Das et al. (2020)
Charging strategy for freight	Teoh (2021)
Determinants of infrastructure economics for public charging	Zhang et al. (2018)
Consumers' charging preferences	Hardman et al. (2018)

To our knowledge, Zhang et al. (2018) focused only on the determinants of the economic aspects of public charging points, a rather different subject of enquiry to the one in the present paper. The review by Hardman et al. (Hardman et al. 2018b) focused on consumers' charging preferences more generally rather than for public charging. The usage habits of home charging and public charging are completely different in terms of temporal patterns (e.g. time and frequency of use). This is not trivial, and a literature review to understand the factors of EV users' public charging choices is needed, and this needs to be looked at separately from home charging. In addition, Zhang et al. (2018) and Hardman et al. (Hardman et al. 2018b), although very informative, are now five years old, which, in the context of a rapidly developing field, calls for an update on the 'stock of knowledge'. This is exactly what this article intends to do, by providing an up-to-date source of reference to an emerging and increasingly important aspect of the electrification of road transport and the deployment of public charging infrastructure for electric vehicles.

This critical review of the literature is aimed at synthesising the published academic and grey literature on public charging preferences and answering the following questions: (1) How were public charging choice studies designed, implemented and analysed? (2) What factors are likely to determine public charging preferences? (3) Are preferences heterogeneous? If yes, what are the factors that may explain heterogeneity in preferences? (4) What are the areas for future research?

In the remainder of this chapter, Section 2.2 provides a summary of studies including study design and analytical approach, respondent profiles, countries of study, and type of choices studied. Section 2.3 discusses the explanatory factors found to be associated with public charging choices. Section 2.4 presents findings regarding observed and unobserved heterogeneity in choices for public charging. Section 2.5 summarises the findings and offers a conceptual framework, which captures how explanatory factors are linked with public charging choices. Finally, Section 2.6 summarises the research gaps in the area of public charging choices and provides recommendations for future research.

2.2 Approach in identifying relevant literature

This targeted critical literature review identified relevant academic publications via three repositories: Web of Science, Scopus and Google Scholar. The keywords used to identify these

studies were: ‘charging preferences’ OR ‘choices’ and ‘electric vehicles’. The searches were limited to journal articles published in English from 2016 onwards to obtain an up-to-date picture of the literature and its emerging findings. In addition to academic sources, the study targeted relevant grey literature from government and inter-government agencies, research institutes, and national laboratories.

2.2.1 Overview of the literature related to public charging choices

Table B1 in the Appendix summarises relevant studies on public charging choices and preferences. The majority of studies employed stated choice experiments, including those that elicited preferences in a hypothetical electric-vehicle charging setting. There were also a handful of studies employing revealed preferences (i.e., actual choices), for example, from EV trials such as Chakraborty et al. (2019), Kim et al. (2017), Lee et al. (2020), Sun et al. (2016), Xu et al. (2017), and Yu and MacKenzie (2016).

Participants involved battery electric vehicle (BEV) users (e.g. Li et al., 2023; Visaria et al., 2022; Zhang et al., 2022), plug-in hybrid electric vehicle (PHEV) users (e.g. Chakraborty et al., 2019; Sheldon et al., 2019), and potential EV users (e.g. Gutjar and Kowald, 2023; Ma et al., 2022). In terms of recruitment strategies, some studies used social media platforms and charging service network providers (Kim et al. 2017; Visaria et al. 2022). In many cases, researchers collaborated with sample service providers (e.g. internet panels, professional survey companies, online crowdsourcing platforms) to recruit respondents (Nienhueser and Qiu 2016; Latinopoulos et al. 2017; Moon et al. 2018; Sheldon et al. 2019; Ma et al. 2022; Zhang et al. 2022), whereas others used official vehicle registration databases (Anderson et al. 2018; Chakraborty et al. 2019; Lee et al. 2020) or lists of postal addresses to send invitations, which were then followed with phone calls (Gutjar and Kowald 2023).

Sample sizes ranged from hundreds to thousands of respondents. The sample sizes of EV users were usually in the hundreds, but if there were official registration databases available, then the number of respondents could reach several thousand (Anderson et al. 2018; Chakraborty et al. 2019; Lee et al. 2020). The reviewed evidence comes from the US (Nienhueser and Qiu 2016; Wen et al. 2016; Yu and MacKenzie 2016; Ge et al. 2018; Ge and MacKenzie 2022), with the state of California being the focus of some papers (Chakraborty et al. 2019; Sheldon et al. 2019; Lee et al. 2020), China (Pan et al. 2019; Wang et al. 2021; Ma et al. 2022; Zhang

et al. 2022; Li et al. 2023), and its capital, Beijing (Pan et al. 2019; Wang et al. 2021), Japan (Sun et al. 2016; Xu et al. 2017), South Korea (Moon et al. 2018), the Netherlands (Kim et al. 2017; Wolbertus and Van den Hoed 2019; ten Have et al. 2020), Denmark (Visaria et al. 2022), Germany (Anderson et al. 2018; Wolff and Madlener 2019), and the UK and Ireland (Latinopoulos et al. 2017).

All reviewed studies involved choices of public charging infrastructure with slow, fast or ultrafast charging with the study outcome (choice studied) being: (1) charging (or not) at public charging stations (Wen et al. 2016; Yu and MacKenzie 2016; Ge et al. 2018; Pan et al. 2019; Wang et al. 2021; Ge and MacKenzie 2022; Zhang et al. 2022; Li et al. 2023); (2) choice of type of public charging (Nienhueser and Qiu 2016; Anderson et al. 2018; Moon et al. 2018; Sheldon et al. 2019; Wolbertus and Van den Hoed 2019; ten Have et al. 2020; Ma et al. 2022; Visaria et al. 2022; Gutjar and Kowald 2023), and (3) choice across home, place of work or public charging point or a mix of locations (Xu et al. 2017; Chakraborty et al. 2019; Wolff and Madlener 2019; Lee et al. 2020).

In terms of type of charging, the majority of published articles did not specify whether it was en route or destination charging. Only four studies focused on en route charging (Ge and MacKenzie, 2022; Li et al., 2023; Sun et al., 2016; Visaria et al., 2022), while five articles looked at destination charging (Latinopoulos et al., 2017; Ma et al., 2022; Pan et al., 2019; Wang et al., 2021; Wen et al., 2016). Regarding charging power, only two articles focused specifically on fast charging (Sun et al. 2016; Visaria et al. 2022), which was generally adopted for charging, while for the five studies that looked at destination charging, three of which mentioned the power of public charging infrastructure were mainly focused on both slow and fast public charging (Wen et al. 2016; Ma et al. 2022).

Only three studies specified the type of trips made by EV users, with two studies focusing on long-distance trips (Ge and MacKenzie 2022; Visaria et al. 2022), and one study looking at commuting trips (Chakraborty et al. 2019). Four studies did not specify the type of trip in their charging scenario, but did mention that these trips were to destinations such as home (Pan et al. 2019; Wang et al. 2021; Ma et al. 2022), workplace (Wang et al. 2021; Ma et al. 2022; Zhang et al. 2022), 'requested public places' (Ma et al. 2022), shopping (Pan et al. 2019; Wang et al. 2021) or recreation (Zhang et al. 2022). The type of trip (commute, leisure, long-distance) was closely associated with the type of charging, with long-distance trips mainly associated

with enroute charging (Ge and MacKenzie 2022; Visaria et al. 2022), and commute and leisure trips in the context of a mall/workplace/home mainly associated with destination charging (Pan et al. 2019; Wang et al. 2021; Ma et al. 2022).

In general, very few studies extended their analyses to derive the relative value of attributes such as willingness-to-pay (WTP). As shown in Table A1 (see, Appendix) only five studies, which focused exclusively on EV users (Nienhueser and Qiu 2016; Wen et al. 2016; Wang et al. 2021; Ge and MacKenzie 2022; Visaria et al. 2022) and three studies on current and potential EV users (Sheldon et al. 2019; Wolff and Madlener 2019; Ma et al. 2022) estimated the WTP for different attributes related to public charging choices, although many studies involve a ‘payment vehicles’ (e.g. charging cost) as part of their stated choice experiment (Ge et al., 2018; Latinopoulos et al., 2017; Moon et al., 2018; Pan et al., 2019; Ten Have et al., 2020; Wolbertus and Van den Hoed, 2019).

The WTP estimates computed in these eight studies are summarised by country (i.e., Denmark, US, China, and Germany) in Table A3 in the Appendix. The relative valuation was estimated for charging location (Sheldon et al. 2019; Wolff and Madlener 2019), cost in relation to detour time (Visaria et al. 2022), power (Wen et al. 2016; Sheldon et al. 2019; Visaria et al. 2022) and duration (Wolff and Madlener 2019; Ge and MacKenzie 2022), number of chargers (Visaria et al. 2022), amenities (Ge and MacKenzie 2022; Visaria et al. 2022), state of charge and excess range (Wang et al. 2021), waiting (Wolff and Madlener 2019) and access time (Ge and MacKenzie 2022), renewable energy (Nienhueser and Qiu 2016; Wolff and Madlener 2019), inductive charging technology (Wolff and Madlener 2019), deviation from planned route (Ge and MacKenzie 2022), and time period of day (Ma et al. 2022).

The analyses of choices mainly employed discrete choice models and included binary logit models (Pan et al. 2019; Wang et al. 2021; Li et al. 2023), multinomial logit (MNL) models (Sheldon et al. 2019; Wolff and Madlener 2019; Lee et al. 2020; Ma et al. 2022; Gutjar and Kowald 2023), mixed logit (MXL) models (Nienhueser and Qiu 2016; Sun et al. 2016; Wen et al. 2016; Yu and MacKenzie 2016; Xu et al. 2017; Moon et al. 2018; Sheldon et al. 2019; Wolbertus and Van den Hoed 2019; ten Have et al. 2020; Wang et al. 2021; Ma et al. 2022; Visaria et al. 2022; Gutjar and Kowald 2023), latent class discrete choice (LC) models (Wen et al. 2016; Yu and MacKenzie 2016; Ge et al. 2018; Pan et al. 2019; Wang et al. 2021; Ge and MacKenzie 2022), random parameter logit (RPL) models and random parameter logit with

error components (RPLEC) models (Li et al. 2023), recursive simultaneous bivariate probit (RSBP) models (Zhang et al. 2022), and dynamic discrete choice (DDC) models (Ge and MacKenzie 2022).

Many binary logit and MNL models captured respondents' taste heterogeneity, i.e., how choices varied across respondents based on observed characteristics (e.g., socio-economic or demographic characteristics). Some MXL and LC models captured the effect of unobserved characteristics (e.g., level of risk aversion or charging concerns) assuming continuous or discrete distribution of related parameters (weights) of charging attributes. Similar to MXL, RPL and RPLEC models also examine unobserved heterogeneity in individual preferences for route and charging-or-not choices en route, by modelling the random parameters and error components.

Trip chain choices and charge-or-not choices were analysed using the RSBP model, which is a statistical model used to analyse the relationship between two binary dependent variables that may be jointly determined (Zhang et al. 2022). To take into account the effect of time, DDC models were used to analyse how EV users made charging decisions over time with a sequence of charging opportunities en route, which allows us to understand how past decisions affect future charging choices (Ge and MacKenzie 2022). In addition to the above, another paper estimated a latent class hazard duration (HD) model, which allowed for the inclusion of duration dependence, unobserved heterogeneity and the effects of time-varying covariates, and for the treatment of charging regularity as a latent variable (Kim et al. 2017). There was also a study in which the heterogeneity of respondents' attitudes towards risk was captured using "Expected Utility Theory", "Rank-dependent Expected Utility Theory", and "Prospect Theory" models (Latinopoulos et al. 2017). These approaches, as the authors argued, were suitable for choices with uncertain outcomes (e.g., the presence of dynamic charging prices; charge now or wait for a lower price).

In parallel, there have been several initiatives across government departments and agencies to capture and report aspects of public transport infrastructure choices for potential and existing EV users. Examples include the California Air Resources Board (2019), the California Energy Commission (Bedir et al. 2018), and the National Renewable Energy Laboratory (Wood et al. 2017) in the United States. In the UK, there have been several studies undertaken by the Department for Transport (Department for Transport 2022b; Department for Transport 2022a),

the Electric Vehicle Association, England (Hink 2021), Transport Scotland (2021), and the National Grid ESO (Dodson and Slater 2019). Also, another study was undertaken on behalf of the Energy Efficiency and Conservation Authority in order to understand public charging choices and improve the user experience (Burroughs et al. 2021) in New Zealand (see, Table A2 of the Appendix).

Most of these reports conducted stated preference surveys involving potential and existing EV users (Hink 2021; Department for Transport 2022b; Department for Transport 2022a). Only the New Zealand (Burroughs et al. 2021) and the National Grid ESO (Dodson and Slater 2019) studies analysed actual charging choices (revealed preferences) and charging events of existing EV users, respectively. The survey-based samples of potential and existing EV users across these studies were around 1,000 whereas those involving the study charging events of EVs reached several million records. The majority of the reports reported descriptive statistics rather than developing any statistical models to identify factors driving public charging choices.

2.3 Determinants of individual public charging choices

The thematic analysis of the literature identified four categories of determinants associated with public charging choices: (1) temporal, (2) vehicle, (3) charging infrastructure, and (4) individual attributes. These are discussed in detail in the following subsections.

2.3.1 Temporal attributes

The temporal characteristics of public charging for electric vehicles (EVs) refer to the patterns of charging-point usage over time, including when and how often charging occurs. Understanding these temporal characteristics is essential for designing and managing efficient and accessible public charging to meet the needs of existing and potential EV users (Gellrich et al. 2022). A summary of temporal attributes and their levels is listed in Table B4 in the Appendix. The value that potential and existing EV owners place on the ‘time of the day’ and ‘day of the week’ can inform the pricing strategies of charging service providers.

Table 2-2 presents a summary of the positive and negative effects of temporal attributes. These temporal attributes can be further categorised into three groups: (a) time of day, (b) weekday (vs. weekend) and (c) charging interval/frequency. In the corresponding studies, the ‘time of day’ either considered day vs. midnight charging choices or different time periods for public

charging during the day. ‘Weekday vs. weekend’ attribute refers to public charging preference variations between weekdays and weekends. The ‘charging interval/frequency’ attribute was used to capture the effect of environmental conditions and on charging choices.

Table 2-2: Temporal attributes associated with public charging choices

Attribute	Effect [positive / negative]	(Association) Study
Time of day	- Midnight [-] - Charging hours [+]:	Xu et al. (2017) ^[1] : 23:00 - 7:00 ; - Ma et al. (2022) ^[2]: 10:00-17:00, 17:00-22:00, 22:00-10:00+1
Weekday vs. weekend	- Working day [+] - Trip chain on working days [+]	Xu et al. (2017) ^[1]: for commercial BEVs using slow company and fast public charging Zhang et al. (2022) ^[2]
Charging interval/frequency	- Weather conditions (high temperatures, strong winds, heavy precipitation) [-] - Days interval for next trip [-]	Kim et al. (2017) ^[3] Xu et al. (2017) ^[1]: only important for commercial BEVs

Notes: references marked in bold refer to results that are specifically applicable to EV users, including PEVs, BEVs, or PHEVs users, while studies in regular fonts were relevant to potential users; the superscripts in the table represent: [1] Japan; [2] China; [3] Netherlands.

Unlike private home charging, which is more likely to occur overnight (Langbroek et al. 2017; Sun et al. 2018), public charging was the preferred method of EV charging during the day (Moon et al. 2018; Ma et al. 2022). This is evident by both observed charging patterns at charging points and preference-based studies. For example, Helmus and Wolbertus (2023) examined over 2 million charging sessions at 1,689 public charging stations in Amsterdam, the Netherlands, and confirmed that public charging was more popular between 8:00 and 23:00, with a peak between 16:00 and 19:00 . Also, the National Grid ESO report in the UK (Dodson and Slater 2019) analysed 8.3 million charging events across the country and found that slow/fast public charging contributed to smaller secondary peak in the morning between 9:00 and 10:00 on weekdays.

As shown in Table 2, Xu et al. (2017) modelled actual (revealed) charging choices across three options: home-slow, public-slow and public-fast charging of EV users in Japan. Their study found a positive association between home charging and a negative association with fast public charging during midnight. Also, Ma et al. (2022) found that all charging time periods (10:00-17:00, 17:00-22:00, 22:00-10:00^{+1day}) were positively associated with public charging choices.

The study introduced two different charging plans each described by the time period during which charging would occur, the cost of charging, ‘walking distance to home/work’, and the ‘type of charger (slow/fast)’. Subsequent WTP estimates (see, also Table B3 in the Appendix) showed that on weekdays, the highest WTP for public charging was between 17:00-22:00. However, during weekends, the highest WTP for public charging was between 22:00 and 10:00 the following day.

Regarding the comparison between ‘weekday’ and ‘weekend’ preferences for public charging Ma et al. (2022) reported that Chinese consumers were willing to pay higher prices between 10:00-17:00 and 17:00-22:00 on weekdays compared to the same time periods on weekends. They were also willing to pay more for public charging between 22:00 and the following day on the weekends (Ma et al. 2022). In Japan, Xu et al. (2017) found there is no significant difference in choices of EV users across slow-home, slow-public and fast-public charging between working days and weekends. However, relative to weekends, business EV users exhibited a significantly higher preference for fast charging at public stations and then slow charging at the workplace during working days. These findings were in line with a report from the UK (Dodson and Slater 2019), which found that the overall demand for charging for EVs on weekends was on average about 25% lower than on weekdays.

The difference in public charging preferences between weekdays and weekends could be associated with travel purpose/type of travel (Xu et al. 2017; Zhang et al. 2022). For example, long-distance travel usually takes place on weekends and local commute/business travel normally occurs on weekdays. Longer and more complex trip chains with two or more destinations are more likely to occur on working days, and this may explain the corresponding preferences for public charging (Zhang et al. 2022). As a result, it is important to consider travel purposes when examining public charging choices.

The study of ‘inter-charging times’ that is the time-interval between charging sessions, also offers interesting insights. For example, Kim et al. (2017) reported data from charging sessions at public charging stations over a four-year period in the Netherlands and found that 90% of their sample charged their EV randomly at public charging stations, and 10% of their sample did so regularly. The inter-charging times were on average 5.65 days and 2.75 days, respectively, with the regular users being more likely to charge their vehicle at a specific charging station (Kim et al. 2017). Charging intervals were significantly associated with

weather conditions including high temperatures, strong winds, and heavy precipitation, which might lead to postponing charging at a public point. The authors suggested that providers might mitigate the negative impact of weather on public charging choice by ‘minimising exposure’ to harsh weather; for example, by reducing walking distance and/or improving shelters (Kim et al. 2017).

2.3.2 Vehicle attributes

Several studies reported that public charging demand was significantly associated with the driving range due to EVs’ different battery capacities (Xu et al. 2017; Chakraborty et al. 2019; Li et al. 2023) and charge status, such as low battery state of charge (SOC) (Xu et al. 2017; Pan et al. 2019; Wang et al. 2021; Zhang et al. 2022), available/remaining range (Zhang et al. 2022; Li et al. 2023), and insufficient excess range to the planned destination (Wen et al. 2016; Pan et al. 2019; Wang et al. 2021) or the next opportunity to charge the vehicle (Wen et al. 2016). Whilst the capacity of the battery and driving range are fixed, the SOC and the excess range are not. The positive and negative effects of these determinants on public charging choices across countries or cities in the reviewed studies are shown in Table 2-3 and a summary of attributes and their levels are listed in Table B5 in the Appendix.

Table 2-3: Vehicle attributes associated with public charging choices

Attributes	Effect	Studies
Driving range	Long driving range¹ [-]	Xu et al. (2017) ^[1]: for commercial BEVs using fast public charging Chakraborty et al. (2019) ^[4]
	Tesla owner [+]	
	- Electric range for PHEVs [+] - Electric range for PHEVs x Multi-point charging [-]	Chakraborty et al. (2019) ^[4]
Charge status	Current state of charge (SOC) [-]	Li et al. (2023) ^[2]; Wang et al. (2021) ^[6]; Pan et al. (2019) ^[6]; Xu et al. (2017) ^[1]; Ge and MacKenzie (2022) ^[5]; Zhang et al. (2022) ^[2]
	- Mean of initial AR at origin [+], mean of average AR at the destination [+], mean of AR uncertainty [-] (the range of the AR interval) - BEV remaining range [-]	Li et al. (2023) ^[2]: not to charge preference

¹ The ‘driving range’ is the distance an EV or a PHEV can travel using the electricity stored in its battery, thus a higher battery capacity will result in a higher average driving range. In the case of PHEVs, of course, the vehicle will be powered on fuel once the battery has depleted.

		• Zhang et al. (2022) ^[2]
	• Excess range [-] • Excess range to home [-], range is enough to next charging opportunity [-]	• Wang et al. (2021) ^[6] • Wen et al. (2016) ^[5]

Notes: AR: available range; references marked in bold refer to results that are specifically applicable to EV users, including PEVs, BEVs, or PHEVs users, while regular fonts indicate studies of potential users; the superscripts in the table represent: [1] Japan; [2] China; [4] California, US; [5] US; [6] Beijing, China

As shown in Table 2-3, Chakraborty et al. (2019) showed that the increased driving range of PHEVs on battery might entice drivers to use public charging (vs. home or workplace). Although this is a counter-intuitive finding, the authors study a specific model of PHEV (i.e., BMW i3) for which owners might have benefited from fast chargers and free charging sessions. On the other hand, the authors found that ‘multiple stops for public charging along the route) were less likely to occur when the ‘electric driving range’ of the PHEV was higher. The study also showed that owners of Tesla with a relatively larger battery capacity were more likely to use public charging stations than owners of other EVs available on the market (Chakraborty et al. 2019). In Japan, although Xu et al. (2017) report no significant association between public charging and the availability of fast chargers, they did find that company EV car users were less likely to use a fast public charger when a slow charger was available at the company’s location.

Insufficient charge status of EVs can trigger range anxiety and incentivise users to opt for public charging (Wen et al. 2016; Xu et al. 2017; Pan et al. 2019; Wang et al. 2021). The charge status of an EV is commonly expressed by three attributes, including the current SOC, the ‘remaining range’/ ‘available range’ and the excess range. SOC is the current charge level displayed on the dashboard of an EV whereas the ‘remaining range’ / ‘available range’ shows the distance that the vehicle can travel at the existing SOC, and the excess range is defined as “the difference between the range at SOC and the distance to the destination”.

Previous studies showed users’ decisions to use public charging were negatively associated with SOC (Xu et al. 2017; Pan et al. 2019; Wang et al. 2021), initial available range at the origin, average remaining range at the destination (considering any uncertainties such as traffic conditions) (Li et al. 2023), excess range to the destination (Wen et al. 2016; Wang et al. 2021) and next charging opportunity (Wen et al. 2016). In terms of driver characteristics, BEV users with little driving experience (<1.5 years) were more concerned about the average remaining

range at the destination and therefore were more likely to use public charging than those with higher driving experience (Li et al. 2023).

In terms of the relative valuation of vehicle characteristics, Wang et al. (2021) reported: (a) when the SOC decreased by 10%, users were willing to pay an increased charging rate of £0.083/kWh (or 0.7 yuan/kWh), and (b) when the excess range decreased by 10 km, users were willing to pay an additional charge of £0.041/kWh (0.346 yuan/kWh). Finally, Li et al. (2023) reported that higher uncertainty regarding the remaining/available range of a BEV at the destination would entice users to charge their BEV at a public charging point and the effect was higher for women and those with lower income.

2.3.3 Charging infrastructure attributes

Important attributes of charging infrastructure as reported in the reviewed studies included: (1) physical attributes, (2) charging price, (3) speed, (4) accessibility, (5) convenience, and (6) charging-point information. As shown in Table 2-4, several studies suggested that EV users would prefer public charging points that are cheaper to use, equipped with high-power chargers and thus shorter charging times, offering convenience and accessibility to other activities and amenities and enhanced information systems (see, also Tables B6 – B11 in the Appendix).

Table 2-4: Infrastructure charging attributes associated with public charging choices

Attributes	Effect	Studies
Physical attributes	Priority of charging points at: - Home (base/reference) vs. (1) work [-], (2) road: charging as side activity [-], (3) road: charging as main activity [-]; - Entertainment (base/reference): (1) Grocery shop [+], (2) mall [+], (3) short, near home [+], (4) short, by freeway [+], (-1) gym [-], (-2) school [-]; - Gas stations [+];	- Wolff and Madlener (2019) ^[9] - Sheldon et al. (2019) ^[4] - Sun et al. (2016) ^[1]
	Amenities: - Restroom [+], all facilities (restroom, restaurant and supermarket) [+]; - Restrooms, dining and WiFi compared with no amenities at all [+]; - No facilities nearby for slow and fast public charging [+], shopping area for slow public charging [+], small shop/café for slow public charging [-]	- Visaria et al. (2022) ^[10] - Ge and MacKenzie (2022) ^[5] - Ten Have et al. (2020) ^[3]
	Charging power [+]	Ma et al. (Ma et al. 2022) ^[2]

		Wen et al. (2016) ^[5]
	• Harsh weather [-]	• Kim et al. (2017) ^[3]
	• Number of charging points [+]	• Visaria et al. (2022) ^[10]
Prices	• Public charging prices [-]	• Please see Table A7 in the Appendix
	• Home charging, at electricity rate paid at home [+] for BEV and not significant for PHEV users	• Lee et al. (2020) ^[4] ; for BEV owners
	• Free workplace charging, not significant for BEV and [-] for PHEV users	• Lee et al. (2020) ^[4] ; for PHEV owners
	• Electricity cost if charge at this stop after the travel day [-], gasoline (petrol) cost if charge at this stop after the travel day [-]	• Ge et al. (2018) ^[5] ; for PHEV
	• Parking price [-]	• Pan et al. (2019) ^[6]
	• Network membership [+]	• Lee et al. (2020) ^[4] ; Chakraborty et al. (2019) ^[4]
Charging station level of service	• Charging time [-]	• Ge and MacKenzie (2022) ^[5] ; Sheldon et al. (2019) ^[4] ; Wolbertus and Van den Hoed (2019) ^[3] ; Wolff and Madlener (2019) ^[9] ; Moon et al. (2018) ^[7]
	• Waiting time [-]	• Wang et al. (2021) ^[2] ; Wolff and Madlener (2019) ^[9] ;
	• Certainty of charging point availability [+]	• Ten Have et al. (2020) ^[3] : for slow and fast public charging
	• Parking time [+]	• Wang et al. (2021) ^[2]
	• Dwell time > 30 min [+]	• Wen et al. (2016) ^[5]
Accessibility	• Coverage of charging facilities in trip chain [+]	• Zhang et al. (2022) ^[2]
	• Density of public charging stations [+]	• Xu et al. (2017) ^[1] ;
	• Distance to access public charging stations [+]	• Ma et al. (Ma et al. 2022) ^[2] ; Moon et al. (2018) ^[7]
	• Access time [-]	• Ge and MacKenzie (2022) ^[5]
	• Detour to public charging stations [-]	• Sun et al. (2016) ^[1]
	• Not having to make a detour [-]	• Ten Have et al. (2020) ^[3] ; for ultrafast charging
	• Deviation from the original plan [-]	• Ge and MacKenzie (2022) ^[5]
Convenience	• Inductive charging [+]	• Wolff and Madlener (2019) ^[9]
	• Self-service charging [+]	• Moon et al. (2018) ^[7]
	• Plug and charge authentication [+]	• Gutjar and Kowald (2023) ^[9]
	• The availability of card-based payment [+]	• Gutjar and Kowald (2023) ^[9]
Charging point information online	• Location, price, status [+]	• Moon et al. (2018) ^[7]
	• Share of renewable resources [+]	• Wolff and Madlener (2019) ^[9] ; Nienhueser and Qiu (2016) ^[5]

Notes: references marked in bold refer to results that are specifically applicable to EV users, including PEVs, BEVs, or PHEVs users, while regular fonts indicate studies of potential users; the superscripts in the table represent: [1] Japan; [2] China; [3] Netherlands; [4] California, US; [5] US; [6] Beijing, China; [7] South Korea; [8] New Zealand; [9] Germany; [10] Denmark

2.3.3.1 Physical attributes

The physical infrastructure attributes of public charging include location, power, number of charging points, and nearby amenities. Previous studies showed when modelled against home and workplace, public charging was the least popular option across EV (Xu et al. 2017; Chakraborty et al. 2019; Lee et al. 2020), PHEV owners (Chakraborty et al. 2019; Lee et al. 2020) and potential EV users (Wolff and Madlener 2019) (see, Table B6 in the Appendix).

In general, it is hard to derive a universal order of location preferences for public charging due to the geographic differences in data and varied location alternatives considered in reviewed studies (Philipsen et al. 2016; Anderson et al. 2018; Sheldon et al. 2019; Wolff and Madlener 2019; Department for Transport 2022a). Table B6 in the Appendix summarises the findings of public charging preferences of current and potential EV users for different locations. As shown in Table 4, the choice of location involved public charging against the place of work and residence or choice across several public locations (Sun et al. 2016; Sheldon et al. 2019; Wolff and Madlener 2019). For example, using a choice experiment, Sheldon et al. (2019) found that potential EV users in California were more likely to charge their vehicles at home than at work or a public charging point. Wolff and Madlener (2019) reported that potential EV users in Germany were more likely to choose grocery stores and shopping malls to charge their EVs and less likely to do so at gyms and schools when compared to entertainment venues, which was the reference category.

The relative valuation of location preference expressed in terms of WTP was reported either at the charging session level (Sheldon et al., 2019) or as monthly payment as part of a subscription with a charging provider (Wolff and Madlener, 2019). Californian respondents were willing to pay up to £2.31 (\$2.81) to charge at grocery shops (the highest valuation in the study) whereas they would be seeking compensation reported as willing to accept up to £1.01 (\$1.23) to charge their vehicle at a school. Under a monthly payment model, German EV users would accept between £19.70/month (€22.31/month) to charge their vehicle at work and £40.84/month (€46.26/month) to charge their vehicle on the road and while en route instead of their home.

Overall, several studies reported a significantly higher preference for faster charging speeds both amongst EV users (Wen et al., 2016) and also potential EV users (Ma et al. 2022). For example, a stated choice study conducted in the US (Wen et al., 2016) found that owners of plug-in electric vehicles (PEVs) prioritised charging their vehicles at stations with the highest (50 kW) and second highest (6.6 kW) over stations with the lowest charging power (1.9 kW).

Similarly, a stated choice study reported that Chinese consumers preferred fast charging compared to slow charging (Ma et al. 2022). The relative valuation of charging power is expressed in terms of users' willingness to pay for driving an extra km (or mile) per minute spent charging. The computed WTP of Danish users was £0.052 (0.44 DKK) the equivalent of making a 0.28 minute-detour to be able to drive an extra km/min (Visaria et al., 2022) whereas US users were willing to pay on average £0.041 (\$0.05) for an extra mile per minute charging (Sheldon et al., 2019). Also, Wen et al. (2016) reported US users' average willingness to pay £1.58/hr (\$1.91/hr) in order to use Level 2 instead of Level 1 charging.

The number of charging points also expressed as the ratio of available over unavailable chargers was an important attribute for BEV users' public charging choices (e.g. Visaria et al., 2022). Similar findings were reported across studies by National Renewable Energy Laboratory (Wood et al. 2017) and California Energy Commission (Bedir et al. 2018), and the Energy Efficiency and Conservation Authority in New Zealand (Burroughs et al. 2021). The relative valuation for charging points was expressed as WTP for an available charger. For example, Visaria et al. (2022) estimated that Danish EV users were willing to make a 7.87-minute detour (valued at £1.46 or 12.32 DKK) to reach an available charger and 0.53 min detour or £0.099 (0.83 DKK) to reach an occupied charger, respectively.

Amenities around public charging stations are expected to address longer waiting times relative to refuelling and have also been reported as being important for their public charging choices (ten Have et al. 2020; Ge and MacKenzie 2022; Visaria et al. 2022). As shown in Table 2-4, examples of preferred amenities included shopping areas around slow public charging points (ten Have et al. 2020) or different attribute-levels with a mix of points of interest such as supermarkets, restrooms and restaurants. Studies also reported significant observed variations in preferences across the surveyed participants. For example, EV users over 60 years of age or households with children were more likely to use public charging services where toilets, supermarkets, and restaurants were available (Visaria et al. 2022). However, there were some counterintuitive findings such as the study by Ten Have et al. (2020) who reported that the absence of amenities near slow, fast, and ultra-fast charging increased the likelihood of EV users charging at these charging points.

The relative valuation of amenities was expressed in terms of WTP to charge at a location with a specific type of service. Visaria et al. (2022) estimated that relative to 'no amenities nearby',

EV users in Denmark were willing to make a 1.23 minute-detour or an equivalent pay £0.23 (1.93 DKK) for the availability of restrooms, and make a 9.55 minute-detour or pay £1.78 (14.97 DKK) to have toilets, restaurants and supermarkets available at the charging station (Visaria et al. 2022). EV users in the US were willing to pay on average £17.25 (\$21) for the availability of restrooms, dining facilities and Wi-Fi (Ge and MacKenzie 2022).

2.3.3.2 Price

The price to charge the battery of a vehicle at public charging stations was introduced using various payment arrangements including: (1) a charging time-based fee (Nienhueser and Qiu 2016; Wen et al. 2016; Ge et al. 2018) (e.g., 5.00 \$/h), (2) a kWh based fee (Latinopoulos et al. 2017; Moon et al. 2018; Pan et al. 2019; Wolbertus and Van den Hoed 2019; Wang et al. 2021; Ge and MacKenzie 2022; Ma et al. 2022) (e.g., €0.40/kWh), (3) a flat rate monthly charging fee (Wolff and Madlener 2019) (e.g., €50/month), (4) a payment for certain ranges (Sheldon et al. 2019; ten Have et al. 2020) (e.g., €5 for 100 km or \$0.04 per mile). Among these payment models, around half of these studies used kWh-based fees, which seemed to be popular, probably because it was analogous to the price per litre or gallon of petrol (Hardman et al. 2018). Also, if parking charges were applied at public charging points, EV users would be less likely to charge their vehicles at those points (Pan et al., 2019).

In terms of what ‘type of payment’ for public charging users would prefer, Gutjar and Kowald (2023) found that relative to a flat-rate charging option (e.g. unlimited charging at a fixed monthly price), kWh-based payment was the most preferred while charging duration-based and ‘fixed-fee for a charging session’ payment was the least preferred among German consumers. Also, Visaria et al. (2022) found that among Danish EV users the ‘flat fee pricing model’ for both public and home charging was the most popular payment method followed in order by the ‘no contract with the charging provider’ (pay as you go) and the ‘monthly subscription fee and kWh-based charging price for each session’. Danish EV users were willing to trade off 5.59 minutes of detour (8.76 DKK) for 1 DKK/kWh lower charging price (Visaria et al. 2022). Also, the results of the Danish study (Visaria et al. 2022) showed that EV users who were male, with higher education qualifications, or owned a Tesla exhibited higher sensitivity to charging prices relative to other EV users.

Several studies also included other related costs and fees. For example, Ge et al. (2018) included petrol prices within a scenario involving a decision to charge before or after a day of

travel. Lee et al. (2020) specified ‘home charging at electricity rate paid at home’ and ‘free workplace’ charging in two models studying the likelihood of public charging by BEV and PHEV users. As shown in Table 4, BEV users in California were more likely to use a public charging point if home charging was paid at the home electricity rate. PHEVs were less likely to charge their vehicle at public charging points when free charging was available at their workplace.

While various public charging opportunities may offer a certain charging fee depending on their payment model, EV owners with network membership can access all public charging stations under the control of the same operator at a special/discounted charging rate. Previous studies have confirmed that EV users who subscribed to a specific EV charging provider were more inclined to use public charging points (Chakraborty et al. 2019; Lee et al. 2020), however, different network memberships may also pose network incompatibility issues within the public charging market. Visaria et al. (2022) measured the effect of interoperability on the choices of different charging pricing schemes and found that in Denmark, BEV users were willing to pay £6.76/month (57.1 DKK/month) to have network access in all of Denmark and a similar price, £7.06/month (59.6 DKK/month), to have access anywhere in the EU, rather than have access to just one network.

Charging prices can be dynamically adjusted by operators to generate gain more revenue in response to fluctuating customer demand for electricity (Limmer and Rodemann 2019; Limmer 2019). This also provides an opportunity for cheaper rates during off-peak periods. Many consumers are risk averse and prefer to charge “now” at a nominal price rather than wait for an uncertain price reduction (Latinopoulos et al., 2017) Visaria et al. (2022) also reported that the monthly subscription model, which considered the peak and off-peak charging price differences for public charging, was the least preferred option for Danish EV users. Both studies suggested the importance of considering potential and existing EV users’ attitudes towards risks for charging service providers to improve their dynamic pricing tools for profitability.

2.3.3.3 Charging station level of service

The level of service at a charging station was expressed in terms of charging and waiting time, certainty of finding a charging point available, parking time and dwell time (see, Table B8 in the Appendix). Charging time was defined either as “the time it takes to fully charge the

vehicle” (Moon et al. 2018; Sheldon et al. 2019; Wolff and Madlener 2019; Ge and MacKenzie 2022) or ‘the time it takes to obtain a certain level of battery charge’ (Wolbertus and Van den Hoed 2019), which indirectly reflected its charging power. The relative valuation of charging duration was reported either at the charging session level (Ge and MacKenzie 2022) or as a monthly payment as part of a subscription with a charging provider (Wolff and Madlener, 2019). EV users in the US were willing to pay £0.33 (\$0.4) for 1 min reduction of charging time (Ge and MacKenzie 2022) and under a monthly payment model, German potential EV users were willing to pay £0.14/month (€0.16/month) for a reduction of 1 min in charging time (Wolff and Madlener, 2019).

Queueing or waiting time was negatively associated with public charging choices (Wolff and Madlener 2019; ten Have et al. 2020; Wang et al. 2021); that is, EV users would prefer to use public charging when waiting times were short (Wang et al. 2021). This was in line with a government report from New Zealand that examined the preferences of 932 EV users (Burroughs et al. 2021). Waiting times were generally measured in the range of 0 - 30 minutes (Wolff and Madlener 2019; Wang et al. 2021). Waiting 30 minutes to charge an EV was the least preferred option for German drivers and they were willing to pay £0.72/month (€0.82/month) for every 1-minute reduction in waiting time. On the other hand, respondents were indifferent across a 5-minute, 10-minute or no waiting at all (Wolff and Madlener 2019). This finding was also in line with ten Have et al. (2020) who reported that a ‘certain’ waiting time of up to 5 minutes was more preferable against charging stations with unknown or uncertain waiting times. Finally, parking (Wang et al. 2021) and dwell times (Wen et al. 2016) had a significant positive effect on public charging choices, as longer dwell and parking time induced drivers to actively make full use of that time.

2.3.3.4 Accessibility

Accessibility to charging stations has been either measured as the ‘distance between the home or destination’ and charging stations (Xu et al. 2017; Moon et al. 2018; Ma et al. 2022; Zhang et al. 2022) or the excess distance (time) required to travel in order to access a charging station (Sun et al. 2016; ten Have et al. 2020; Ge and MacKenzie 2022). Several reports also confirmed that accessibility is an important factor for public charging choices (Burroughs et al. 2021; Hink 2021; Department for Transport 2022b; Department for Transport 2022a) (see, also Table B9 in the Appendix).

Overall, EV users preferred public charging stations involving shorter distances (Moon et al. 2018; Wolbertus and Van den Hoed 2019; Ma et al. 2022) and access times (Ge and MacKenzie 2022). For example, Ma et al. (2022) reported that Chinese consumers were more likely to use public charging when the distance between the charging stations and home/workplace/requested locations was shorter. Meanwhile, shorter detours were preferred by EV users when they employed en route charging in Japan (Sun et al., 2016) and Denmark (Visaria et al. 2022). The Danish study also revealed that EV users would opt-in for shorter detour times in order to charge their vehicles at a public charging point (Visaria et al. 2022).

In terms of the relative valuation of accessibility, Ge and MacKenzie (2022) reported. that EV users in the US were willing to pay £2.05 (\$2.5) for a reduction of 1 minute to access the charging point. They were also more likely to avoid charging en route if they could reach the next charging station without deviating from the originally planned route and were willing to pay £200.37 (\$244) to avoid the deviation (Ge and MacKenzie 2022). Finally, an indirect measure of accessibility relates to the coverage (or density) of public charging stations, which was expressed as the number of charging points within an area. For example, Zhang et al. (2022) found that when the coverage of charging facilities at the parking locations in the trip chain increased, Chinese BEV users were more likely to use public charging as part of the trip chain.

2.3.3.5 Convenience

Convenience involves several features of a charging point which facilitate improved user experience and more effective use of infrastructure. These features as reported in empirical studies included: inductive charging, serviced charging, plug and charge authentication and card-based payments (see, also Table B10 of the Appendix).

Overall, any added features at charging points had a positive association with public charging choices (Moon et al. 2018; Wolff and Madlener 2019; Gutjar and Kowald 2023). For example, consumers in South Korea were more likely to opt for ‘self-charging’ instead of serviced charging by station employees (Moon et al. 2018). All else being equal, German EV users were more likely to use inductive charging than traditional cable charging, and they were willing to pay £7.40/month (€8.38/month) extra for that feature (Wolff and Madlener 2019). Inductive charging only requires a driver to park their EV at a specific location and charging would commence automatically.

EV authentication refers to the ability of the operator to automatically identify an EV and its user to enable faster charging and payment. Gutjar and Kowald (2023) found that German consumers intending to buy an EV perceived ‘plug and charge’ (i.e., automatic authentication and payment) as the most convenient method compared to app-based solutions, which might involve internet connection issues, low battery or cold weather, and RFID-card (Radio Frequency Identity Card) because of incompatibility issues among different charging networks. Finally, Gutjar and Kowald (2023) also found that German potential EV users preferred web-based (e.g., PayPal) and card-based (e.g. credit card) payment methods rather than automatic debit transfer for customers who have accepted a contract with a charging provider.

2.3.3.6 Charging station information

Charging station information may include location, price, and availability of charging spaces, as well as the energy source of electricity. As shown in Table 2-4, these features were also associated with users’ and potential users’ decisions to charge at a public station. Similarly, open data (websites such as Zap-map in the UK, app of charging providers, or vehicle onboard maps) and sustainability on public charging points have been identified as important elements of relevant reports (Hink 2021).

Offering more information would be more likely to attract EV users to those public charging stations (Moon et al. 2018; Wolff and Madlener 2019). For example, Moon et al. (2018) found that potential EV users in South Korea were more likely to use public charging when station information (e.g. location, charging fees, charging station status) was available online on via Korea's EV Charging Station Monitoring System, an online information platform. Information on energy sources was also important for public charging choices for potential and existing EV users. Also, Wolff and Madlener (2019), Nienhueser and Qiu (2016) and Wolff and Madlener (2019) found that charging stations with a higher share of renewable energy, are more likely to be chosen.

The relative valuation of renewable energy preference expressed in terms of WTP was reported either at the hourly payment level (Nienhueser and Qiu 2016) or as monthly payment level (Wolff and Madlener 2019). PEV users in the US were willing to pay £0.50 (\$0.61) per hour for a 1% renewable fraction upgrade at Level 2 chargers and £1.49 (\$1.82) per hour for a 1% renewable-energy fraction upgrade at Direct Current Fast Chargers (DCFC) (Nienhueser and

Qiu 2016). Also, German potential EV users were willing to pay £0.37/month (€0.42/month) for a 1% increase in renewable energy at the public charging point (Wolff and Madlener 2019).

Gutjar and Kowald (2023) revealed potential German EV users with the following socio-economic characteristics were more sensitive to share of renewables at public charging points and were more likely to use public charging due to this reason: young, female, men with high environmental awareness. In comparison, Nienhueser and Qiu (2016) reported that PEV users who have higher income, lower level of education, female, and older age were more willing to use renewable energy at fast charging stations, while women on higher incomes preferred to use renewable energy at AC level 2 public charging infrastructure.

2.4 Preference heterogeneity for public charging

As potential and existing EV users are the subjects of making public charging choices, it is also useful to examine the personal (observed) characteristics and efforts to capture unobserved heterogeneity of public charging choices (see Table B12 in the Appendix).

EV users most likely to use public charging were identified across the reviewed studies as: younger (Wang et al. 2021), female (Lee et al., 2020; Pan et al., 2019; Wang et al., 2021; Zhang et al., 2022), with lower education qualifications (Pan et al. 2019) and income (ten Have et al. 2020). They were also more experienced drivers (Wang et al. 2021) and had owned an EV for more than a year (Pan et al. 2019), living in an apartment (Chakraborty et al. 2019; Lee et al. 2020), without a home charging point (Zhang et al. 2022), with long and complex trip chains (Zhang et al. 2022), and holding risk-averse attitudes towards EV range (Pan et al. 2019). On the other hand, EV users with previous experience (Xu et al. 2017) and higher frequency of using public charging (Ten Have et al. 2020) were more likely to use fast charging. Also, those who placed importance on driving comfort and had higher education qualifications preferred ultra-fast charging (Ten Have et al. 2020).

As shown in Table 2-5, some studies captured unobserved heterogeneity in public charging choices by dividing the sample into different groups via latent class discrete choice modelling (Wen et al. 2016; Latinopoulos et al. 2017; Ge et al. 2018; Pan et al. 2019; Wang et al. 2021). Differences in public charging choices were explained by charging concerns (Wen et al. 2016; Wang et al. 2021) and risk-taking attitudes (Pan et al. 2019). For example, Wang et al. (2021)

found that 76.2% respondents in their sample were ‘charging-service concerned’ and valued the SOC, the queuing time and charging station satisfaction. These respondents were younger, female, users with driving experience, higher income, and risk-averse. The reference group, which comprised the remaining 23.8% of the sample, were pragmatic about their charging needs and valued the stated of charge of their EV, ER, parking time and charging fee. Similarly, Wen et al. (2016) identified three subgroups of EV users based on their charging concerns: those who: (1) ‘chose to charge based on price and charging needs; (2) ‘charged at every opportunity’; and (3) ‘charged taking into consideration other factors such as SOC, dwell time and home charging price’.

When considering risk attitudes towards the SOC, Pan et al. (2019) showed that most EV users belonged to a ‘risk-seeking group’ (70% of the sample), and their choices were driven by price, SOC and parking price. The choices of the ‘risk averse group’ (30% of the sample) were driven by the ER and its members were males, those earning more than 5,000 yuan/month (\$687/£600), and EV owners for more than 12 months.

PHEV users may act differently compared to EV users when facing the same charging options, as they can either use a public charging point or refill their cars at petrol stations. Ge et al. (2018) segmented PHEV users into two groups: ‘petrol anxiety’ and ‘cost-minimising’ users. The majority of PHEV users were more likely to be in the ‘petrol anxiety’ group, who would avoid using petrol as much as possible, and they were willing to pay four times the cost of charging than refuelling due to their environmental attitudes. The ‘cost-minimising group’, only 34% of the sample, was more pragmatic and placed equal importance on charging and refilling and would charge or refuel depending on the cost of electricity and petrol.

EV users charge-or-not decisions for public charging were influenced by risk-averse attitudes towards dynamic charging pricing (Latinopoulos et al. 2017). The results showed that the majority of current and potential EV users were more likely to be risk-averse and preferred to charge immediately at the current tariff price rather than charging strategically and waiting for a better offer.

Table 2-5: Unobserved heterogeneity in choices and segmented groups

Subject	Reference	Segments	Personal characteristics
EV users	Wang et al. (2021)	Group 1 Charging service concerned group (76.2%): value SOC, queueing time, and satisfaction	Younger, female, have richer driving experience, higher income, more risk averse
		Group 2 Pragmatic concerned group (23.8%): SOC, ER, parking time, charging fee	Senior, male, low income, less risk aversion
	Pan et al. (2019)	Group 1 Risk averse group (30%): value ER	Male, earning more than £600/month (5,000 yuan/month), purchased EVs more than a year
		Group 2 Risk seeking group (70%): SOC, charging price, and parking price	Female, with income less than £600/month (5,000 yuan/month), purchased their EV in the past year
	Wen et al. (2016)	Group 1 (20.3%): value charging price, ER, if the vehicle has enough battery to reach the next EVSE	-
		Group 2 (58.7%): price, ER, charging point power, cost at home, and dwell time	Number of vehicles owned or leased
PHEV users	Ge et al. (2018)	Group 3 (21%): value cost at home	Higher income level
		Gas anxiety group (66%): have higher willingness to charge at public places to avoid using petrol	Had a longer using experience, buy PHEVs not only by financial benefits
Consumers	Latinopoulos et al. (2017)	Cost-minimizing group (34%): value recharge and refuel cost the same	Had a shorter using experience, buy PHEV because of financial benefits
		Risk averse (pricing) group (67.9%)	Aged over 60, employed, not having children, lower education level, not owning or leasing an EV, have multiple trip chains, doing work-based tour, driving EV < 1 year, higher EV loyalty, EV daily mileage < 40 miles,
		Risk seeking group (32.1%)	Characteristics are in the opposite with risk averse group

Note: The percentages in the brackets refers to the proportion of the sample being allocated into a specific group.

2.5 Conceptual mapping of public charging choices

This section proposes a conceptual framework to capture the determinants of public charging choices for potential and existing EV users. Figure 1 reveals that public charging has and will continue to have an increasingly important role in road transport. The empirical work examined in this study has the odd outlier and counterintuitive conclusion, but there is a clear set of common themes that emerge. The determinants of public charging choices can be categorised into four levels: (1) temporal, (2) vehicle, (3) charging infrastructure, and (4) individual attributes. Public charging tends to take place during the day rather than during the night and may be different during weekdays or weekends and even during holidays. Vehicle attributes include battery capacity and driving range, which are fixed, but also the SOC, remaining range, and the excess range to destination. According to Figure 1, charging infrastructure attributes are categorised into physical attributes, price, charging station level of service, accessibility, convenience, and station information. Individual attributes refer to the observed heterogeneities reported across studies and include socio-economic and demographic characteristics, and level of risk aversion.

The lines and arrows in Figure 2-1 show how the four levels of determinants (temporal, vehicle, infrastructure, and individual attributes) are linked with public charging choices. Temporal attributes are an important consideration as the daily, weekly, and in-between recharging patterns are essential for understanding the public charging preferences of EV drivers. Vehicle attributes are also important because higher fixed battery capacity/mileage creates more opportunities for EVs to use public charging. As some public charging networks are (still) free and have high efficiency compared to home and workplace charging, while constantly changing SOC, the remaining range and excess range to the destination may be influenced by range anxiety, which drives EV users to use public charging. However, this does not mean that they will necessarily charge at public stations, as temporal and vehicle attributes, and the characteristics of the public charging infrastructure in terms of physical aspects, price, level of service, accessibility, convenience, and station information also influence charging choices. At the same time, individual attributes, including socio-economic and demographic characteristics and level of risk aversion contribute to preference heterogeneity.

Vehicle manufacturers are all too aware of what EV users want, but this review is a reminder that range is absolutely crucial when it comes to vehicle choice. The indirect evidence provided in this review is clearly saying that range is an important determinant in charging choices.

The individual and temporal attributes identified determine public charging choices, but they cannot be changed with policy. Policy, can, however, seek to adapt public charging infrastructure to better satisfy EV users' requirements. All in all, public infrastructure needs to be easily accessible, frequent, and with enough fast charging points to satisfy demand at peak times, especially in the morning and afternoon. It needs to be sheltered, somehow, to protect drivers from harsh weather conditions, and amenities, especially restrooms, are important. The slower the charging speed, the more important extra amenities, such as shopping and leisure facilities, are. All information regarding the public charging station, including pricing and methods of payment needs to be clearly and quickly accessible, and payment needs to be hassle-free. There is also incipient evidence that EV users prefer electricity generated in a clean manner, which is not surprising, as users are likely to be environmentally conscious. Clean electricity generation is, in any case, a must when it comes to road transport electrification, as there is plenty of evidence that shows that emissions will increase, rather than decrease, otherwise (Liu and Santos 2015; Woo et al. 2017; Gómez Vilchez and Jochem 2020; Cox et al. 2022).

The recommendations above are blindingly obvious and intuitive, and one may wonder what the point of even listing them is. The point is threefold: (a) as of 2023, no country has public charging stations that fulfil the requirements set above, so, as obvious as they may seem, action has not been taken yet; (b) academics and policymakers have devoted substantial time and resources over the last ten years trying to identify what these requirements are, and the present study synthesises them all in one place; and (c) ensuring these requirements are met will guarantee that EV users' demand is satisfied.

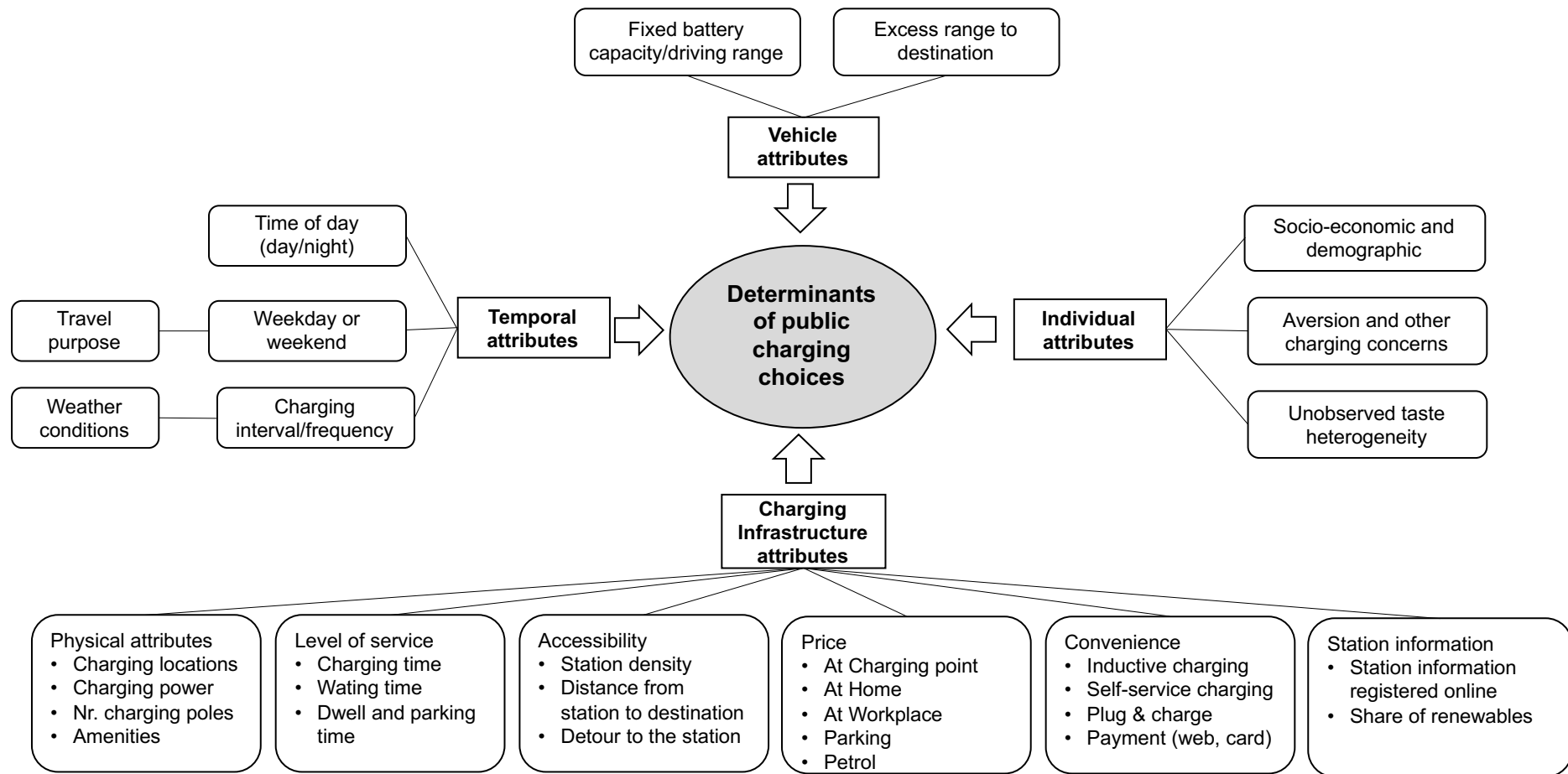


Figure 2-1: A conceptual framework of determinants of public charging choice

2.6 Conclusion

This chapter provides an up-to-date critical review of the academic and grey literature on public charging choices and their determinants. Findings from this critical analysis and synthesis of the literature show what determinants contribute to the public charging choices of potential and existing EV users. This evidence will not only benefit public charging providers in planning and making investment decisions regarding charging infrastructure but will also facilitate government policy measures to further deploy public charging infrastructure and promote electric vehicle uptake. The synthesis of the empirical evidence is also integrated into a conceptual framework that illustrates the complexities and dimensionality of public charging choices and shows how these are linked with the range of determinants identified. This framework explains the importance of temporal, vehicle, charging infrastructure, and individual attributes for current and potential EV users, who make or will potentially make those choices.

On the basis of the reviewed material, a number of research gaps can also be identified. Firstly, the evidence regarding temporal charging preferences is far from conclusive, with different patterns across and within different countries, which in itself is not a problem per se, except that it is difficult to find any reasons for these differences given the number of studies, the different sampling strategies and the different approaches used. Temporal charging preferences therefore should be further explored, especially in relation to travel purpose, trip length and charging speeds. Secondly, further research is needed to fully understand EV users' preferences for charging locations and payment models (e.g. monthly, pay as you go), especially in relation to safety, battery size of EVs, type of charging (destination or en route charging), and travel purpose. Preferences for charging locations are influenced by those factors but the evidence is sparse. Thirdly, more research is needed on preferences for different charging models and compatibility of payment methods. Exploring those themes further would allow to build a more solid evidence base.

Chapter 3 Designing a stated preference discrete choice experiment for public charging

3.1 Introduction

Modelling the actual charging choices of existing EV users is difficult as EV penetration in the UK is still low thus it is difficult to obtain a representative sample. Therefore, the stated preference (SP) approach is planned for this study. A major advantage of SP is that it allows researchers to obtain data efficiently to study choices made by hypothetical situations (Hensher et al. 1988). Therefore, the respondents of this study can be extended from existing EV users to potential EV buyers by using SP to study stated public charging choices, which simplifies data collection.

The main SP methods include the contingent valuation methods (CVM) and discrete choice experiments (DCE). Contingent valuation is a method for estimating the value that a person places on a good. The method requires people to directly report their willingness to pay (WTP) to obtain a specified good, or willingness to accept (WTA) compensation to give up a good, rather than inferring them from observed behaviours in regular marketplaces (Bateman et al. 2005). Stated choice (SC) experiments can also estimate the WTP, which is not obtained by direct questions for monetary valuations, but from respondents' choices of alternatives.

Stated choice (SC) experiments have been widely used in previous studies to reveal the preferences of potential and existing EV users (Wen et al. 2016; Moon et al. 2018; Pan et al. 2019; Sheldon et al. 2019; Wolbertus and Van den Hoed 2019; Wolff and Madlener 2019; Ashkrof et al. 2020; ten Have et al. 2020; Wang et al. 2021). It is a good tool to present hypothetical scenarios that do not exist in the market in the form of a controlled choice experiment, showing respondents with attributes and attribute levels, and asking them to evaluate the attribute and make a final choice among competing alternatives (Guerra and Daziano 2020). For example, this research includes possible future scenarios for public charging stations. To address the research questions posed in Section 3.1, a SC experiment was conducted in this study to investigate the preferences of potential and existing EV users for public charging infrastructure.

3.2 Experimental design

An experiment is the observation of the effect on the response variable (also known as the dependent variable) by manipulating the levels of one or more other attributes (also known as independent variables/factors) (Hensher et al. 2015). An experimental design is to scientifically manipulate/design the allocation of attribute levels among alternatives in accordance with experimental design theory to ensure that it does not affect the reliability of the model output. As shown in Figure 3-1, the experimental design process of generating the SC experiment consisted of eight (8) stages, which will be further discussed in the following subsections.

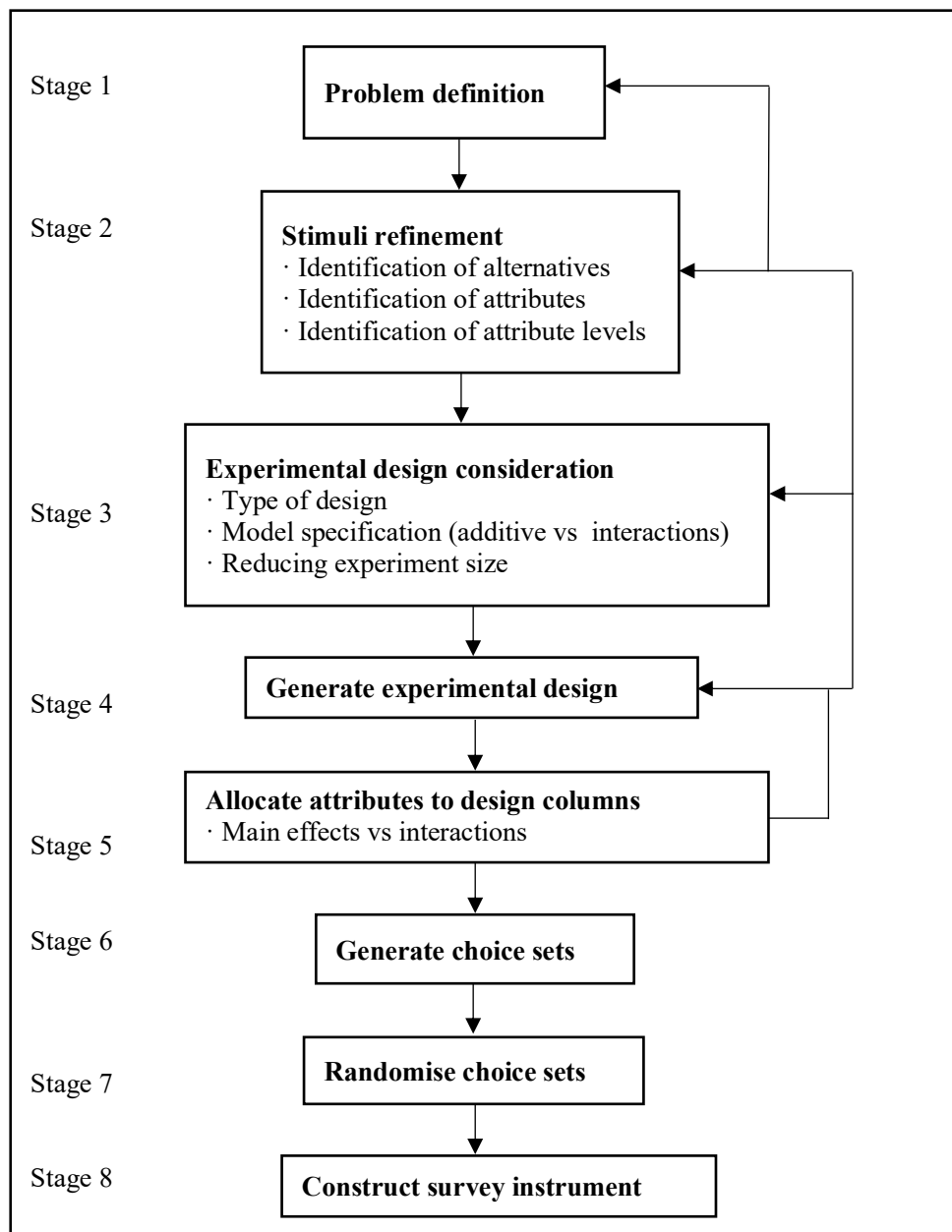


Figure 3-1: Experimental design process

Source: Hensher et al. (2015)

3.2.1 Stage 1: Problem definition

The design process begins with problem definition, which requires the analyst to define the research questions to refine their understanding of the problem being studied, and it is a good way to help hypothesis generation (Hensher et al. 2015). As this research objective is to investigate the preferences towards public charging stations for potential and existing EV users, the following problems need to be resolved based on the research questions asked in Section 3.1:

- What public charging stations (alternatives) will be available?
- What are the attributes/characteristics of these public charging stations?
- What determinants influence public charging choices?
- Who are the public charging users?
- Are the public charging preferences different by time of day?

The following sections will attempt to address these identified questions mentioned here in detail by several research approaches.

3.2.2 Stage 2: Stimuli refinement

Following the problem definition, the next stage is to identify alternatives and attributes for the choice experiment. The first is to identify the universal but limited number of alternatives available to decision-makers in terms of public charging stations. The second is to determine the attributes and attribute levels of these alternatives, all of which were selected based on the synthesis of previous literature in Chapter 2.

- Identification of alternatives

The universal alternatives for public charging choices are all available public charging stations on the market. It is obvious that these numbers are so many that it is impossible to include them all. Therefore, a finite number of alternatives are needed to be identified within the universal set of alternatives.

Stated choice experiments can be categorised into labelled and unlabelled depending on the naming of alternatives presented to the respondents. Labelled experiments refer to which the

alternatives are clearly defined and are described by labels, for example, slow or fast charging stations, while the unlabelled ones use generic titles for the alternatives (Hensher et al. 2015) such as charging station A or B (see Figure 3-2).

Labelled experiment: I would choose: ☐ Slow charging station ☐ Fast charging station ☐ I would choose none of these Unlabelled experiment (used in this research): I would choose: ☐ Charging Point A ☐ Charging Point B ☐ I would choose none of these

Figure 3-2: The example of the alternative selection of the unlabelled and labelled choice experiment

Deciding whether to use labelled or unlabelled experiments is important for the experimental design as both have their own advantages and need to be used according to the specific research needs (see Table 3-1). Labelled experiments are suitable for studies interested in estimating alternative-specific parameters or where the label of alternatives has a rich emotional attachment for the public so they tend to downplay the role of observed attribute levels (Hensher et al. 2015). This research is only interested in exploring the effect of attributes on public charging choice, thus the unlabelled experiment was developed. The main benefit of unlabelled experiments is that they do not require to identify and include all possible alternatives that labelled experiments do. Taking this study as an example, public charging stations A or B can be used to present all possible public charging stations, regardless of whether their charging rate is slow, fast, or ultrafast. Second, unlike the labelled experiments, the labels may be correlated with some attributes of the alternatives and thus have the risk of not meeting the IID (independent and identically distributed, which requires the alternatives,

and their attributes should be mutually exclusive) model assumption. For example, the labelled alternative, ‘fast charging point’, may be correlated with charging time and charging power attributes. Therefore, as shown in Figure 3-2, the alternatives are set as charging points A and B with charging station features, and an opt-out option.

Table 3-1: The applicable situations of labelled or unlabelled experiments

Categories of experiments	Applicable situations
Labelled	• Alternative-specific parameter estimates • Label of alternatives is important to respondents or the study subject
Unlabelled	• Generic titles for the alternatives would not cause any difference in the study • Strict requirement of IID assumption

Source: Hensher et al. (2015)

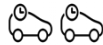
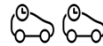
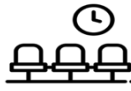
- Identification of attributes and attribute levels

The choice experiment was designed to focus on seven (7) attributes related to public charging infrastructure, including charging locations (Hardman et al. 2018a; Baresch and Moser 2019; Gnann et al. 2019; Delmonte et al. 2020), whether it is fast charging or not, charging price (Hardman et al. 2018a; Wolbertus and Gerzon 2018; Dorcec et al. 2019; Pagani et al. 2019; Delmonte et al. 2020), waiting time (Hardman et al. 2018a; Globisch et al. 2019; Ma et al. 2019; ten Have et al. 2020; Pevec et al. 2020), payment methods (Chakraborty et al. 2019), and amenities (Chakraborty et al. 2019; Csonka and Csiszár 2019; ten Have et al. 2020; Welsh Government 2020). These factors were selected based on the listed previous studies which have confirmed their importance in charging choices. Different levels of these 7 attributes are presented in Table 3-2.

Previous studies on **charging choices** have mainly considered home, work, and public locations (Xu et al. 2017; Chakraborty et al. 2019; Sheldon et al. 2019; Wolff and Madlener 2019; Lee et al. 2020). They found that 50%-80% of all charging events occurred at home, while charging at work and public charging stations ranked second and third (Hardman et al. 2018b). In terms of the locations of public charging stations, previous studies have considered multiple places in the public. For potential consumers, a study in the United States showed a clear preference for charging at the workplace and grocery stores, followed by malls, then fast chargers near home and on freeways, with schools and gyms being the least desired charging

locations (Sheldon et al. 2019). However, a study in Germany showed a different order, with a significant preference for roadside charging as a side activity rather than as a primary goal (Wolff and Madlener 2019). While these studies do provide valuable insights into the distribution design of future public charging infrastructure, the number of suitable locations for public charging posts in the public is infinite and hardly exhaustive. Therefore, for the sake of simplicity and generality, charging locations were classified into four different types of parking spaces. This is also an innovative aspect of this study, as no other study has previously focused on this point. As a result, in the choice experiment, charging locations were chosen based on different types of parking spaces, including (i) street parking space, (ii) surface car park, (iii) multi-storey car park, and (iv) underground car park.

Table 3-2: Attributes and levels in the public-charging choice experiment

Attributes	Levels					
	1	2	3	4	5	6
Location	On street 	Surface-level car park 	Multi-storey car park 	Underground car park 		
Fast charging	✓	X				
Cost (p/kWh)	Current price (45)	10% more than current price (50)	20% more than current price (54)	30% more than current price (59)	40% more than current price (63)	
Distance from charging point to your destination (metres)	100	250	500	1,000		
Waiting time for an available charging point (minutes)	Available right away 	2 	5 	10  		
Method of payment	Card or contactless payment 	Card or contactless payment or via supplier's app 	Card payment or via universal app 	Payment taken automatically 		
Amenities	None	Waiting room 	Small shop or café 	Shopping mall 		

Evidence from previous is robust indicating that fast charging is generally preferred over slow charging due to time savings (Xu et al. 2017; Dorcec et al. 2019; Globisch et al. 2019; Sheldon et al. 2019; Wolff and Madlener 2019; Illmann and Kluge 2020). Instead of using charging time as an attribute, this choice experiment presents the charging speed of the charging station in terms of whether it is **fast charging or not**, as this way can reduce some complexity of assuming charging powers and corresponding charging times.

Previous studies have reported a negative association between **charging prices** and charging choices (Wen et al. 2016; Xu et al. 2017; Moon et al. 2018; Dorcec et al. 2019; Globisch et al. 2019; Pan et al. 2019; Wolff and Madlener 2019; Ashkrof et al. 2020; Azarova et al. 2020; ten Have et al. 2020; Lee et al. 2020). The levels of charging price in this choice experiment are the cost to charge the electric vehicle from 20% to 80% of its battery level. Based on the charging price at public charging points under the operation of bp pulse (see Table 3-3), the baseline charging price is assumed to be (i) 45 p/kWh. The following 4 levels were set with a 10% increase in the baseline level, which is (ii) 50p/kWh, (iii) 54p/kWh, (iv) 59p/kWh, (v) 63p/kWh respectively. Among these 5 levels, the first three levels can be used for estimating slow public charging, while the last three levels can be used for fast charging.

Table 3-3: An overview of charging prices from different public charging providers – as of date April 2022

Charging provider	Charging Prices of charging points with different power capacity		
Bp pulse (PAYG)	7 kW – 45p/kWh	50 kW – 56p/kWh	150 kW – 59p/kWh
Osprey	PAYG – 50 KW - 49p/kWh		
Swarco E.Connect	Type 2 (7kW) – 31p/kWh		
ubitrlicity	Type 2 (5kW) – 24p/kWh		
Source London	PAYG – 7.4kW and 22 kW – 59p/kWh	Overnight cape of £14.16 (20:00 – 07:00)	
Pod point	Rapid charger – 28p/kWh	Most network rapid chargers cost 44p/kWh which is about £11 for 30 minutes of charging (as of April 2022)	

Note: ‘PAYG’ refers to pay as you go.

Previous studies generally used time (ten Have et al. 2020) and distance (Sun et al. 2016; Latinopoulos et al. 2017) to evaluate the ease to access to public charging points. For example, Latinopoulos et al. (2017) adopted the walking distance from the charging place to the destination (e.g., 4 min/20 min walking from your destination evaluate the accessibility of public charging points. In general, potential and existing EV users prefer higher accessibility to public charging stations. Ten Have et al. (2020) found that always making a time-based

detour (e.g. 5 minutes) makes the charging point less appealing. A study of private BEV users in Japan showed they preferred to make a 1,750-metre detour on weekdays, and a maximum of 750 metres on non-working days to use fast charging, respectively (Sun et al. 2016). Based on the studies mentioned above, this choice experiment chose 4 levels for **the distance from the destination to charging points**, ranging from (i) 100m, (ii) 250m, (iii) 500m to (iv) 1000m.

The availability of charging points also needed to be considered in empirical charging sessions (Chakraborty et al. 2019; Wolff and Madlener 2019; Ashkrof et al. 2020; ten Have et al. 2020; Wang et al. 2021). Otherwise, people will have to spend extra time, such as taking a detour to the next charging service or waiting longer at the current charging station, or they may have to simply give up the charging activity. Previous studies used queueing/waiting time to measure the availability of public charging points and found it has a negative effect on the charging choice (Ashkrof et al. 2020; ten Have et al. 2020; Wang et al. 2021). [Based on the review of the waiting time level design in the literature review section \(Section 2.3.3.3\)](#), in this choice experiment, waiting time refers to the time EV users need to wait for charging points to become available. Four **waiting time** levels were chosen in this study, including (i) 0 minutes (no wait), (ii) 2 minutes, (iii) 5 minutes, and (iv) 10 minutes.

Payment methods have not been discussed in previous studies, and only the subscription (membership) to an EV charging provider has been reported as an important factor in public charging choice (Hardman et al. 2018a; Chakraborty et al. 2019). Typically, EV owners are required to sign up for a charging network, such as ChargePoint or EVgo, to gain access to their range of public charging stations. Chakraborty et al. (2019) found that charging network membership had a positive effect on BEV users' choice of public charging infrastructure. A clear impact of this factor by this study suggested that when all other factors were equal, a BEV user who was a member of a charging network was 1.2% more likely to use public charging than non-members. However, there is still a lack of focus on the impact of payment methods. Therefore, this study incorporates various payment methods that have been used by public charging infrastructure providers^{2,3} (bp pulse 2022; Osprey 2024), including card payment, contactless payment, and payment via the supplier's app. In general, these apps provided by

² Osprey: contactless payment with a credit or debit card, or mobile wallet (e.g. Apple Pay); osprey charging app is available for regular users who want access to monthly billing and VAT receipts; 3rd party payment methods including Zap-Pay (enable EV drivers to use a single app to pay for charging across different networks) and the Octopus Juice Network; fleet cards including Allstar, NewMotion, DKV, Mina and Paua.

³ Bp pulse: contactless bank card, Apple Pay or Google Pay, network access card (RFID card), bp pulse app.

different charging operators allow EV users to view live charging session information and the charge history of the vehicle, download VAT receipts, and monthly billing through adding credit/debit cards (Osprey 2024). In addition to these existing payment methods, this study further includes two other possible payment methods in the future. One is a universal app that would be able to collect information on all available public charging points from different service providers and allow payments to be made through this app. In the current case, there are many public charging infrastructure providers, all of which have their own apps for making payments. However, this is not convenient for EV users' charging choices, as they have to trade off between offers promised by these providers and then make a final choice among these charging providers. Otherwise, they would be faced with a situation where they would have to download multiple apps and use different charging networks to get the best deals. Another scenario is that in the near future, new technology will be feasible to allow automatic payments once the EV is connected to the charger, as new electric cars will have built-in authentication data⁴. Therefore, this choice experiment chose four levels for estimating the impact of payment methods on public charging choice, varying from (i) card or contactless payment to (ii) card or contactless payment or via supplier's app, (iii) card or contactless payment or via a universal app, (iv) card-free with payment taken automatically once the electric vehicle is connected to the charger.

Amenities refer to proximal facilities near public charging points. Ten Have et al. (2020) explored different amenity scenarios around public charging stations, such as waiting rooms, shopping malls, small shops or cafés, or places without facilities. The results showed that having a slow charging point near a shopping area increased its attractiveness. The authors also found that in the absence of any other facilities, the propensity to choose fast and slow charging points was higher than ultrafast charging. This study also chose the same levels mentioned in the literature, including (i) a waiting room, (ii) a small shop or café, (iii) a shopping mall within walking distance, and (iv) no other facilities (ten Have et al. 2020).

3.2.3 Stage 3: Experimental design considerations

Having identified the alternatives, attributes, and attribute levels, then it is time to make decisions on how to do the *design*. This is important because the behaviour of the research will

⁴ 'New electric cars will have in-built authentication data. You will simply connect to the charging station for payment to be made automatically' - <https://www.motoringelectric.com/charging/do-electric-car-charging-points-take-credit-cards/>.

affect the decision when considering the statistical characteristics of the design (Hensher et al. 2015).

- Type of design

The designs available can constrain the behaviours that the analyst is able to explore (Hensher et al. 2015). Two common types of design are the full factorial and fractional factorial design. A full factorial design consists of all possible combinations of attribute levels. For example, this choice experiment contains seven (7) attributes, where five (5) attributes contain four (4) levels, one (1) attribute contain two (2) levels, and one (1) attribute contain five (5) levels. According to the calculation function L^A (Hensher et al. 2015)⁵ for unlabelled experiments (Hensher et al. 2015), this choice experiment, therefore, yields $4^5 \times 2 \times 5^1 = 10,240$ possible combinations of attribute levels.

It is impossible to ask respondents to undertake 10,240 choice tasks, thus reducing the size of the experimental design is very important to simplify the choice experiment. Reducing the number of levels in a design will greatly reduce the size of the design, however, such a reduction comes at the cost of the amount of observational information gained by the design (Hensher et al. 2015). The fractional factorial design, in which a fraction of the total number of attribute level combinations is extracted across all possible choice sets, applies in this case. However, random selection may result in producing statistically inefficient or sub-optimal designs (Hensher et al. 2015). Therefore, scientific methods/experimental design theories are needed to select the optimal attribute level combinations for the choice experiment.

There are two common types of fractional factorial design, including orthogonal and optimal/efficient design. Orthogonal design requires orthogonality, which requires that all attributes be statistically independent of one another (zero correlation), which means each possible pair of attribute levels appears an equal number of times over the design. Therefore, orthogonal design is suitable for linear regression models, as it allows for an independent estimation of the influence of each design attribute on choice. However, discrete choice models are non-linear models. Efficient designs aim to produce data with parameter estimates that have the smallest possible standard errors (Choicemetrics Pty Ltd 2022). These designs make use of

⁵ This is the function to calculate possible choice sets for unlabelled experiments, where L is the number of levels and A is the number of attributes.

the asymptotic variance-covariance (AVC) matrix (the roots of the diagonal of this matrix are the asymptotic standard errors) of the parameters derived based on the prior information of parameters (e.g., parameter estimates available in the literature from similar studies, or parameter estimates from pilot studies). However, instead of assessing a whole AVC matrix, it is easier to assess a design based on a single value. Therefore, D-error, A-error, S-error, and C-error were proposed as the efficiency measures (Choicemetrics Pty Ltd 2022). Then, the objective of an optimal design is to find the minimal efficiency error. D-error is a widely used measure to reflect the efficiency of a design. A design with the lowest D-error is called D-optimal. In practice it is difficult to find the design with the lowest D-error, therefore it is satisfied if the design has a sufficiently low D-error.

Table 3-4 summarised the requirement, advantages, and shortcomings of orthogonal and optimal design. Orthogonal design is efficient only in cases where there is no knowledge about the parameters, but whenever there is any prior parameter information available (perhaps just knowledge of the sign of the parameter) then the design can be improved. This choice experiment assumes that the a priori estimates of these parameters are zero for all variables.

Table 3-4: The comparison of two common fractional factorial designs

Design type	Requirement	Advantages	Shortcomings
Orthogonal	Attribute levels for each attribute column in the design need to be uncorrelated	• Easy to construct or obtain • Suitable for linear regression models where the orthogonality of data is considered important	• Cannot avoid choice situations in which a certain alternative is clearly more preferred over the others; • A carefully determined orthogonal experimental design is likely to produce non-orthogonal data.
Optimal/ Efficient	Designs with parameter estimates have smallest standard errors based prior information about the parameter estimates	• Design can be improved whenever there is any prior parameter information available	• Prior parameter estimates need to be available and the results of standard errors rely on the accuracy of the prior parameter estimates

Source: Hensher et al. (2015); Choicemetrics Pty Ltd (2022)

- **Model specification**

As alternatives, attributes and attribute levels were identified, it is important to use them to compose utility models, which can help researchers better understand the choice experiment and design process. Firstly, in this choice experiment, two (2) alternatives and one (1) opt-out option were introduced, which means the respondents could make a choice between the two charging options, each described by seven (7) attributes with varying levels, or they could also be allowed to choose neither of the options offered.

Secondly, dummy coding was considered as it allows for non-linear effects in the levels of the attributes (Hensher et al. 2015). This was accomplished through the creation of several variables for all categorical attributes ('location', 'fast charging', 'payment methods', 'amenity'), and the number of new variables created is equivalent to the number of levels of the attribute being coded, minus one. This dummy coding techniques enable researchers to view the impacts of each level of the attributes. Taking the charging location as an example (See Table 3-5), it is clear that when the chosen level of charging location represents 'surface car park', then the new variable 'Location (on street)' will equal to '1', otherwise it will be equal to '0'. In the models, three dummy variables ('Location (on street)', 'Location (surface-level car park)', 'Location (multi-storey car park)') were generated for charging location. Similarly, three dummy variables were generated for 'payment methods', and 'amenity', and one for 'fast charging'. Through dummy coding, different value of utility can be associated with each level of the attributes, which overcome the linear effect of levels of traditional coding method. It is important to note here that the first three levels associated with the 'location' attribute used to generate new variables are called dummy variables, while the last level is considered the basis for comparison with the other three levels, in this case, i.e. when the selected level of the charging location represents 'underground car park'.

Table 3-5: Example of dummy coding for 'location' attribute

Attribute level \ Variable	Location (on street)	Location (surface-level car park)	Location (multi-storey car park)
On street	1	0	0
Surface-level car park	0	1	0
Multi-storey car park	0	0	1
Underground car park	0	0	0

Based on these alternatives, attributes and attribute levels, and the dummy coding considerations, the representative component of the utility of the three alternatives (ignoring interactions) can be written as linear functions considering the non-linear effects, as follows:

$$\begin{aligned}
 V_A = & \beta_{0A} + \beta_{1A} * \text{location}(\text{on street}) + \beta_{2A} * \text{location}(\text{surface} - \text{level car park}) \\
 & + \beta_{3A} * \text{location}(\text{multi} - \text{storey car park}) + \beta_{4A} * \text{fast}(\text{yes}) + \beta_{5A} \\
 & * \text{price} + \beta_{6A} * \text{distance} + \beta_{7A} * \text{wait} + \beta_{8A} * \text{pay}(\text{card or contactless}) \\
 & + \beta_{9A} * \text{pay}(\text{card or contactless or via supplier's app}) + \beta_{10A} \\
 & * \text{pay}(\text{card or contactless or via universal app}) + \beta_{11A} \\
 & * \text{amen}(\text{waiting room}) + \beta_{12A} * \text{amen}(\text{small shop or cafe}) + \beta_{13A} \\
 & * \text{amen}(\text{shopping mall})
 \end{aligned}$$

$$\begin{aligned}
 V_B = & \beta_{0B} + \beta_{1B} * \text{location}(\text{on street}) + \beta_{2B} * \text{location}(\text{surface} - \text{level car park}) \\
 & + \beta_{3B} * \text{location}(\text{multi} - \text{storey car park}) + \beta_{4B} * \text{fast}(\text{yes}) + \beta_{5B} \\
 & * \text{price} + \beta_{6B} * \text{distance} + \beta_{7B} * \text{wait} + \beta_{8B} \\
 & * \text{pay}(\text{card or contactless}) + \beta_{9B} \\
 & * \text{pay}(\text{card or contactless or via supplier's app}) + \beta_{10B} \\
 & * \text{pay}(\text{card or contactless or via universal app}) + \beta_{11B} \\
 & * \text{amen}(\text{waiting room}) + \beta_{12B} * \text{amen}(\text{small shop or cafe}) + \beta_{13B} \\
 & * \text{amen}(\text{shopping mall})
 \end{aligned}$$

$$V_C = 0$$

- Reducing experiment size

As discussed in stage 3 above, the efficient design is appropriate for the experimental design. Therefore, instead of a full factorial design, it is important to determine the minimum number of attribute level combinations for the efficient design. To achieving this, the researcher is obligated to establish how many degrees of freedom are required for estimation purposes. This decision depends on the number of parameters to be estimated in the modelling, which in turn depends on how the researcher may specify the model. The degrees of freedom for an experiment are given as $S \times (J - 1)$, where S is the number of the choice situations and J is the number of alternatives (3) in each choice situation. This number must be greater than or equal to the number of independent (linear) constraints placed upon it during the modelling process. The independent (linear) constraints are the β parameters we estimate, including any constant. Thus, in terms of the utility equations, a total of 28 parameters are required to be

estimated (ignoring interactions), which means the above model specification would require a minimum of 28 degrees of freedom. Given $S \times (J - 1) \geq 28$, the minimum number of choice situations would be 14. To balance the number of alternatives (3) and attributes levels (5, 4, 2), as well as considering the minimum number of choice situations (14) calculated by the degree of freedom required, 60 choice cards (rows) were generated.

However, even 60 choice cards for each respondent will be too much burden, thus a procedure called blocking is needed, which is another method used to reduce the number of choice situations shown to each respondent. Blocking requires the researcher introducing another orthogonal column to the design, the attribute levels of which are used to segment the design. Thus, a blocking technique (12 blocks) was adopted to reduce the choice cards to a feasible number (five) for each participant.

3.2.4 Stage 4: Generating experimental design

Ngene (<http://www.choice-metrics.com>) is a comprehensive tool developed by choicemetric Pty Ltd with the capability to design the wide range of choice experiments and to provide syntax examples for experimental designs. Based on the Ngene manual (Choicemetrics Pty Ltd 2022), the Ngene code for the experimental design is as follows (see, Figure 3-3), where the text in red represents the annotation of the code and the black text is the original syntax.

```
? Design.ngs --- Experimental Design --- 04. 10. 2022

? Total 7 Attributes
? [1] location[1,2,3,4] --- Charging locations, including 4 levels
?     [1] On street; [2] Surface-level car park; [3] Multi-storey car park; [4]
Underground car park

? [2] fast[0,1] --- 0 represents slow public charging, 1 represents fast public
charging
?     [0] Slow charging; [1] Fast charging

? [3] price[0.45 (base),0.50 (+10%),0.54 (+20%),0.59 (+30%),0.63 (+40%)] ---
Charging price, including 5 levels; 0.45 is the base price for public slow charging
and the rest are the increasing percentage prices based on the base level
respectively.
?     [1] 0.45 £/kWh; [2] 0.50 £/kWh; [3] 0.54 £/kWh; [4]0.59 £/kWh; [5] 0.63 £/kWh
```

```

? [4] distance[100,250,500,1000] --- Distance from charging point to your
destination (metres), including 4 levels
?      [1] 100 metres; [2] 250 metres; [3] 500 metres; [4] 1000 metres

? [5] wait[0,2,5,10] --- Waiting time for an available charging point (minutes),
including 4 levels
?      [1] 0 (Available right away); [2] 2 minutes; [3] 5 minutes; [4] 10 minutes

? [6] pay[1,2,3,4] --- Method of payment, including 4 levels
?      [1] Card or contactless payment; [2] Card or contactless payment or via
supplier's app; [3] Card or contactless payment or via universal app; [4] payment
taken automatically

? [7] amen[1,2,3,4] --- Amenities, including 4 levels
?      [1] No amenities; [2] Waiting room; [3] Small shop or café; [4] Shopping mall
within walking distance

? Each choice card will include 2 unlabelled options and a none alternative
? 60 potential choice cards into 12 blocks so that each respondent receives 5 cards
(scenarios)
? The aim to generate several choice cards is to exhaust respondents. More choice
cards (normally 5 to 10) for each respondent then more observations we can generate,
which may lead to more valid results

Design;
alts=alt1*,alt2*,None; ? number of alternatives
rows=60; ? number of choice cards
block=12; ?number of blocks in the design matrix
eff=(mnl,d); ? Set of efficiency measure: using the D-error for finding an efficient
design for the MNL modle
? alg = mfederov(stop=total(2000000 iterations));
? Use swap not mfederov algorithm is because it cannot be used with a condition
(cond:)

alg = swap(stop=total(10 mins));

? set a condition:
? If the alternative is assumed to use slow charging (alt1/2.fast = [0]), then the
charging price for this alternative will be chosen randomly from [0.45, 0.50,
0.54]; if the alternative is assumed to use fast charging (alt1/2.fast = [1]), then
the charging price for this alternative will be chosen randomly from [0.54, 0.59,
0.63];
? The setting is the potential charging prices for fast charging are higher than
slow charging

```



```

cond:
If (alt1.fast = [0], alt1.price = [0.45, 0.50, 0.54]),
If (alt1.fast = [1], alt1.price = [0.54, 0.59, 0.63]),
If (alt2.fast = [0], alt2.price = [0.45, 0.50, 0.54]),
If (alt2.fast = [1], alt2.price = [0.54, 0.59, 0.63]);

? For 'fast' variable, we put '1' before '0' (base) is because 1 represent fast
charging and thus we assume a dummy variable for fast charging
? For dummy variables, we can assume a starting point of the parameters by
estimating whether the effect of this variable is negative (e.g., -0.000001) or
positive (e.g., 0.000001)
?utilities
model:
U(alt1)=b1.dummy[0|0|0]*location[1,2,3,4]
      +b2.dummy[0]*fast [1,0]
      +b3[0]*price[0.45, 0.50, 0.54, 0.59, 0.63]
      +b4[0]*distance[100,250,500,1000]
      +b5[0]*wait[0,2,5,10]
      +b6.dummy[0|0|0]*pay[1,2,3,4]
      +b7.dummy[0|0|0]*amen[2,3,4,1] /

U(alt2)=b1*location
      +b2*fast
      +b3*price
      +b4*distance
      +b5*wait
      +b6*pay
      +b7*amen/

? Set an opt-out option
U(None) = none[0]
$

```

Figure 3-3: Syntax code in Ngene

The first part of the annotation is a description of the variable names to presents alternatives, attributes, and attribute levels. Then the syntax 'rows=60;block=12;' shows 60 choice situations and 12 blocks intended to be generated, which indicates that eventually 5 choice situations will be created to be presented to each respondent. Following syntax 'eff=(mnl,d);' presents the prior setting of the efficiency measure D-error of the efficient design to finding the design for the MNL model. Different search algorithms can be developed to generate a design, for

example, RSC (relabelling-swapping-cycling), swapping, and Modified Federov (Choicemetrics Pty Ltd 2022). The default swapping algorithm was chosen for this design (see, syntax `'alg = swap(stop=total(10 mins));'`) instead of the Modified Federov, as the latter cannot be used when conditions need to be applied. The final part of the syntax is the model, which has already discussed in model specification part in stage 3. As no information is available, then we set $\tilde{\beta} = 0$.

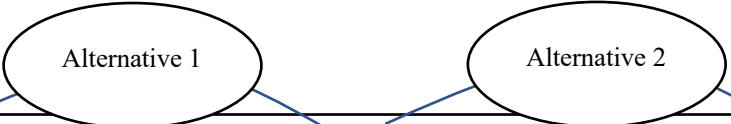
It should be noted in the syntax that in order to avoid generating unrealistic alternatives, for example, charging services with lower charging prices and slow charging services with higher prices, constraints/conditions need to be set on the attribute levels. This choice experiment chose five (5) charging prices respectively (£0.45/kWh, £0.50/kWh, £0.54/kWh, £0.59/kWh, £0.63/kWh), but these prices could not be selected randomly when generating the choice sets because the former three levels of charging prices are designed for slow public charging points, and the later three levels of charging prices are designed for fast charging. The 'cond' property can be used to include these conditions, which are basically if-then statements (Choicemetrics Pty Ltd 2022). The conditions set in the experimental design are shown in Table 3-6, which can be used to prevent unrealistic scenarios, for example, if the condition is not applied then a cost of £0.45/kWh for alternative 1 using fast charging and £0.63/kWh for alternative 2 using slow charging could occur.

Table 3-6: The explanation of the condition syntax in showing the choice experiment

Condition	Possible scenario		
‘If (alt1.fast = [0], alt1.price = [0.45, 0.50, 0.54]), If (alt1.fast = [1], alt1.price = [0.54, 0.59, 0.63]), If (alt2.fast = [0], alt2.price = [0.45, 0.50, 0.54]), If (alt2.fast = [1], alt2.price = [0.54, 0.59, 0.63]);’	Attributes	Charging station A	Charging station B
	Fast charging	No	Yes
	Charging price	Choice from £0.45/kWh, £0.50/kWh, £0.54/kWh	Choice from £0.54/kWh, £0.59/kWh, £0.63/kWh
If not apply the condition	Possible scenario		
	Attributes	Charging station A	Charging station B
	Fast charging	No	Yes
	Charging price	Choice from £0.45/kWh, £0.50/kWh, £0.54/kWh, £0.59/kWh, £0.63/kWh	Choice from £0.45/kWh, £0.50/kWh, £0.54/kWh, £0.59/kWh, £0.63/kWh

3.2.5 Stage 5: Allocating attributes to design columns

After the 10-minute algorithm iterations, the design with the lowest D-error (0.066275) was chosen for later process of generating choice cards. The design matrix was generated from the design and then exported it into Microsoft Excel (see, Figure 3-4). The first column of the design matrix is 12 blocks with five (5) choice situations per block, which is exactly as expected in the study. The second column represents the choice situation (60 in total). From column three (3) to nine (9) are the attribute levels chosen for corresponding attribute of alternative one (1). Similarly, column 10 to 16 represents the attribute levels for alternative two (2).



Block	Choice situation	alt1.locati	alt1.fast	alt1.price	alt1.distan	alt1.wait	alt1.pay	alt1.amer	alt2.locati	alt2.fast	alt2.price	alt2.distan	alt2.wait	alt2.pay	alt2.amer
1	4	3	2	3	4	2	1	3	4	1	3	1	3	4	2
1	5	2	1	1	2	2	1	1	3	2	5	3	3	3	4
1	19	4	2	4	4	4	2	3	2	1	2	1	1	4	2
1	43	2	2	4	2	1	4	3	3	1	2	3	4	1	2
1	59	2	1	3	4	2	3	4	3	2	3	1	3	2	3
2	2	1	1	3	3	4	3	1	2	2	3	2	1	1	2
2	8	1	2	4	3	4	2	2	2	1	2	2	1	3	4
2	36	4	1	2	2	1	3	4	3	2	4	4	4	1	1
2	44	1	2	3	2	1	3	3	4	1	3	3	4	1	2
2	47	4	2	5	2	1	1	2	1	1	1	3	4	2	4
3	16	4	2	3	2	2	4	1	3	1	3	3	3	1	2
3	30	1	1	1	3	2	1	4	2	2	5	2	3	4	1
3	40	3	1	2	2	1	4	1	2	2	4	3	4	3	2
3	48	1	1	2	1	3	3	3	4	2	4	4	2	1	1
3	58	2	1	2	3	4	1	1	3	2	4	2	1	2	3
4	3	2	1	3	3	3	2	1	1	2	3	2	2	4	2
4	18	2	1	3	4	1	2	3	1	2	3	1	4	3	4
4	50	2	2	3	1	2	3	1	1	1	3	4	3	4	2
4	51	3	1	1	1	3	3	4	1	2	5	4	2	4	3
4	56	3	2	5	1	2	2	4	4	1	1	4	4	3	3
5	14	4	1	1	4	3	3	4	1	2	5	1	3	1	1
5	17	3	1	3	3	2	3	3	1	2	3	2	2	1	1
5	24	1	2	5	3	3	2	4	4	1	1	2	2	3	3
5	52	3	2	3	3	3	4	1	4	1	3	2	2	2	2
5	54	4	2	5	1	4	2	4	3	1	1	4	1	3	3
6	7	4	1	3	2	4	3	1	1	2	3	3	1	4	4
6	28	2	1	2	4	3	2	3	4	2	4	1	2	3	4
6	38	1	2	3	1	2	3	2	3	1	3	4	3	4	4
6	41	2	2	4	2	4	1	3	4	1	2	3	1	3	1
6	57	4	2	4	1	4	4	2	2	1	2	3	1	2	4
7	32	4	1	1	3	3	4	4	1	2	5	2	2	3	1
7	42	1	1	1	4	4	4	2	3	2	5	1	1	2	1
7	46	4	2	5	2	4	1	3	2	1	1	3	1	4	2
7	49	3	1	1	3	3	2	2	2	2	5	2	2	4	4
7	55	2	1	3	1	4	4	2	3	2	3	4	1	1	4
8	1	3	2	5	1	2	3	2	4	1	1	4	3	2	1
8	20	2	2	4	2	2	4	3	1	1	2	3	3	2	1
8	23	4	1	1	1	1	4	1	2	2	5	4	4	3	3
8	34	3	2	3	3	4	3	1	1	1	3	2	1	2	3
8	45	3	1	1	2	2	1	2	4	2	5	3	3	4	3
9	10	1	1	2	3	2	2	2	4	2	3	2	3	1	1
9	13	3	2	5	4	3	2	2	1	1	1	1	2	1	3
9	35	2	1	2	4	1	1	2	4	2	4	1	4	2	3
9	53	2	2	4	2	4	1	4	3	1	2	3	1	4	2
9	60	3	2	5	4	3	4	4	1	1	1	1	2	2	3
10	6	1	2	5	4	1	4	1	2	1	1	1	4	1	4
10	11	2	2	3	2	1	2	1	1	1	3	3	4	1	4
10	26	4	1	3	1	1	2	4	2	2	4	4	4	4	3
10	31	4	2	4	4	1	1	2	2	1	2	1	4	4	4
10	33	4	2	3	4	1	2	2	3	1	3	1	3	1	1
11	12	4	1	2	4	3	4	3	2	2	4	1	2	3	2
11	15	3	2	5	1	2	1	3	2	1	1	4	3	2	1
11	22	1	1	3	4	1	1	4	2	2	3	1	4	2	2
11	37	1	2	4	3	3	3	2	4	1	2	2	2	1	3
11	39	1	2	3	2	3	4	4	3	1	3	3	2	3	3
12	9	3	1	2	1	3	2	1	4	2	4	4	2	3	2
12	21	3	1	1	1	4	4	3	1	2	5	4	1	3	1
12	25	2	2	4	3	2	1	4	3	1	2	2	3	4	1
12	27	1	1	3	1	1	1	3	3	2	3	4	4	2	4
12	29	1	1	2	3	4	3	1	4	2	4	2	1	2	4

Figure 3-4: The generated design matrix of the public charging experiment

3.2.6 Stage 6: Generating choice sets

The choice set not only presents decision-makers with information on the alternatives, attributes and attribute levels that exist in the hypothetical scenario under study, but also facilitates researchers to gather information from the responses of sampled decision-makers to the given alternatives, attributes and attribute levels (Hensher et al. 2015). Typical choice sets contain two parts, the first part is an introductory text showing the hypothetical context, and the second part is the choice cards that requires respondents' choices.

- **Introduction to the experiment and assumptions**

An introductory text is needed to provide context prior to showing the choice cards to the respondents. The following points are essential aspects to consider in order to exclude the effect of other factors:

- 1) This choice experiment needs to assume that EV drivers feel the need to recharge now. This is because previous studies have confirmed that EV drivers' willingness to charge decreases dramatically when their EVs own a sufficient amount of charge (Sun et al. 2016; Xu et al. 2017; Dorcec et al. 2019; Pan et al. 2019; Ashkrof et al. 2020; Pevec et al. 2020; Wang et al. 2021). This hypothesis avoids situations where someone might feel that this is not a critical point for them to make a charging decision then they may defer their charging demand.

- 2) Also, this choice experiment needs to assume the EV driver is now away from their home but within the area they normally live. The main reason for this assumption is to limit EV drivers to focus on their daily travels rather than the less frequent long-distance trips. Meanwhile, by assuming people all live in their own residence zone and make their daily travel, the geographical and regional characteristics of respondents can be incorporated into this study. For example, people who reside in urban or rural areas may have varied preferences for public charging infrastructure and value attributes of public charging stations differently. Pevec et al. (2020) provided evidence that people living in larger settlements such as cities and metropolitan areas prefer a lower spatial distribution of public charging stations, while in smaller places such as towns and villages, people prefer longer distances between these stations. This assumption is valuable for the design of future public charging infrastructure considering the geographic differences between urban and rural areas.

- 3) The choice experiment requires a hypothesis of how much power the EV will get at the end of the charging session. This choice experiment assumes that the original state of charge (SOC) is 20% and an 80% charge will be guaranteed at the end. Although there is evidence showing that most non-EV owners are more inclined to charge when SOC drops below 15%, a level at which most EVs prompt a warning about the low battery capacity (Pevec et al. 2020), this choice experiment chose a charging demand from 20% to 80% to facilitate the calculation of charging time and price. Otherwise, respondents may choose to charge at different SOC levels and end charging sessions at

different battery charge levels based on their travel plans and the length of stay (dwell time) at the destination. On the other hand, dwell time is also a factor that may influence charging choices. Pan et al. (2019) found that EV users' planned dwell time did not appear to significantly influence charging decisions. In contrast, the study by Yun et al. (2019) showed that dwell time was one of the main predictors of charging location choice for PHEV users. Although there is no consensus on the impact of dwell time on charging choice, it is clear that active dwell time naturally poses a temporal constraint on the charging time and parking time of EVs. Therefore, assuming specific dwell times can be avoided under the assumption of this fixed charging demand (from 20% to 80% of charge).

- 4) Finally, the experiment assumes the scenario occurs 'during the day' because previous studies have found that potential and existing EV users prefer to charge at home overnight and use public charging infrastructure during the day (Xu et al. 2017; Moon et al. 2018).

In addition to these hypotheses needing to be considered in the introductory text to control other factors, this choice experiment also needs to make two additional assumptions. These assumptions will not be presented to the respondents as this is extra information that might distract them.

- 1) This choice experiment assumes that the respondent owns a Nissan Leaf with a 40kWh battery capacity (Electric Vehicle Database 2022). The Nissan Leaf was chosen for the choice experiment because it has been the best-selling EV in the world for the past few years due to its wide range of advanced driver-assistance features and affordability. It is also ranked fourth in the UK with 7,474 registered sales in 2021 (Mer 2022), while all of the top three are much more expensive compared to it.
- 2) The exact charging powers at the charging points. Evidence from previous studies suggested that consumers (Xu et al. 2017; Dorcec et al. 2019; Globisch et al. 2019; Sheldon et al. 2019; Wolff and Madlener 2019; Illmann and Kluge 2020) and EV drivers (Chakraborty et al. 2019; Lee et al. 2020) generally have positive attitudes towards fast charging, especially for those unable to access home charging. However, charging power is not selected as an attribute in this choice experiment because it might be too specialised for consumers to understand.

Thus, to control for other variables in the charging choice experiment and explain the charging situation more clearly, a short introduction to the charging scenario will be provided to the respondents as follows (see. Figure 3-5):

Imagine, that you are away from your home but within the area you normally live during the day and your electric car is at 20% of its charging level and needs recharging.

You wish to charge your vehicle at an 80% charging level, and you have two options available within the range of your current charging level (20%).

We will present you with a total of 5 cards.

In turn, each card will present you with two charging options (points) with different characteristics including the type of the location (e.g., on-street, at the surface car park, multi-storey car park, or underground car park), whether fast charging, charging cost, amenities within walking distance from the charging point, etc.

Please, carefully read each card and indicate which charging point you would choose to charge your electric car at 80% charging level.

Figure 3-5: Introductory text of the choice experiment

- **Choice sets**

The choice sets were generated in Microsoft Excel from the design matrix (see, Figure 3-4) to the choice set (see in Figure 3-6).

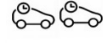
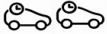
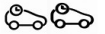
Description	Option A	Option B
Distance from charging point to your destination (metres)	1000	100
Rapid charging	✓	×
Cost (p/kWh)	20% more than current price	20% more than current price
Method of payment	Card or contactless payment 	Payment taken automatically 
Amenities	Small shop or café 	Waiting room 
Waiting time for an available charging point (minutes)	2 	5 
Location	Multi-storey car park 	Underground car park 
I would choose option:	☐	☐

Figure 3-6: The example of the choice cards for one respondent

3.2.7 Stage 7: Randomising choice sets

Randomisation has been done to switch the order of the attributes shown in the choice cards, trying to avoid bias caused by the order of appearance of these attributes (Hensher et al. 2015). Three (3) patterns of choice cards regarding different orders of attributes were generated (see, Figure 3-7).

Pattern 1		
Description	Option A	Option B
Location	Underground car park 	On street 
Rapid charging	×	✓
Method of payment	Card or contactless payment or via universal app 	Card or contactless payment 
Waiting time for an available charging point (minutes)	5 	5 
Cost (p/kWh)	Current price	40% more than current price
Amenities	Shopping mall within walking distance 	No amenities
Distance from charging point to your destination (metres)	1000.00	100
I would choose option:	☐	☐

Pattern 2

Description	Option A	Option B
Distance from charging point to your destination (metres)	1000	100
Rapid charging	✓	×
Cost (p/kWh)	20% more than current price	20% more than current price
Method of payment	Card or contactless payment 	Payment taken automatically 
Amenities	Small shop or café 	Waiting room 
Waiting time for an available charging point (minutes)	2 	5 
Location	Multi-storey car park 	Underground car park 
I would choose option:	☐	☐

Pattern 3

Description	Option A	Option B
Method of payment	Payment taken automatically 	Card or contactless payment 
Rapid charging	✓	×
Cost (p/kWh)	20% more than current price	20% more than current price
Distance from charging point to your destination (metres)	250	500
Location	Underground car park 	Multi-storey car park 
Waiting time for an available charging point (minutes)	2 	5 
Amenities	No amenities	Waiting room 
I would choose option:	☐	☐

Figure 3-7: An example of different orders of choice cards (continued from the previous page)

3.2.8 Stage 8: Constructing survey instrument

The survey consisted of two parts, the first part containing a number of background questions and the second part a choice experiment to be completed by the respondents. For the background information section, the questions included were screening questions, questions on public charging, and demographic questions. The target sample for this study was electric vehicle users and people with a driver's license, both groups being over 18 years old. Firstly, a screening question 'Do you drive an electric car?' will be asked for the respondents, and the 'Yes' and 'No' answers will be provided to them to choose. If they chose 'Yes', then they will be directed into 'EV users' part, if they stated 'No', then they will be directed into 'Non-EV users' part.

The first part of 'Non-EV users' is some other questions related to their car use. Questions such as 'Do you have a driving licence', 'Do you drive a conventional car', 'What type of conventional car are you driving (gas, diesel)', and 'How long have you been driving' will be asked in this part. If they do not have a driving licence then the survey will be forwarded to the end, which states they are not eligible for this survey (doesn't meet our sample requirement). If they have a driving license or are driving a conventional car, then they are directed to the next part of questions about 'non-EV users'. These respondents then will be asked questions regarding public charging, such as 'What is your understanding of public charging for electric vehicles', 'How do you perceive the current public charging infrastructure/stations/points', and 'If you were an EV user, what do you think it is important for you to consider when using public charging infrastructure/stations/points'. This section was designed to understand non-EV users' prior knowledge about EVs and public charging, their perceptions of current public charging infrastructure, and the potential barriers for them to use public charging in the future.

As for the EV users, the follow-up question was 'What type of car do you usually drive?' and the different types of EVs were provided for them to choose from. If the respondent's answer is battery electric vehicle or plug-in hybrid electric vehicle, then the respondent will be directed to the EV user-related section, which contains a number of questions related to EV purchase and usage, charging and related range attitudes. The reasons for EV purchase are of interest in this study because Ge et al. (2018) found PHEV users were more likely to be the gas anxiety group who tended to avoid using gasoline whenever possible, characterised by the fact that they purchased PHEVs for more than just financial benefits. This indicates that the reason for

purchasing an EV may influence their public charging choices. Then charging availability questions will be asked to this group, as well as the availability of private home chargers (Ge et al. 2018; Lee et al. 2020) and workplace charging (Lee et al. 2020) which may potentially influence public charging preferences. In addition, questions such as ‘Do you have access to public charging’ and ‘Do you have access to fast charging’ are also interested in this study, as previous studies have shown that experience (Xu et al. 2017) and high frequency of use (Ten Have et al. 2020) of fast charging were also confirmed to be significant for public charging choices. After this, range attitude questions will be asked to discover respondents’ attitudes towards range anxiety. According to Pan et al. (2019), EV users’ attitudes to range anxiety are actually a reflection of their attitudes towards risk. This study categorised risk attitudes into two types: risk aversion and risk seeking. The last part of questions for EV users are the same as those for non-EV users, including respondents’ understanding of public charging and their perceptions of the current infrastructure, as well as the factors that influence their public charging preferences.

The final part for both groups is the personal information, which not only involves the collection of demographic information of respondents, but also their attitudinal characteristics. For the demographic section, questions related to gender (Pan et al. 2019; Lee et al. 2020; Wang et al. 2021), age (Wang et al. 2021), education level (Pan et al. 2019; Ashkrof et al. 2020; ten Have et al. 2020), income level (Ten Have et al. 2020), ethnicity (Sheldon et al. 2019), housing type (Chakraborty et al. 2019; Lee et al. 2020), vehicle ownership (Lee et al. 2020), and postcode will be asked, as most of them (ones with reference) have been confirmed to be important for public charging choices in previous studies. In terms of the attitudinal question section, air pollution perception (Sheldon et al. 2019), climate change attitude (Sheldon et al. 2019), safety perception, and driving comfort (Ten Have et al. 2020) will be asked to better understand the respondents’ psychological attitudes.

Following the background questions section will be the discrete choice experiment. In this part, respondents will be presented with 5 choice cards and asked to choose between two different public charge scenarios or opt out. 12 groups of choice cards (each group has 5 choice cards) are divided into 3 different patterns which have different attribute orders to avoid respondent bias. Thus, 4 groups of choice cards (each with 5 choice cards) will be randomly assigned to the respondents to make sure that if one pattern of choice cards presented to the current respondent, then a different pattern of choice cards will be presented to the next respondent.

Chapter 4 Cognitive interviews of the public charging choice experiment

4.1 Introduction

Research on EV charging choices has focused on either modelling actual charging choices of EV users (Lee et al. 2020) or hypothetical choices using stated preference discrete choice experiments (SPDCE) (Gutjar and Kowald 2023), which were employed to investigate the significance of various factors and derive monetary valuations (e.g., willingness to pay). While quantitative analyses and related models provide significant insights, they do often under-report (or assume) the underlying decision-making process on why individuals make specific choices. Most importantly, surveys involving SPDCE need to be thoroughly tested to ensure face and construct validity of the generated choice tasks, in order to enhance the robustness of the study findings and conclusions.

Reliability and validity are important psychometric properties of the research instrument (Andrade 2018). The validity of research includes internal and external validity. Internal validity assesses whether the study's design, implementation, and analysis effectively address the research questions while minimising bias; external validity, on the other hand, evaluates the extent to which the study's findings can be applied to broader contexts (Andrade 2018). Qualitative methods, especially prior to large-scale surveys, can provide insight into the cognitive processes and decision-making rationale (Payne et al. 1992) of both EV and non-EV users as well as help enhance the validity of subsequent quantitative analyses (Murphy et al. 2018).

Qualitative interviews are commonly employed to influence the refinement of primary surveys (Jia et al. 2018; Philipsen et al. 2018; Visaria et al. 2022). Notably, cognitive interviewing has emerged as a leading approach for conducting comprehensive assessments of survey questions (Willis 2015). It has been defined as providing a draft of survey questions while collecting additional verbal information about the survey responses, which are used to evaluate the quality of the response or to help determine whether the question yielded the information that its author wants (Beatty and Willis 2007).

Cognitive interviews are an important tool not only for closely examining survey questions but also for assessing the validity and effectiveness of discrete choice experiments. For example, Hagggar et al. (2022) employed cognitive interviews to examine the validity of a choice experiment on people's information-sharing preferences within buildings. In addition, the 'think aloud' technique in cognitive interviewing approaches was commonly found in health-related choice experiments (e.g. Ryan et al., 2009; Whitty et al., 2014). Ryan et al. (2009) reported how well the quantitative tests were combined within a discrete choice experiment to explore the completeness, monotonicity, and continuity of choice utility theories. In a similar vein, Whitty et al. (2014) compared the validity and acceptability of a traditional choice experiment and a best-worst scaling choice task. However, it's worth noting that these applications are less common in transportation-related studies including the choices of vehicle types and public charging infrastructure.

As cognitive interviews can not only help refine the presentation of choice experiments but also test their validity and quality, thus this tool was used in the study to explore:

- (a) how people understand various terminologies in the realm of public charging,
- (b) and their inclinations towards factors associated with public charging choices.

These understandings towards existing and potential EV users will also provide valuable insights for researchers with a vested interest in this area, beyond the quantitative analysis of the EV charging choice experiment. To achieve these objectives, the cognitive interviews in this study tested:

- (1) The overall cognitive understanding of the background questions.
- (2) The overall cognitive understanding of the stated choice experiment including comprehension of:
 - a. the introductory text (the choice context),
 - b. the alternatives, attributes, and
 - c. attribute levels were shown to respondents as part of describing the alternatives.
- (3) Respondents' ability to complete the choice context of the experiment.

The next section of this study provides a more detailed description of the methods used. Then, the main findings of this study are presented. Finally, a discussion section is provided to offer suggestions for conducting a choice experiment on public charging preference.

4.2 Cognitive testing of a choice experiment for public charging

4.2.1 Cognitive interview materials

Survey questionnaires have been the standard approach to capturing participants' charging attitudes and preferences in order to explore public charging preferences (Wolff and Madlener 2019). However, cognitive interviews prior to survey questionnaires have been employed less often.

The questions employed during cognitive interviews are outlined in Table 4-1. The screening question "Do you drive an electric car?" (Q3) first classified participants into EV and non-EV users. For non-EV users, they were asked whether they held a driver's license, whether they drove a conventional car, and their corresponding driving experience (Q4-Q6). Comparably, EV users were asked about the type of EV they used and their corresponding driving experience (Q7 and Q8). The type of car used and the length of driving experience were of interest due to findings from previous studies suggesting that more experienced drivers (Wang et al. 2021) and those who owned an EV for more than a year (Pan et al. 2019) were more inclined to utilise public charging.

In addition, EV users were asked about charging availability options at different places including work, home and public charging. This is because the availability of private home chargers (Ge et al. 2018; Lee et al. 2020) and workplace charging (Lee et al. 2020) may potentially influence public charging preferences. Also of interest was the accessibility of fast charging, as there is evidence that the experience of fast charging (Xu et al. 2017) and high frequency of use (Ten Have et al. 2020) were also important for public charging choices.

Another set of three common questions (see, Q13, Q14, Q15) followed by these questions targeted participants' understanding, knowledge and perceptions of factors that may influence public charging choices. Given the substantial variation in existing EV users' understandings of public charging (Delmonte et al. 2020), it becomes crucial to understand the knowledge of both potential and current EV users regarding public charging. Surveys focusing on consumer attitudes towards EV adoption suggested that range is a greater concern than price as a barrier, with charging infrastructure availability being one of the key factors (N. Kinnear, J. Anable 2019). Therefore, gaining insights into people's perceptions of the available public charging infrastructure, including aspects such as density, visibility, and service satisfaction, holds

significant importance. Finally, as the choice experiment chose a number of factors related to public charge choice, it would be better to test the importance of these factors to participants in a survey question to see if the perceived order of preference would be consistent with the modelling results. Additionally, an open answer option was provided to participants, giving them the opportunity to include any additional factors they deemed important but were not included in the provided options.

Meanwhile, demographic questions regarding to participants' place of residence and age were asked (Q1 and Q2) for both EV and non-EV users. These demographic questions, coupled with gender, are important in describing participants' characteristics and help in understanding variations in preferences (Pan et al. 2019; Wang et al. 2021). Other important demographic questions, such as gender, age, education, ethnicity would be provided by the market research agency where the participants were recruited.

Table 4-1: Participant introductory questions

Category	Participant introductory questions	
Demographics	Q1. What city do you live in currently?	
	Q2. May I know your age?	
EV driving	Q3. Do you drive an electric car?	
	[1] No	
	[2] Yes	
	Non-EV users	EV users
Driving licence	Q4. Do you have a driving licence?	
Car driving type	Q5. Do you drive a conventional car?	Q7. What type of electric car do you drive?
Car driving experience	Q6. How long have you been driving?	Q8. How long have you been driving the electric car?
Charging availability		Q9. Do you have access to private charging at home? How often you use it?
		Q10. Do you have access to workplace charging? How often you use it?
		Q11. Do you have access to public charging? How often you use it?
		Q12. Do you have access to fast charging? How often you use it?

Knowledge of public charging	Q13. What is your understanding of public charging for electric vehicles?
Perception of public charging infrastructure	Q14. How do you perceive the current public charging infrastructure/stations/points?
Perception of factors for public charging	Q15. (If you are EV users) What do you think it is important for you to consider when using public charging infrastructure/stations/points? • Location, charging time/speed, amenities • Pricing • Easy to access • Convenient to use • Information provided is clear (location, availability, pricing, energy source) • Safety (personal, vehicle, information security) • Reliability • Other [please state]: _____

4.2.2 Choice experiment as a tool for qualitative interviews

A stated discrete choice experiment (SPDCE) is a good tool to present hypothetical scenarios that do not exist in the market in the form of a controlled choice experiment, showing participants with attributes and attribute levels, and asking them to evaluate the attribute and make a final choice among competing alternatives (Guerra and Daziano 2020). SPDCE has been widely used in previous studies to reveal the charging preferences of potential and existing EV users (Wen et al. 2016; Moon et al. 2018; Pan et al. 2019; Sheldon et al. 2019; Wolbertus and Van den Hoed 2019; Wolff and Madlener 2019; Ashkrof et al. 2020; ten Have et al. 2020; Wang et al. 2021).

However, transportation choice modellers often prioritise quantitative analyses and complex model estimations, neglecting the crucial aspect of ensuring the ‘internal validity’ of their experiments, that is, whether respondents truly comprehend and interpret the intended message conveyed through the experiments. To address this issue, cognitive interviewing serves as a useful tool in assessing the validity and effectiveness of discrete choice experiments.

A set of slides related to the choice experiment were used as the interview materials for the participants, including, the scenario description (see, Figure 4-1), the choice cards (see an example in Figure 4-2), and the attributes and levels (see, Table 4-2). Before the choice cards,

the scenario of the choice experiment was carefully depicted in an introductory text. The scenario was a destination charging scenario during the day. The reason for why this scenario was assumed can be found in Chapter 3 Experimental Design section for detailed explanation. Using NGENE software, an optimal design comprising 60 rows was created for the choice experiment (see, Chapter 3 in the Experimental Design). To ensure the manageability of the experiment, the 60 choice cards were divided into 12 blocks. This means that participants were presented with five choice cards each. Additionally, to account for potential ordering bias, three versions of the choice cards were generated, with different attribute orders within each block. This guarantees that every participant encountered blocks with distinct attribute orders.

Imagine, that you are away from your home but within the area you normally spend time during the day and your electric car is at 20% of its charging level and needs recharging.

You wish to charge your vehicle at an 80% charging level, and you have two options available within the range of your current charging level (20%).

We will present you with a total of 5 cards.

In turn, each card will present you with two charging options (points) with different characteristics including the type of the location (e.g., on-street, at the surface car park, multi-storey car park, or underground car park), whether fast charging, charging cost, amenities within walking distance from the charging point, etc.

Please: carefully read each card and indicate which charging point you would choose to charge your electric car to the 80% charging level or you can choose neither options if they are not what you want.

Note: fast charging can charge an EV in several minutes to 30 minutes, while public slow charging usually takes 1-4 hours, depending on the charging power.

Figure 4-1: Introductory text in the choice experiment

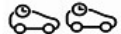
Description	Option A	Option B
Method of payment	Payment taken automatically 	Card or contactless payment or via universal app 
Distance from charging point to your destination (metres)	250	500
Rapid charging	✓	×
Amenities	Shopping mall within walking distance 	Small shop or café 
Cost (p/kWh)	20% more than current price	20% more than current price
Waiting time for an available charging point (minutes)	5 	2 
Location	On street 	Multi-storey car park 
I would choose option:	☐	☐

Figure 4-2: An example of a choice task (scenario)

As the choice experiment was designed to investigate the factors that influence public charging choices of both potential and existing EV users, through a synthesis of previous literature (see, Chapter 2 in the Literature Review), the attributes and levels for the choices included charging locations, whether fast charging is available, price, waiting time, distance from the charging point to the destination, and payment methods. Different levels of these attributes are presented in Table 4-2.

Table 4-2: Attributes and levels in the public-charging choice experiment

Attributes	Levels			
	1	2	3	5
Location	On street	Surface-level car park	Multi-storey car park	Underground car park
Fast charging	✓	X		

Cost (p/kWh)	Current price (45)	10% more than current price (50)	20% more than current price (54)	30% more than current price (59)	40% more than current price (63)
Distance from charging point to your destination (metres)	100	250	500	1,000	
Waiting time for an available charging point (minutes)	Available right away	2	5	10	
Method of payment	Card contactless payment	or Card contactless payment or via supplier's app	or Card contactless payment or via universal app	or Payment taken automatically	
Amenities	None	Waiting room	Small shop or café	Shopping mall	

4.2.3 Approaches for cognitive interviews and qualitative analyses

The think-aloud interview, rooted in a psychological procedure introduced by Ericsson and Simon (1993), involves instructing participants to vocalise their thoughts while responding to survey questions. The think-aloud technique offers several advantages: first, it minimises interviewer bias as the interviewer's role is primarily limited to reading questions; second, it requires minimal interviewer training due to its straightforward nature; and third, its open-ended format can elicit unexpected responses from participants. Verbal probing, increasingly preferred by cognitive researchers as an alternative to the think-aloud technique, involves the interviewer seeking additional specific information from the participants after they provide an initial answer to a survey question. A big advantage of verbal probing is to control the interview. The use of targeted probing to guide the respondent to communicate in a manner that is largely controlled by the interviewer.

Table 4-3 summarises some examples of probing questions used in the cognitive interview for different purposes, checking for understanding and asking about paraphrasing. General probing includes asking reasons for choices or indecisiveness. Alternatively, specific probing can be

used for specific matters mentioned by the participant or things shown in the material that the researcher believes may be difficult for the participant and wants to test whether they are understandable.

Table 4-3: Examples of different probing questions

Cognitive probe techniques	Examples
Comprehension	• What does the “distance” mean to you? Do you have any picture in your mind?
Paraphrasing	• Could you please briefly describe to us what is the context of the choice task?
Specific probe	• Do you see there is any difference between supplier’s app and the universal app?
General probe	• Why did you choose that option? Was that easy or hard to choose/answer? • I noticed that you hesitated - tell me what you were thinking

Source: (Willis 2011)

4.2.4 Recruitment of participants

The group of participants in this study included individuals of diverse attitudes towards electric vehicle (EV) public charging infrastructure. The study was aimed at involving existing EV users, consumers interested in EVs including those who were planning to purchase an EV soon, and those individuals who were less informed or were indifferent about EVs.

Since the purpose of the cognitive interviews was to ensure that the choice cards were clear, useful, and not ambiguous or misleading, it was not necessary to consider the representativeness of the sample at this stage. Overall, 20 participants were recruited through Respondents.io, a market research agency with the aim to recruit 10 EV and 10 non-EV users. Participants satisfied the following criteria:

- (a) To classify as EV users, at the time of the interviews, participants had access to an EV (battery electric vehicle or plug-in hybrid electric vehicle); and
- (b) All participants were 18 years of age or older and held a driving license.

4.2.5 Interview procedure

The interviews were conducted online between 5 and 16 December 16, 2022, via Zoom, a video conference software and screensharing. The invitations were sent via the Respondents. io

platform and were attached to the Consent Form and Research Information Sheet. An oral consent for the video and audio recordings was also sought at the beginning of the interview. All signed consent forms were otherwise returned by the participant at the time of accepting the invitation, or before, during, or after the interview.

The cognitive interviews followed the protocol in Table 4-3. A short introduction to the study and the purpose of the cognitive interview was given to participants to provide them with a basic understanding of the study. The cognitive interview consisted of three parts, which were consistent with the presentation of the materials for the cognitive interviews. The first part was targeted to ask some basic questions to understand participants' demographics, knowledge and perception of public charging, and perceived important factors for public charging choices, all of which are listed in Table 4-1. Following the question section, participants were introduced to the choice experiment concept and provided with an example of a choice experiment through a slide presentation, which aimed to familiarise them with key terms such as "choice card" and "attribute and attribute levels". After the introduction of these terms, the second part of these cognitive interviews was to observe participants' understanding of attributes and attribute levels in Table 4-2. Finally, five choice cards (see an example in Figure 4-2) were presented to each participant and the participant was asked to make a choice, which could reflect participants' decision-making process. The sections with blue colour are the three parts which involved both the thinking aloud and verbal probing techniques in the cognitive interview, as elucidated by Willis (2011).

Table 4-4: Interview protocol

Inception	• Thank you for your willingness to participate and be interviewed in this study. • I am ...Rongqiu Song, and I am a PhD student from Cardiff University. This is Paul⁶ and is here to help me with the interview. • Do you consent to this meeting being recorded and me to view the recording? • Paul and I, also, will be taking notes during the interview, if that's alright. • Do you have any questions before we begin? • I will start sharing my screen. Can you see the title of this research? So the title of the research is investigating public charging preferences of potential and existing electric
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⁶ Paul Haggard is an experienced researcher in qualitative interviewing from Bath University who oversaw the whole cognitive interview process.

	vehicle users. Basically, it means that we are interested in what factors are important for them to make choices for public charging stations. • We will do a survey to explore people's preferences towards public charging, but before the survey, we need to test whether the factors/attributes and choices we will show you later in a choice card are clear or not. This is exactly the aim of today's cognitive interview. We hope you can think and say aloud whatever comes in your mind while reading about the materials.
Part 1: Basic questions	• The first part of the interview is some of the basic questions that participants will see in the first part of the survey. Could you please answer these questions one by one? Another thing is, if you find anything confusing or misleading, you can just mention it while you are reading through these questions (see, Table 1).
Introduction to the choice experiment	Show an example of choice experiment with the introductory text and a choice card which contains attributes and attribute levels. • To give participants a basic understanding of these terms
Part 2: First think-aloud	Show respondents attributes and levels: • In this part, I am mostly interested in knowing what is going through your mind to make sure that attributes and attribute levels are clear, useful and not ambiguous or misleading. Again, you can say anything comes through your mind while reading the table. Please know there are no wrong answers. • Great, how did you find that? • But you found those the sentences on the screen are easy enough to understand or are there any difficult one? • Can we tell the difference between Card or contactless payment or via supplier's app and Card payment or via universal app?
Part 3: Choice card – introductory text	Now, we will move to the second part of the survey. The choice cards. This part starts with an introduction. Again, you can say anything comes through your mind while reading it. • Could you please read that and once you get to the end I'll just ask you one or two questions about it? • Great, how did you find that? • But you found those the sentences on the screen are easy enough to understand or are there any difficult one?
Part 3: Choice card – making choices	This part includes five (5) choice cards. Could you please read them and then make a choice? Again, you can say anything comes through your mind while reading them and please give us the reason of why you make that choice.

When the participant pauses	• What is going through your mind? • What you're looking at on the screen?
Probe questions	Question part: a) How easy or difficult was this question to answer? Why? b) Why did you choose the option for this question? Attributes and attribute level part: c) Did you find anything unclear about the attributes and attribute levels? Or was there anything that you found difficult to understand? d) When you saw the "the distance from the charging point to the destination" attribute, what did you perceive the "distance" mean? Where was the "destination" for you? e) Are "supplier's app" and "universal app" the same? What do they mean for "supplier's app" and "universal app"? Choice card section: f) Did you find anything unclear, or did you feel anything difficult to understand? g) I'd like to ask you, in your own words, how would you describe the introductory text/task? h) Why did you choose that option? Others: i) (Optional) Could you tell me a bit more about that? j) (Optional) You said 'xxx', perhaps you could elaborate on that for me?
Closing	• Thank you for taking time to answer these questions. Your participation is extremely valuable for our research. • Any questions do you have? • Your input will be very helpful. I do appreciate your time and help. Thank you very much and have a good day.

4.2.6 Analytical approach

During the cognitive interviews, notes were taken as a preliminary observation of key points of each participant's response to the research resources. The interviewer's own thoughts and impressions of the interview were also recorded. Then, the recorded audio was transcribed by

using a transcribing software (Otter). The notes were combined with the transcripts as initial data for thematic analysis (Braun and Clarke 2006). The interviewer created a thematic table by using the data, with one column for participants and one row for themes/codes. This analysis process was also inspired by Beatty and Willis (2007). The thematic table was divided into four parts, including the background questions, attributes and attribute levels, introductory text, and the choice cards in the SPDCE. The issues (codes) mentioned for each section were summarised in the corresponding cells for each participant in the thematic table. The results section below summarise themes identified in the thematic table.

4.3 Participants' characteristics

A total of 20 participants were recruited for the study, comprising 10 non-electric vehicle (EV) users and 10 EV users who met the conditions outlined in Section 4.2.4. The participants' demographic information, car ownership details, and driving and EV charging experience were summarised in Table 4-5.

Table 4-5: Participants' characteristics

Non-EV users					EV users				
#	Gender	Age	Education	Car Type	#	Gender	Age	Education	Car Type
1	Male	27	Postgraduate	ICEV	11	Male	29	Postgraduate	BEV
2	Female	26	Postgraduate	ICEV	12	Male	46	Postgraduate	PHEV
3	Female	32	Postgraduate	ICEV	13	Female	28	Postgraduate	BEV
4	Male	30	Postgraduate	ICEV	14	Male	32	Postgraduate	PHEV
5	Male	31	Undergraduate	N/A	15	Female	40	Some college, no degree	BEV
6	Male	42	Undergraduate	ICEV	16	Male	29	Postgraduate	BEV
7	Female	29	Postgraduate	ICEV	17	Female	48	Some college, no degree	BEV
8	Male	44	Undergraduate	ICEV	18	Male	31	Some college, no degree	PHEV
9	Male	28	Undergraduate	ICEV	19	Female	29	Undergraduate	PHEV
10	Female	40	Postgraduate	ICEV	20	Male	32	Undergraduate	PHEV

As shown in Table 4-5, all non-EV users held at least a bachelor's degree, were aged between 26 and 45 years, and possessed a valid driving license. The majority of non-EV users who owned a driving license had conventional cars, with some specifying them as petrol or diesel vehicles. Furthermore, most of them had more than 5 years of driving experience, were located in England (including London), and identified as white/Caucasian. In terms of gender difference, it was relatively balanced, although there were slightly more males than females.

For EV users specifically, half of them drove battery electric vehicles (BEVs), while the rest drove plug-in hybrid electric vehicles (PHEVs). Most of the EV users had been driving their EVs for a period ranging from one year to five years. Additionally, the majority of them had access to both public charging (including fast charging) and home charging, while only a few had access to workplace charging.

4.4 Findings from the cognitive testing of the stated choice experiment

The thematic analysis of the cognitive interview data revealed three key themes regarding participants' public charging choices: (1) the choice context and its cognitive challenges, (2) attribute non-attendance, and (3) the definition of the 'payment methods' attribute and its varying interpretations by respondents. As shown in Figure 4-3, each of the three themes further comprised several sub-themes.

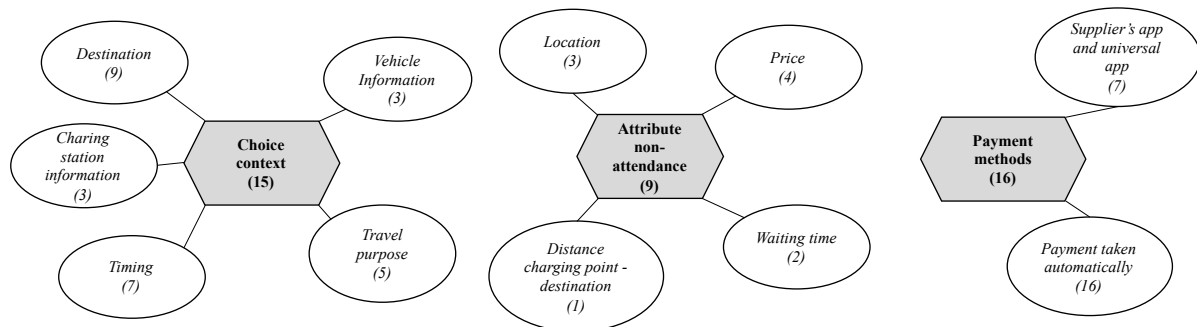
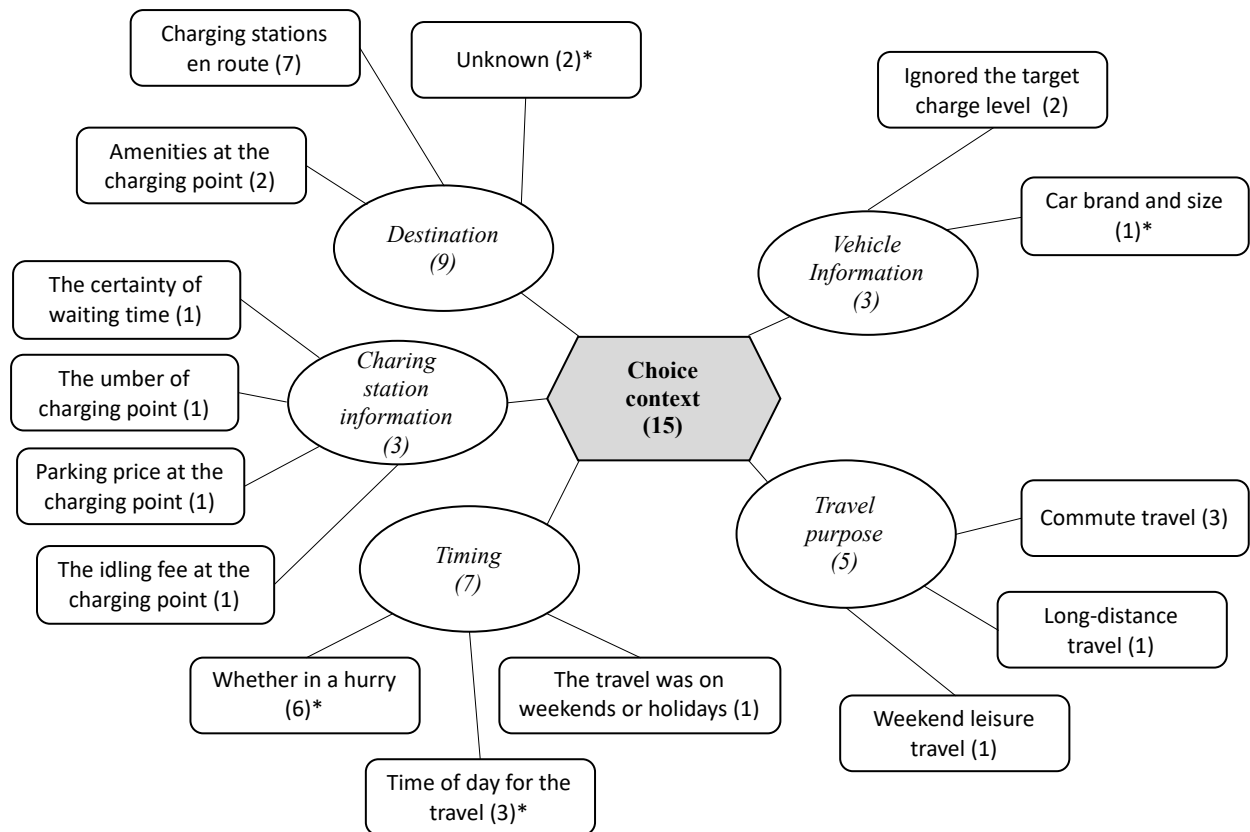


Figure 4-3: Themes and subthemes identified by thematic analysis

Note: Figures in parentheses indicate the number of participants who mentioned the theme

4.4.1 Choice context

The majority of participants were ultimately able to make choices based on the charging scenarios presented to them. Fifteen participants, including nine non-EV users and six EV users, expressed concerns about the lack of clarity of the choice context. As shown in Figure 4-4, five sub-themes and further codes related to the charging context were identified: (1) charging destination; (2) time for travel; (3) travel purpose; (4) vehicle information; and (5) charging station information.



Note: Figures in parentheses indicate the number of participants who mentioned the theme.

* a participant was unable to make a choice for the reasons listed

Figure 4-4: Subthemes within the 'choice context' theme

4.4.1.1 Destination

The scenario was based on the premise of being “away from your home but within the area you normally spend time”. Likewise, the inclusion of the factor “the distance from charging point to your destination” on the choice task was meant to depict a destination charging scenario. However, five non-EV and four EV users experienced challenges in pinpointing their destination. Two non-EV users wished the destination to be more specific:

“[It] says distance from charging point to your destination. What is my destination in this context? Where I’m living, for example, or where I’m working, that kind of thing?”
(#6)

Seven participants, three non-EV users and four EV users, perceived the destination as charging stations en route. For example, they considered charging stations on their way home or during a long journey to another destination:

“It feels as if I was almost to the end of a long journey, where I thought, alright, I can sort of top up to charge my car, it’ll get me to my destination, but then I need to return back.”(#4)

A non-EV and an EV user perceived the destination as the amenities available at the charging point. They imagined scenarios of entertainment or errands while waiting for their vehicle to charge. This may reflect their perceptions of the importance of amenities when charging electric vehicles:

“[The amenities are] probably more things nearby. For example, yesterday, I needed to charge, and I needed to do food shopping. So for me, having that there is great, because I’ve got an hour at lunchtime, and I can do both things.” (#16)

4.4.1.2 Timing

Although the scenario specified that the charging session would occur “during the day”, six non-EV users and an EV user wished to know when they travelled. Respondents stated that the time of day and day of the week would influence their public charging decisions because of their time schedule. As a result, five non-EV users and an EV user also emphasised the importance of knowing their ‘time budget’. For example, a non-EV user enquired whether the trip would take place on a weekend or a holiday because charging preferences would be different on weekdays and weekends. This participant needed to charge quickly on weekdays to keep up with work but would prefer slow charging on weekends or holidays because of the scheduling flexibility. Overall, this group of participants would use fast charging when time-limited but were content with more affordable, slower charging when charging their vehicle was less urgent:

“If it was only going to take an hour, I could spend an hour but that would be dependent on how much of my journey have I got left. Is it worthwhile for me to spend an hour of my day at a slower charger or am I just going to have to suck it up and pay the extra 40% because I’m in a hurry?” (#15)

Finally, the time of day at which charging occurs greatly influenced the public charging decisions of the three non-EV-user female participants because of safety concerns:

“If it was daytime I would definitely go for option A just because I wouldn’t be so concerned about hanging around for a bit longer.” (#3)

4.4.1.3 Travel purpose

Since the purpose of the travel was not explicitly stated in the scenario, three non-EV users and two EV users assumed different travel purposes. For example, three participants thought it was a commute travel, one participant believed it was a long-distance travel, and another participant interpreted the scenario as leisure travel over the weekend:

“In that scenario, I’m coming to the office.” (#13)

“It feels as if I was almost to the end of a long journey, ... I’m almost at the end of my journey. I’m just going to add on a bit more, I’ll get to them to my journey, but then I need to return back where I’m going.” (#4)

“I think about this, it’s mostly a weekend trip. And not exactly a trip. I’m just going out for a ride. Or maybe getting some grocery or something. Like a casual journey.” (#11)

Finally, an EV user also highlighted that different trip purposes sometimes can lead to completely different public charging choices:

“So, it’s different for me when I’m coming into the office versus if I was doing a long journey to go somewhere or like a leisure visit.” (#13)

4.4.1.4 Vehicle information

Participants wanted further details about the vehicle including vehicle model/size, and target charge level. Even though the charging scenario assumed an initial state of charge of 20% and a target charge level of 80%, a non-EV and an EV users missed this factor. Instead of waiting for the vehicle to reach the 80% charge level, they expressed an intention to quickly charge the vehicle with enough power for the next trip. In this case, they did not mind choosing the more expensive fast-charging option because it would not be too expensive to charge the vehicle for a short period of time:

“I don’t need to do the whole 80% charge I think here. I imagine if the price is significantly lower than I could, I could go with a with a 40% more. But if it was really if it was as expensive as petrol, then I will definitely shop around for the cheapest option, especially now.” (#10)

The model/size of the vehicle would also affect their choice of public charging. One non-EV user was unable to make a choice because the participant felt that smaller EVs were better suited for street parking, while larger and more luxury models were more suitable for large parking spots such as underground parking lots.

“I think it would depend [on] what car I’m driving. If it was a small electric car, like I’ve seen recently, like the Honda II, ... I probably parked that on the street, because that’s super easy to park, it’s small. But if I was in a Porsche Taycan, and I’d be in the underground car parks, I’d be parking that in a much bigger, bigger spot, and I would want to park down the street.” (#7)

4.4.1.5 Charging station information

Three participants, a non-EV user and two EV users, wished to know more about charging points such as waiting times, number of charging points, parking prices and idling fees (fees incurred to minimise the amount of idle time at a charging station after a vehicle has finished

charging), as they felt that these factors would be crucial in their decision to charge or not. Although the choice task included the ‘time waiting for available charging point’ attribute, an EV user was still concerned about the uncertainty of waiting times based on their own experience of public charging:

“I keep coming back to the waiting time for an available charging point. As well, it’s just never ending, never a way of knowing how long it’s going to be doing.” (#12)

One non-EV user was concerned about the limited number of available charging points at the public charging station. The participant emphasised the importance of knowing the number of charging points at a charging station before deciding where to park. As stations with only a small number of charging points may be consistently busy, leading to potential delays. However, stations with more charging points are seen as more convenient for planning purposes.

“So now number of charging points that you get? Because if I’m driving a car, and I’m thinking where should I park ... this one spot only has two charging points. That’s always busy. But the other one has 10 charging points. So they’ve got more, even before I go there and see the waiting time I can sort of plan about that.” (#10)

Another EV user emphasised the importance of parking costs at charging points and preferred locations with lower charges.

“The underground carpark I’m thinking here, if it was in Leeds, I would be paying to park in there as soon as I drove in, and they’re really expensive in comparison to on-street parking.” (#13)

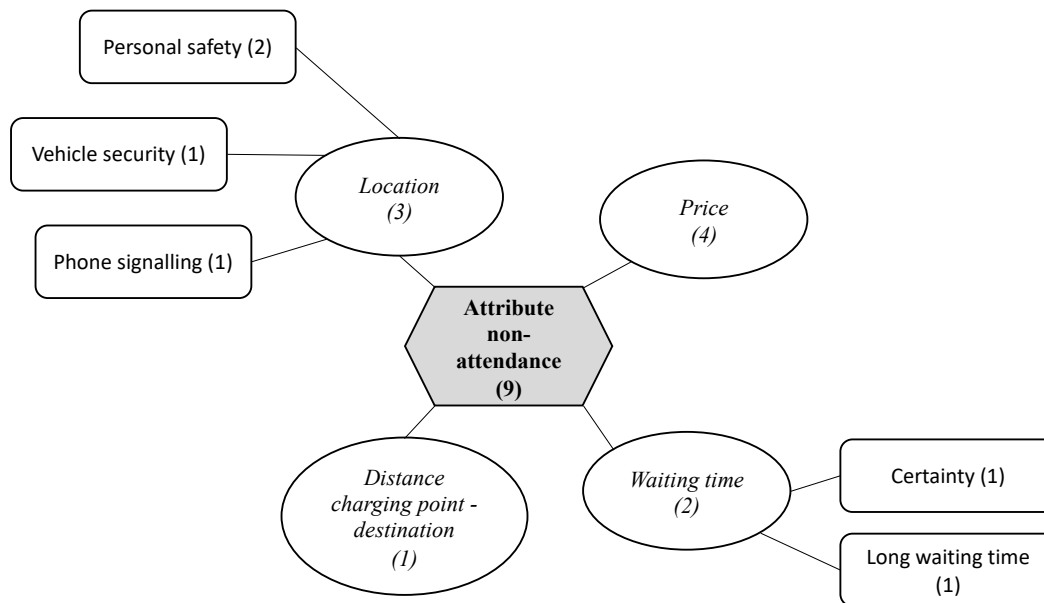
At the same time, this participant felt that whether or not public charging stations charge for idling would also change the choice of public charging, especially for fast charging.

“So this the issue that I’ve mentioned before about sort of rapid charger finishes in half an hour, and you’ve got to go back and move are you paying idling fees?” (#13)

4.4.2 Attribute non-attendance

Some participants’ choices were driven by specific factors. For example, charging location, price, waiting time, and the distance from the charging point to their destination. This is known as ‘attribute non-attendance’ and occurs when participants do not consider or pay attention to one or more attributes of the options presented to them when making their choices (Hensher 2006). This is common in real-life decision-making processes, individuals may not always thoroughly assess or consider every attribute, especially when faced with a complex set of

options. However, attribute non-attendance should be accounted for in a study to satisfy the presumption of choice experiments and the Random Utility Theory supporting them. Figure 4-5 summarises the sub-themes and codes of the attribute non-attendance theme.



Note: Figures in parentheses indicate the number of participants who mentioned the theme

Figure 4-5: Subthemes of the ‘attribute non-attendance’ theme

Three female non-EV users prioritised their choices based on charging location. Two of them value more on the different types of parking lots for personal safety reasons. They disliked to charge at multi-storey car parks the most, especially at night.

“It’s mainly the location. Being like when I earlier was talking about multi-storey car parks, like you don’t know who’s arranging ... you don’t know how to get help a lot of the time or if anyone will hear you if you shout out, which is a bit scary.” (#3)

Another non-EV user, placed higher importance on vehicle security, and mentioned spacious parking lots over narrow streets to avoid possible damage to the car.

“On the street here that looks like a really narrow street with loads of cars parked on the left and right-hand side... it looks really tight if somebody else was to park ... maybe scratch my car or, or damage it and then just drive away. In a car park like this seems to be there’s more space, there’s a little bit more security.” (#10)

Also, one non-EV user also considered phone signalling in the parking lot when it comes to the charging locations. The participant highlighted the importance of having a car park with above-ground levels, as it provides better signal reception.

“Multi-story car park, great. So you’re above ground level so you’ve got signal so that then would influence if you need amenities because obviously if you’re an underground

carpark if you sat there waiting, well you can't even do anything like check your phone or anything like that.” (#2)

Four participants (one non-EV user and three EV users) valued the charging price more when making public charging choices. They consistently preferred a lower public charging option, even if it was not fast charging.

“I would select Option A because of the cost majorly though it doesn't have rapid charging and I'll have to wait for a really long time. But it costs 40% less.” (#11)

Two EV users were concerned about waiting times. One of them expressed frustration about the unpredictable waiting times for an available charging point, highlighting the lack of information on the duration of the wait.

“I keep coming back to the waiting time for an available charging point. As well, it's just never ending, never a way of knowing how long it's going to be doing.” (#12)

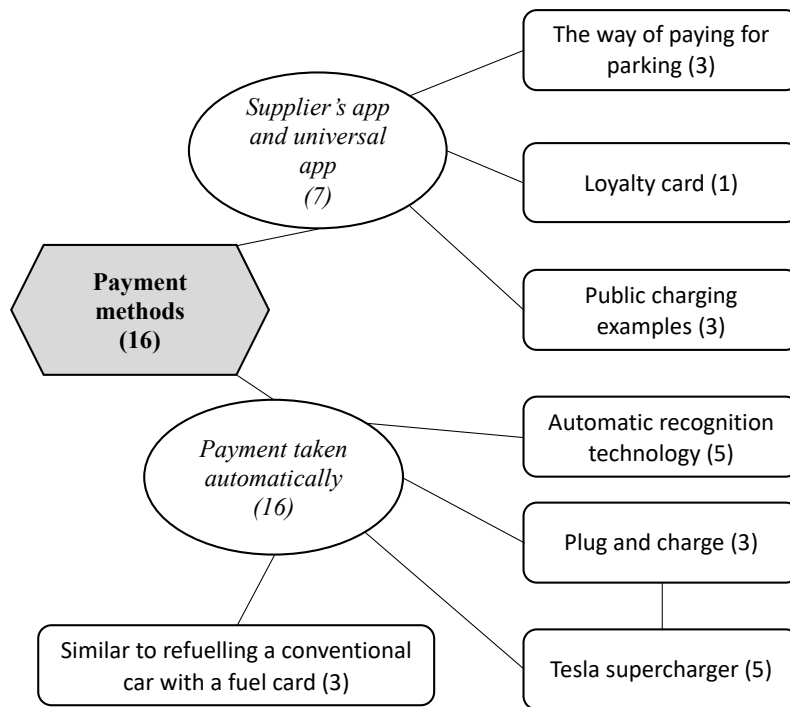
The other EV user prioritised minimising waiting times and preferred an option with immediate availability, despite other disadvantages.

“I would choose option A because it's available right away, although I don't like it's in an underground car park and there isn't rapid charging.” (#17)

Unlike other participants, one EV user primarily considered the distance between the charging point and the destination when choosing a public charging point, and continuously chose the closest option by explaining “it is closer”.

4.4.3 Interpretation of the payment method

Another finding from the cognitive interview results was that participants tended to have different understandings of payment methods, in particular, the difference between “supplier's app” and “universal app”, and “payment taken automatically”. Figure 4-6 presents the sub-themes and further codes of understanding of payment methods.



Note: Figures in parentheses indicate the number of participants who mentioned the theme

Figure 4-6: Various interpretations of ‘payment methods’

4.4.3.1 The understandings of “supplier’s app” and “universal app”

Seven participants in this cognitive interview showed different understandings of “supplier’s app” and “universal app”. Three (one non-EV user and two EV users) linked the two payment methods to the way of paying for parking fees. For example, “a supplier’s app is like a specific app for parking, such as RingGo⁷” (#6) and due to “different cities, different companies, different locations have different methods and different apps” (#10) therefore “they can have several different apps” (#20). Regarding a universal app, one EV user thought of it like a universal parking app.

One non-EV user associated these two payment options with a loyalty card. According to this participant, a membership card for each shop was similar to the supplier’s app, while a universal app would be similar to an app that “stores all of your different loyalty cards on one universal third party app” (#7).

Only three participants (one non-EV user and two EV users) linked these two payment methods with public charging examples. They perceived the supplier’s app as being like “network or

⁷ RingGo is a UK-based cashless phone parking provider to local authorities and private operators. Users can pay parking fees by phone with the RingGo app.

charges” (#8), such as “pod point” (#15, #19) and “BP pulse charging station” (#18) or “the brand of car” (#8) such as “Tesla charging points” (#19). In relation to the universal app, one EV user said this could refer to “third-party organisations that have agreements with many other charging companies such as BP Pulse” (#18), while one participant mentioned the “ChargePlace Scotland” (#15), which is a national EV charging information network developed by the Scottish Government.

In addition to articulating their understanding of the two payment methods, nine participants (including two non-EV users and seven EV users) expressed their views on using these apps for payment. One non-EV user was indifferent to using the supplier’s app or the universal app. Four of them (one non-EV user and three EV users) favoured the use of a universal app because it was more convenient than using a supplier’s app, as their phone may need to download many different apps. In contrast, four EV users indicated that they did not like the idea of using apps at all because of the inconvenience they perceived, such as downloading apps, registering, and potential risks when using apps, such as low battery or no signal on the phone.

4.4.3.2 The understanding of “payment taken automatically”

As for the understanding of automatic payment method, three non-EV users imagined them as similar to traditional car refuelling methods by recalling their own refuelling experiences, such as paying at the “pump source” (#2), “putting your card details in and you put the amount of petrol and it takes the money out there” (#1), or use the “fuel card” (#6) where the car driver can track purchases on an app status and make payments at the end of the month, or pre-fund a pre-deposited account.

Six participants (three non-EV users and three EV users) linked automatic payment to the automatic recognition technology. One non-EV user envisioned this technology recognising EVs, where the driver would simply drive the car away at the end of the charge and the bill would be done automatically via an app. Some participants saw this as similar to the technology used in the London Road Charging Zone or the Congestion Charge, where charging would begin when the driver pulled their EV into a specific zone. Whereas some participants imagined EVs could be recognised through the “car license plate” (#3, #11, #16, #20), or “a barcode or a QR code” on the window or windscreen (#11), or “an account” that the EV charging station can obtain details of the vehicle and then automatically charge the EV (#9).

While one EV user believed that billing starts when the charger is plugged in, and the bill is automatically generated and paid when the charger is unplugged. Five participants (two non-EV users and three EV users) associated this automatic payment method with “Tesla Supercharger”. Two of them were non-EV users, although they expressed that they did not know how these chargers worked. The other three were EV users, and one of whom was a Tesla owner. These EV users reported that with a Teala account, drivers did not need to perform any additional steps to charge at a Tesla Supercharger station. They simply needed to tap their phone or bank card and plug in the charger, and once their car’s light turned green, they knew that it was charging.

In addition to their different understandings of automatic payment technology, seven participants expressed their attitudes toward this technology, with four (one non-EV user and three EV users) being positive because they found it inconvenient to carry a card and “no need to interact with people”, while the other three (one non-EV user and two EV users) thought “it is scary” and did not trust it.

4.5 First-round revisions

4.5.1 Revisions on background questions

4.5.1.1 Type of car

In the previous background question section, four questions were asked to identify the type of car the participants were driving, including “Q4 Do you have a driving licence?”, “Q3 Do you drive an electric car?”, “Q4 Do you drive a conventional car?”, “Q6 What type of electric car do you drive?”. Based on cognitive interviews, some participants showed problems understanding the term “conventional car” for Q4 and were unsure if Q6 was asking about the car model. Therefore, in order to simplify the question in the final questionnaire, a new question with multiple specified answers emerged, which is “Do you drive a car and what type of car do you drive?” in Table 4-12. With this revised question, different types of car users can be easily identified, for example, EV users and non-EV users or BEV and PHEV users. Placing the question at the top of the questionnaire as this helps the study to screen out unwanted samples, i.e., UK adults without a driving license, and to validate that all other samples were suitable for this study and can be categorised into different groups.

4.5.1.2 Region of residence and rurality of the location

The initial question, “Q1 What city do you live in currently?” was designed to find out participants’ location of residence. However, cognitive interviews with participants suggest that this question presumed that all participants live in a city, which may have overlooked the possibility that some participants might reside in small towns or rural areas or indirectly forced them to answer the name of the nearest city around them.

The purpose of knowing the location of participants’ residences was to find the situation, including the quantity and user satisfaction of public charging infrastructure at that location. As Section 4.4.1 shows, four participants stated the differences in the quantification of public charging infrastructure between urban and rural areas, especially between London and other regions. Therefore, it can be concluded that the name of the city or the public charging infrastructure itself of the city is not interested in this study, but the disparities in the coverage of the public charging infrastructure are based on the rurality of the location. Based on a survey of 1,006 non-EV users without access to off-street parking at home and 848 EV drivers conducted by BritainThinks (Department for Transport 2022a), two new questions emerged to capture the region of residence and rurality of the location, which are “Where do you live in currently?” and “Do you live in an urban or rural area?” respectively (see Table 4-12 below).

4.5.1.3 Frequency of usage of different charging infrastructure

The EV user-specific section is interested in capturing the availability and frequency of usage of different charging infrastructures (e.g., home, workplace, public charging) and the performance of the EV, such as driving range. In the previous questionnaire, the series of these questions (see Table 4-1) did not provide participants with the designed frequency of charge options. However, by collecting the frequency of occurrence of different answers through cognitive interviews, such as “every day” and “every other night” for home charging and “once a month” and “every two weeks” for public charging, and combining the option settings of similar questions posted in previous academic articles (Anderson et al. 2018; ten Have et al. 2020) and a governmental report (Department for Transport 2022a), this study yielded the same questions with multiple specified charging frequency options. Especially for public charging, fast and slow chargers may lead to very different charging behaviour. Therefore, there is a need to classify them, which leads to the question “What type of public charging service do you use more often?”.

After analysing the findings from the cognitive interviews, the “perception of public charging infrastructure” question was divided into two separate questions. The first focused on participants’ perception of the quantity of public charging infrastructure, while the second assessed the evaluation of the service provided for EV users. Furthermore, the factors related to public charging choices were adjusted based on the insights gathered during the cognitive interviews to mitigate potential ambiguity.

Table 4-6: Revised background questions

Non-EV users	EV users	Reference
Q1 Where do you live in currently? [1] London [2] England excludes London [3] Scotland [4] Wales [5] Northern Ireland		(Department for Transport 2022a)
Q2 Do you live in urban or rural area? [1] City/urban [2] Small town/suburban area [3] Village/fringe of town [4] Isolated rural area		(Department for Transport 2022a)
Q3 May I know your age? [1] 18 – 25 [2] 16 – 35 [3] 36 – 45 [4] 46 – 55 [5] 56 – 65 [6] 65 +		
Q4 Do you drive a car and what type of car do you drive? [1] Yes, an internal combustion engine (ICE) car (e.g., petrol or diesel) [2] Yes, a hybrid car [2] Yes, a plug-in hybrid car [3] Yes, a full battery electric car [4] Yes, other type of car, please specify____ [5] No, I do not drive a car but I have a driving license [6] No, I do not drive a car and I do not have a driving license → end of the survey		
Q5 How long have you been driving the car you mentioned in last question (if answer is Yes)? [1] Less than 1 year [2] 1-5 years		

[3] 6-10 years																																										
[4] Over 10 years																																										
	EV user-specific section																																									
	Q6 Do you have access to following charging infrastructure? How often do you use it? <table border="1"> <thead> <tr> <th></th> <th>Daily</th> <th>5-6 times per week</th> <th>3-4 times per week</th> <th>1-2 times per week</th> <th>1-2 times per month</th> <th>Less frequently</th> <th>Never</th> </tr> </thead> <tbody> <tr> <td>Home</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Work</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Public slow</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Public fast</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> </tbody> </table>		Daily	5-6 times per week	3-4 times per week	1-2 times per week	1-2 times per month	Less frequently	Never	Home	☐	☐	☐	☐	☐	☐	☐	Work	☐	☐	☐	☐	☐	☐	☐	Public slow	☐	☐	☐	☐	☐	☐	☐	Public fast	☐	☐	☐	☐	☐	☐	☐	Ten Have et al. (2020); (Department for Transport 2022a); Anderson et al. (2018)
		Daily	5-6 times per week	3-4 times per week	1-2 times per week	1-2 times per month	Less frequently	Never																																		
Home	☐	☐	☐	☐	☐	☐	☐																																			
Work	☐	☐	☐	☐	☐	☐	☐																																			
Public slow	☐	☐	☐	☐	☐	☐	☐																																			
Public fast	☐	☐	☐	☐	☐	☐	☐																																			
	Q7 How do you perceive the service of current public charging infrastructure? [1] Very dissatisfied [2] Dissatisfied [3] Unsure [4] Satisfied [5] Very satisfied	Wang et al. (2021)																																								
Q8 What is your understanding of public charging for electric vehicles? Please select which one describe you the most. [1] I know public charging very well, such as locations, speeds, prices, payment methods, and concepts of different technologies involved in public charging and electric vehicles (e.g. smart charging, V2G). [2] I know quite well about public charging, such as locations, speeds, prices, and payment methods. [3] I know common public charging locations, but I do not know how it works, charging speeds and prices, and how to make payment. [4] I only heard public charging from the news. [5] I do not know anything about public charging.																																										
Q9 How do you perceive the quantity of current public charging infrastructure? [1] Strongly sufficient. [2] Sufficient [3] Unsure																																										

[4] Lacking [5] Extremely lacking	
Q10 (If you were EV users) How important do you find the following aspects of public charging infrastructure? Please rank the following factors _____ Location _____ Charging speed _____ Amenities (e.g., toilets, shops) _____ Pricing _____ Easy to access (e.g., high density, public charging points with enough parking space, high visibility, and enough quantity of chargers) _____ Convenient to use (e.g., easy to pay, multiple payment methods, universal app) _____ Information about the public charging point provided is clear (e.g., the information of location, availability, pricing, whether use clear energy) _____ Safety (e.g., personal, vehicle, information security) _____ Reliability (e.g., whether the charger is working or not) _____ Others (Please specify)	Ten Have et al. (2020);

4.5.2 Revisions on the discrete choice experiment

From the results of cognitive interviews on the stated preference discrete choice experiment (SPDCE), two participants could not make a choice due to unclear choice context. Other participants who had made their final choices also reported that there was an issue of an unclear choice context. For example, temporal attributes, such as time of day, weekdays or weekends, holidays, or if they were in a hurry may influence their choice of whether or not to recharge. This is also consistent with the literature (Ma et al. 2022) that consumers had different charging preferences at different time periods. Based on the results of the cognitive interviews and previous literature, it was found that temporal attributes were also closely associated with travel purpose/ type of travel (Xu et al. 2017; Zhang et al. 2022), such as commute, leisure, or long-distance travel. For example, long-distance travel usually takes place on weekends and local commute/business travel normally occurs on weekdays.

Therefore, without clarity on the destination and what activities participants were to do during EV charging, participants may feel quite confused. During the choice-making process, six participants misinterpreted the destination in different ways, such as a public charging station en route and the amenities around a public charging point. However, the activities and

destinations involved in public charge choice studies can create a lot of complexity and may require different choice contexts and descriptions, leading to the design and implementation of a series of choice experiments.

For example, Ge and MacKenzie (2022) developed specifically stated-choice experiments for public charging choices en route for long-distance travel. Also, Li et al. (2023) focused on individuals' choice for different routes along a 30 km travel between the origin and the destination of a trip. Similarly, Visaria et al. (2022) focused on public charging choices en route during a long-distance journey. All three studies examined the en route public charging choices for long-distance travel.

While there were some studies focused on destination charging, Wang et al. (2021), Pan et al. (2019), and Wen et al. (2016) examined whether or not charge at a destination, where Wang et al. (2021) and Wen et al. (2016) did not specify the actual location of the destination, while Pan et al. (2019) assumed the scenarios to be at home, workplace or shopping mall for public charging. Similarly, Wolbertus and Van den Hoed (2019) primarily examined choices related to public charging stations with varying charging speeds in proximity to the home location. Multiple scenarios of the locations for the destination were further explored in previous studies. Wolff and Madlener (2019) considered choices among multiple destinations, including home, work, and roadside where the charging is the main goal, and where the charging is a side activity. Sheldon et al. (2019) also explored consumers' preferences towards various destination locations, including work, transit, gym, mall, fast charging stations near home, fast charging stations near the freeway, grocery, school, and entertainment. Zhang et al. (2022) investigated destination charging for work and recreation by integrating public charging behaviour with the trip chain behaviour on working days and non-working days.

To accommodate the objective of this study (i.e., public charging choices) but retain a form of generality, this study places emphasis on 'what configurations' and 'which locations' would be more attractive for public charging to existing and potential EV users. By doing so the complexity associated with the impact of these attributes can be avoided and the initial stated choice experiment was modified to measure the attractiveness of different public charging stations. This allowed us to focus only on the main characteristics of the public charging stations themselves.

Several studies have been conducted similar work in this research domain. For example, Gutjar and Kowald (2023) explored the preferred “configuration” of public charging stations among potential EV users in Germany, examining aspects such as authentication, payment methods, charging prices, and the proportion of renewable energy. Similarly, Visaria et al. (2022) investigated the effects of various variables, including detour time, number of available chargers, charging speed, charging cost, and amenities, on EV users’ choices regarding fast chargers. Furthermore, Globisch et al. (2019) estimated the attractiveness levels of the two unlabelled public charging options, taking into account factors such as monthly charging costs, charging point density, and charging duration for a 100 km distance. In another study, Moon et al. (2018) examined “the most preferred type of public EVSE (Electric Vehicle Supply Equipment) among the four hypothetical options” with the consideration of charging cost, equipment type, availability of station information, availability of charging service, and station accessibility. Lastly, Nienhueser and Qiu (2016) explored EV users’ preferences for Level 2 chargers and DC fast chargers, considering different shares of renewable energy and corresponding charging prices.

4.5.2.1 The alternatives of the new SPDCE

Most of these choice experiments are unlabelled (Moon et al. 2018; Globisch et al. 2019; Visaria et al. 2022; Gutjar and Kowald 2023). However, from the conclusion part of the previous literature review section, one thing can be found the evidence that preferences for charging locations are influenced by other factors is sparse. Therefore, the experiment was modified to a labelled experiment in which ‘location’ was used to describe the different alternatives. Another reason for this was that some female participants (#2, #3, and #10) showed different preferences for different parking lots due to safety concerns. However, safety issues regarding different locations have not been explored in previous literature for public charging choices, although Zhao et al. (2020) suggested that safety (personal and charging safety, information security) should be used in models to estimate the private and public charging share. The new choice experiment includes four alternatives, which are: (i) on the street, (ii) surface-level car park, and (iii) multi-storey car park.

4.5.2.2 The attributes of the new SPDCE

The selection of attributes in this SPDCE was derived from the planning of public charging infrastructure perspective. The design of the choice experiment was to explore which characteristics of public charging points could improve the user experience and to find out what

potential and existing EV users expect from a “public charging service”. For example, which attributes related to the above they would value more (or less) and how the overall “service” would be more attractive to them. With these in mind, **nine (9)** attributes were involved in the revised stated choice experiment (see Table 4-7), including car park types at different charging locations, charging prices, payment methods, waiting time, energy source, and amenities.

The “distance from charging point to your destination” was removed in the new choice experiment because the focus of this choice experiment was to figure out the attractiveness of the different public charging options, thus it did not matter whether the charging point was used at the destination or en route.

The charging price attribute stays the same pricing model (p/kWh) for the new choice experiment. Firstly, half of previous public charging choice studies which involved charging cost attributes used kWh-based fees to measure charging price (Sun et al. 2016; Latinopoulos et al. 2017; Moon et al. 2018; Pan et al. 2019; Wolbertus and Van den Hoed 2019; Lee et al. 2020; Wang et al. 2021; Ge and MacKenzie 2022; Ma et al. 2022), which indicates its popularity among potential and existing EV users. Secondly, cognitive interview results reported that most participants felt fine with using this pricing model, with only one participant suggesting changing it to cost per session, and one mentioned removing the “pence per kilowatt hour” and keeping the comparative pricing percentage information. However, based on the pricing information from the official websites of some public charging infrastructure providers in the UK (bp pulse 2022; Osprey 2024), the charging price range was modified to be much larger, from £0.45/kWh to £0.6/kWh for slow charging and from £0.75/kWh to £0.9/kWh for fast charging. The reason for this was because it is important to distinguish between the charging prices of the two types of charging points with different charging speeds.

The levels of the attribute “waiting time for an available charging point (minutes)” remained unchanged for the newly introduced attribute “waiting time”. However, during the cognitive interviews, two participants repeatedly expressed concerns regarding uncertain waiting times. Notably, Ten Have et al. (2020) conducted a study that examined the influence of certainty on waiting time for public charging choices. Their findings revealed a preference for a ‘certain’ waiting time of up to 5 minutes compared to charging stations with unknown or uncertain waiting times. In light of this, the new choice experiment aimed to further investigate the issue of uncertainty and thus introduced a new attribute called **“number of charging points”**.

Participant #10, in particular, emphasised the significance of the number of charging points in influencing EV users' decision-making process as it directly impacts waiting time. Consequently, this study incorporated the uncertainty of waiting time by introducing the "number of charging points" attribute. The four levels for this attribute include: (i) 2, (ii) 4, (iii) 6, and (iv) 8.

In the new choice experiment, the attribute of "payment method" has been retained. Due to feedback from the cognitive interviews, participants had different understandings and imaginations of "supplier's app" and "universal app", thus the "supplier's app" was modified to "operator's app" and the "universal app" was modified to "an app for all operators". Findings from a government report (Hink 2021) conducted by the Electric Vehicle Association of England (EVA) with a sample of 1,216 EV users indicated that 45% of drivers perceived contactless credit or debit cards as the most convenient payment option, closely followed by smartphone apps at 14%. Meanwhile, a similar proportion of respondents found using membership (RFID) cards to be a convenient payment method. Given the comparable popularity of RFID cards and smartphone apps, the new choice experiment incorporated RFID cards as an additional payment option.

Interoperability issues can be found between public charging networks offered by different operators (Hardman et al. 2018b). Visaria et al. (2022) examined the level of pricing interoperability (all networks in EU, one network in DK, all networks in DK) of different payment models (flat fee, monthly subscription, no contract) in Denmark. However, no other studies have focused on the compatibility of charging networks among various charging providers for public charging choices. Hence, this study also addresses this gap by investigating compatibility issues related to payment methods, including operator-specific or a universal app, and access to one operator's charging network or all charging networks by one RFID chip card. To capture the various possibilities, the "**payment method**" attribute included five levels as follows: (i) card or contactless, (ii) card, contactless or operator's app, (iii) card, contactless, or an app for all operators, (iv) card, contactless, or an operator's card with RFID chip, (v) card, contactless, or card with RFID chip for all operators.

EV authentication refers to the process of the operator identifying an EV and its user to enable faster charging and payment. A new attribute "**authentication**" was added to the new choice experiment by the inspiration of the study by Gutjar and Kowald (2023) with similar attribute

levels, including: (i) via the operator's app, (ii) an operator's card with an RFID chip, and (iii) automatic via Plug an Charge.

Previous studies conducted by Wolff and Madlener (2019), Nienhueser and Qiu (2016) and Wolff and Madlener (2019) have indicated a positive impact of charging stations with a higher proportion of renewable energy on public charging choices. Building upon these findings, the new choice experiment incorporates a similar attribute of “**% of renewable sources (e.g. wind, solar)**” to further examine its influence. The attribute consists of five levels: (i) 0, (ii) 25, (iii) 50, (iv) 75, and (v) 100, representing the varying degrees of renewable energy in the charging station's power supply.

The “**amenities**” attribute was kept the same for the new choice experiment, with only “shopping mall within walking distance” being modified to “shopping centre”. Therefore, the four levels for this attribute include: (i) none, (ii) a waiting room, (iii) small shops or caf  s, and (iv) a shopping centre.

Finally, the new choice experiment added a new attribute “**station rating**” as EV drivers' as an overall rating of EV drivers' service at charging points. In a previous study (Wang et al. 2021), a five-point Likert scale was also used to evaluate EV users' satisfaction with charging services, which proved to be important. The attribute levels included in the new choice experiment were: (i) 3 *, (ii) 4 *, and (iii) 5 *. Since low scores for public charging services are unlikely to be selected by EV users, this choice experiment excluded the cases of 1* and 2* scores.

Table 4-7: Revised attributes and attribute levels

Attribute	Levels					
	1	2	3	4	5	6
Fast Charging Available	V	X				
Method of Payment	- Card - Contactless	- Card - Contactless - Operator's app	- Card - Contactless - App for all operators	- Card - Contactless - An operator's card with RFID chip	- Card - Contactless - A Card with RFID chip for all operators	
Waiting time (minutes)	Available right way	2	5	10		
Amenities at the charging station	None	Waiting room	Small shop or café	Shopping centre		
Cost (p/KWh)	45	55	60	75	85	90
% of renewable sources (e.g. wind, solar)	0	25	50	75	100	
Authentication	Via the Operator's app	An operator's card with RFID chip	Automatic via Plug and Charge			
Number of charging points	2	4	6	8		
Station rating	3 *	4 *	5*			

4.5.2.3 Revised Ngene syntax for the new SPDCE

Based on the assumption of alternatives and attributes in previous sections, the revised Ngene syntax is as follows:

Figure 4-7: Revised syntax code in Ngene

```
? Design.ngs --- Experimental Design --- 10. 05. 2023

? Total 9 Attributes
? [1] fast[0,1] --- 0 represents slow public charging, 1 represents fast public
charging
?      [0] Slow charging; [1] Fast charging

? [2] price[0.45 (base),0.55, 0.60, 0.75 (base),0.85, 0.90] --- Charging price,
including 6 levels; 0.45 is the base price for public slow charging and 0.75 is
the base level for public fast charging.
?      [1] 0.45 £/kWh; [2] 0.55 £/kWh; [3] 0.60 £/kWh; [4]0.75 £/kWh; [5] 0.85 £/kWh;
[6] 0.90 £/kWh

? [3] wait[0,2,5,10] --- Waiting time for an available charging point (minutes),
including 4 levels
?      [1] 0 (Available right away); [2] 2 minutes; [3] 5 minutes; [4] 10 minutes

? [4] number[2,4,6,8] --- number of charging points at the public charging stations,
including 4 levels
?      [1] 2; [2] 4; [3] 6; [4] 8

? [5] renewable[0, 0.25, 0.50, 0.75, 1] --- the share of renewable sources (e.g.
wind, solar), including 5 levels
?      [1] 0; [2] 0.25; [3] 0.50; [4] 0.75; [5] 1

? [6] authen [1,2,3] --- Methods of authentication of the EV or the EV driver,
including 3 levels
?      [1] Via the operator's app; [2] An operator's card with RFID chip; [3]
Automatic via Plug and Charge

? [7] pay[1,2,3,4] --- Method of payment, including 5 levels
?      [1] Card or contactless; [2] Card, contactless, or via operator's app; [3]
Card, contactless, or app for all operators via; [4]Card, contactless, or an
operator's card with RFID chip;

? [8] amen[1,2,3,4] --- Amenities, including 4 levels
?      [1] No amenities; [2] Waiting room; [3] Small shop or café; [4] shopping
centre
```

```
? [9] rating[1,2,3] --- ratings of previous EV users of a public charging point,
including 3 levels
?      [1] 3*; [2]4*; [3] 5*
```

```
? Each choice card will include 3 labelled options
? 60 potential choice cards into 12 blocks so that each respondent receives 5 cards
(scenarios)
```

```
? The aim to generate several choice cards is to exhaust respondents. More choice
cards (normally 5 to 10) for each respondent then more observations we can generate,
which may lead to more valid results
```

```
Design;
```

```
alts= street, surface, multi_storey; ? alternatives: (a) on street, (b) Surface-
level car park, (c) multi-storey car park
```

```
rows=60; ? number of choice cards
```

```
block=12; ?number of blocks in the design matrix
```

```
eff=(mnl,d); ? Set of efficiency measure: using the D-error for finding an efficient
design for the MNL modle
```

```
? alg = mfederov(stop=total(2000000 iterations));
```

```
? Use swap not mfederov algorithm is because it cannot be used with a condition
(cond:)
```

```
alg = swap(stop=total(120 mins));
```

```
? set a condition:
```

```
? If the alternative is assumed to use slow charging (alt1/2.fast = [0]), then the
charging price for this alternative will be chosen randomly from [0.45, 0.55,
0.60]; if the alternative is assumed to use fast charging (alt1/2.fast = [1]), then
the charging price for this alternative will be chosen randomly from [0.75, 0.85,
0.90];
```

```
? The setting is the potential charging prices for fast charging are higher than
slow charging
```

```
cond:
```

```
If (street.fast = [0], street.price = [0.45, 0.55, 0.60]),
```

```
If (street.fast = [1], street.price = [0.75, 0.85, 0.90]),
```

```
If (surface.fast = [0], surface.price = [0.45, 0.55, 0.60]),
```

```
If (surface.fast = [1], surface.price = [0.75, 0.85, 0.90]),
```

```
If (multi_storey.fast = [0], multi_storey.price = [0.45, 0.55, 0.60]),
```

```
If (multi_storey.fast = [1], multi_storey.price = [0.75, 0.85, 0.90]);
```

```

? For 'fast' variable, we put '1' before '0' (base) is because 1 represent fast
charging and thus we assume a dummy variable for this attribute
? For dummy variables, we can assume a starting point of the parameters by
estimating whether the effect of this variable is negative (e.g., -0.000001) or
positive (e.g., 0.000001)
?utilities
model:
U(street)= b10[0]
    +b1.dummy[0.000001]*fast [1,0]
    +b2[0.000001]*price[0.45, 0.55, 0.60, 0.75, 0.85, 0.90]
    +b3[0]*wait[0,2,5,10]
    +b4[0]*number[2,4,6,8]
    +b5[0]*renewable[0,0.25,0.50, 0.75, 1]
    +b6.dummy[0|0]*authen[1,2,3]
    +b7.dummy[0|0|0]*pay[2,3,4,1]
    +b8.dummy[0.000001|0.000002|0.000003]*amen[2,3,4,1]
    +b9.dummy[0.000001|0.000002]*rating[2,3,1]    /

U(surface)= b11[0]
    +b1*fast
    +b2*price
    +b3*wait
    +b4*number
    +b5*renewable
    +b6*authen
    +b7*pay
    +b8*amen
    +b9*rating    /

U(multi_storey)= b1*fast
    +b2*price
    +b3*wait
    +b4*number
    +b5*renewable
    +b6*authen
    +b7*pay
    +b8*amen
    +b9*rating
$

```

4.5.2.4 The introductory text of the new SPDCE

Some participants in the cognitive interviews reported that the scenario descriptions were too long and difficult to read, and also with reference to other similar choice experimental designs (Nienhueser and Qiu 2016; Moon et al. 2018; Globisch et al. 2019; Visaria et al. 2022; Gutjar

and Kowald 2023), the following revised introductory text describing the assumed scenario was generated in order to keep the scenario's simplicity:

We will now present you with 5 cards each showing different locations that you could charge an electric vehicle. Each location is described by several characteristics (e.g. price, payment method, etc.). After carefully considering each location, please, indicate which would be your most preferred option in each card.

Figure 4-8 Revised introductory text of the new choice experiment

Accordingly, by using the design matrix generated from the Ngene syntax, the following choice card can be created (see an example in Figure 4-9).

Description	On street 	Surface-level car park 	Multi-storey car park 
Fast Charging Available	✓	✗	✓
Cost (p/kWh)	90	45	85
Authentication	An operator's card with RFID chip 	Via the operator's app 	Automatic via Plug and Charge 
% of renewable sources (e.g. wind, solar)	50	25	75
Waiting time (minutes)	10 min	5 min	Available right away
Amenities at the charging station	Small shop or café 	Waiting room 	Shopping centre 
Number of charging points	6	6	4
Method of payment	Card or contactless 	Card, contactless, or via an app for all operators 	Card, contactless, or an operator's card with RFID chip 
Station rating	★★★★★	★★★★★	★★★★★
I would choose option:	☐	☐	☐

Figure 4-9: The example of the new choice cards

4.6 Validation of revisions through a second round of cognitive interviews

Retesting the modified choice experiment was essential to assess participants' understanding of the modified choice cards and also useful to validate whether previously identified problems still existed among participants. Five participants were recruited from the Respondent.io platform again from 24 to 26 May, 2023. Three of the participants were non-electric vehicle users and the other two were electric vehicle users. Detailed demographic characteristics and car ridership as well as EV charging availability are listed in Table 4-8 below.

Table 4-8: Characteristic summary of non-EV and EV users

Categories	Characteristics	Non-EV users	EV users
Gender	Male	2	1
	Female	1	1
Age group	26-35	1	1
	36-45	2	1
Education	Undergraduate	2	2
	Postgraduate	1	0
Ethnicity	White/Caucasian	1	1
	Black or African American	1	1
	Asian or Pacific Islander	1	0
Location of residence	London	2	1
	England (exp. London)	1	1
Conventional car ownership	Yes	3	
EV driving type	BEV		1
	PHEV		1
Driving experience	Less than 1 year		1
	1-5 years	2	1
	6-10 years		0
	Over 10 years		0
Home charging	No		2
Workplace charging	No		2
Public slow charging	Yes		2
Public fast charging	Yes		1

Again, participants were first presented with some introductory questions in Table 4-12, followed by a list of attributes and attribute levels in Table 4-13, and finally were asked to

participate in a choice experiment by providing feedback on the introductory text in Figure 4-8 and five choice cards similar to that in Figure 4-9.

4.6.1 Introductory questions

In terms of the knowledge about the public charging question, four participants (#21, #22, #23, #24) thought it was clear and they liked the way the question and question options were put. For example, participant #23 expressed “I think that I like what you did here with examples like location, speeds, prices, because it makes people think and remember information maybe they have in their minds and they weren’t aware of it”, which facilitates making choices. Compared to simply using scales to describe different knowledge levels of public charging for participants, participant #24 preferred the question options with detailed descriptions (as what it is now), as “this is more accurate, and it is easier for you to read for you to really make sure that people understand what they mean. If you say I know public charging very well, and I know quite well, then it's like, for me, there is no much difference”. Conversely, participant #25 preferred the question options just using scales as the option situation may not be applicable to all participants, as some people may know the charging price, but they may not know other things. Meanwhile, two participants (#23 and #25) both believed the text was too “long” (#25) and “a lot of text to read” (#23).

Participant #24 mentioned that the participant had two cars, one was an ICE car, and one was a BEV car, which indicates the question did not consider the situation that people have multiple cars. This participant also thought “public slow” and “public fast” were a bit hard to understand, maybe adding charging power to describe public slow and fast charging would be clear “I think the slow charger is like seven kilowatt per hour or something”.

In terms of the perception of service of public charging infrastructure, participant #22 mentioned it can lead to two understandings of the question, one is the “unit itself”, and the second is “are there enough units around the city”. Then the interviewer expressed the intention was the service of the individual charging unit. Then the participant mentioned dissatisfaction with the charging speed as most public charging in Oxford was slow charging and the participant thought most of the public charging points should be fast. Then the participant mentioned the incompatibility issue of different charging networks, “each unit comes with different brands” and “if I’m already using an app, let’s say with loyalty points or something like this, if I buy that specific branded unit, I have to go out of my way to kind of find that unit.

They are just not making it easy for us”. Participant #25 also questioned whether the question was asking “the quantity of public charging infrastructure” in the area where the participant lives or in the UK, and the participant thought he could only answer the question within the area that the participant lives otherwise “I am not sure”.

Participant #22 perceived all factors as important the first time they saw them as the participant said “oh my gosh, so many of them are like on my top agenda”. Then the participant felt that “easy to access”, “pricing”, “charging speed”, and “location” were the top priorities for the participant and the participant found it hard to rank them. Similarly, for participant #24 it was very hard to rank them as all the factors were quite important. Then the participant suggested maybe setting different scales for each factor would make it easier for the participant to make a choice. Conversely, participant #23 can successfully rank all the factors one by one. In terms of additional important factors for public charging choices, participant #21 mentioned “loyalty point”. However, it was less important than lower prices, as “if I had one, I give me 30 points, but it’s more expensive than this one that gives me no loyalty points, but this one is cheaper, I will go to the cheaper one.” Participant #25 questioned who was providing the information for the “information about location...” factor.

Table 4-9: Summary of the frequency of occurrence of issues in the introductory questions, and examples of evidence

The original question in Table 12	Issues	Number of participants (out of 5)	Example of evidence
<i>“What is your understanding of public charging for electric vehicles? Please select which one describe you the most.”</i>	Scales	1	Just using Likert scale (#25)
	Too long	2	“A lot of text to read” (#23)
<i>“Do you drive a car and what type of car do you drive?”</i>	Situation not applicable	1	Have multiple cars (#7)
<i>“How do you perceive the quantity of current public charging infrastructure?”</i>	Range specification	2	“Unit itself” or “are there enough units around the city”. (#23) - In the area that the participant live or in the UK (#25)

<i>“(If you were EV users) How important do you find the following aspects of public charging infrastructure? Please rank the following factors”</i>	Hard to rank	2	Hard to rank them as all the factors were quite important (#25)
	Other unmentioned factors	1	“Loyalty point” (#21)
	Ambiguity	1	Not clear about who was providing the information for the “information about location...” factor (#25)

4.6.2 Understanding attributes and attribute levels

- Authentication

The understanding and interpretation of the term “authentication” varied significantly. Participant #22 acknowledged a general comprehension of the term but believed it might not be clear to everyone. Even when the term was modified to “car authentication,” confusion persisted as the participant associated it with different EV brands. The participant commented, “It’s about the brands that you want to use, isn’t it?”

Participant #21 also expressed confusion and questioned what exactly they were authenticating. When prompted to make a guess, the participant proposed “car authentication.” This participant perceived authentication as a “broad” concept, potentially involving “authentication between the charging point and the car”.

Participant #23 was similarly unsure about the meaning of “authentication” and suggested it could be comparable to checking in at a hotel. The participant speculated that a machine at the charging station could authenticate the user by touching a chip, possibly even addressing them by name.

In contrast, participant #24 demonstrated a clear understanding of “authentication.” The participant described it as the process of obtaining the driver’s profile, encompassing various attributes such as car profile, payment details, and personal information. However, this participant acknowledged that without specific contextual cues like the attribute levels, “the

operator's app" or "RFID", understanding the term initially would have been challenging. The participant suggested adding "(of your profile)" to provide additional clarity to this attribute.

Four participants indicate the term "authentication" might be too ambiguous and requires a more specific and detailed explanation to ensure a consistent understanding among all users. Additionally, incorporating contextual elements and emphasising the connection to the driver's profile could enhance comprehension.

- RFID card

Both participant #23 and participant #24 had different levels of familiarity with RFID technology. Participant #23 expressed unfamiliarity with the term "RFID card," stating, "I don't know what RFID chip is, but I imagine it's something they use when charging at the charging station." This participant lacked knowledge about RFID technology but made an association with its potential usage during the charging process. Similarly, participant #24 and #25 raised concerns about the clarity of the term "RFID card." They understood its meaning but believed it might be too technical and challenging for other participants to comprehend. For example, "I know because I come in tech world, so I know what RFID is. You asked my mom, my dad, they wouldn't know" (#25).

- Automatic plug and charge

Participant #24 initially expressed uncertainty regarding the meaning of "automatic plug and charge." The participant was "not too sure" about its definition. However, the participant imagined the context correctly although the participant had not personally experienced it.

- Others

Participant #21 commented not sure what it was for the renewable source attribute ("% of renewable sources (e.g. wind, solar)") and asked "is it where to get the energy from"? Hard to understand it because "the way it was written. So I'm understanding it as the amount of renewable energy that it powering the charging points", which interpreted correctly. Then the participant suggested to change it to "percentage of renewable energy used". Participant #25 thought it would be useful to give the definition of "fast charging".

Table 4-10: Summary of the frequency of occurrence of issues in attributes and attribute levels, and examples of evidence

The original attributes and attribute levels	Issues	Number of participants (out of 5)	Example of evidence
<i>“% of renewable sources (e.g. wind, solar)”</i>	Ambiguity	1	“Is it where to get the energy from”? (#21)
<i>“Fast charging”</i>	Terminology	1	Give the definition of “fast charging” (#25)
<i>“Authentication”</i>	Terminology	4	Unsure about the meaning of “authentication” (#23)
<i>“RFID card”</i>	Terminology	3	“I don’t know what RFID chip is, but I imagine it’s something they use when charging at the charging station” (#23)

4.6.3 The feedback on the choice cards

Participant #21 expressed the need for visual cues, stating that without the image, the participant would not have understood the term “surface-level car park.” The participant suggested that terms like “ground car park” or simply “car park” might be more commonly used and easily understood. The participant also questioned the importance of icons, as the participant believed the words alone were clear enough. The participant remarked, “I don’t think they are doing much more than just occupying the space. The words are clear enough.”

On the other hand, participant #23 and #24 both mentioned that their choice would depend on the proximity of the public charging points to their location. They considered the convenience factor and how closely the charging points were situated to them when making their decision.

Participants #21 and #22 presented a preference for mobile apps as a payment method over RFID cards. Their reasons include convenience (#21), the likelihood of misplacing physical cards (#21), environmental concerns (#22), and issues related to postal services (#22), for example:

- “I just wonder if I can have it as an app on my phone. It’s fine rather than having somewhat occurred to be kind of my wallet. So somewhere else I could easily misplace cards. But I would highly misplace my phone” (#21);
- “I would expect none of the companies actually using physical cards anymore, because everything, first of all, because we do not want to use plastic. And the second thing is also because you have to wait for it to be delivered to the house. Whereas like, I want to use my charging, I’ve signed up for the app, I want to go and charge now I can’t wait three days. And especially as I’ve got issues with my post, my post sometimes does not get paid” (#22).

Participant #22, as a PHEV user, displayed a strong environmental consciousness, expressing a desire to be eco-friendly by stating, “considering the renewable sources because I quite I tried to be a green person. But the last thing I want to do is spend extra money so I am actually spending extra money for the 50% here.” Meanwhile, the participant was also a pro-technology person, “I’m like, technically savvy I’m always prepared. You know what, I would probably have the card, I would probably also have the app on me. I’m the type of person you know. And that’s in my daily life.”

Table 4-11: Summary of the frequency of occurrence of issues in choice cards, and examples of evidence

The original items in the choice cards	Issues	Number of participants (out of 20)	Example of evidence
<i>Picture for “surface level car park”</i>	Picture	1	• Cannot understand the term “surface level car park” if without the picture (#21)
<i>Icons for attribute levels</i>	Unhelpful	1	• Unhelpful but occupy the space (#21)
Making choices	Choice context	2	• Choice would depend on the proximity of the public charging points to their location (#23 and #24)

4.7 Final revisions of the survey questions and the choice cards

Based on the issues reported in Section 4.6 of the second round of cognitive interviews, the question “(If you were EV users) How important do you find the following aspects of public charging infrastructure? Please rank the following factors” which just listed different factors for participants to choose from, was changed into Likert scale because some participants indicated that it was difficult to rank the importance. Meanwhile, in the new questionnaire in Table 4-12 (a full version of the survey questionnaire can be seen in the Appendix), multiple car family situation was considered and other issues such as the wording issues were also addressed.

Table 4-12: Final version of survey questions

Non-EV users	EV users			Reference
Q1 Do you have a driving license? [1] Yes [2] No				
Q2 Do you drive a car? [1] Yes [2] No				
Q3 What type of car do you drive most often? [1] An internal combustion engine (ICE) car (e.g., petrol or diesel) [2] A hybrid car [3] A plug-in hybrid car [4] A full battery electric car				
Q4 How long have you been driving the car you mentioned?				
	Less than 1 year	1-5 years	Over 5 years	
An internal combustion engine (ICE) car	☐	☐	☐	
A hybrid car	☐	☐	☐	
A plug-in hybrid car	☐	☐	☐	
A full battery electric car	☐	☐	☐	
Q5 What is your understanding of public charging for electric vehicles? [1] I am very familiar with all aspects of public charging including locations, speeds, prices, payment methods as well as concepts of different technologies involved (e.g. smart charging, V2G). [2] I am familiar with some aspects of public charging; for example, locations, speeds, prices, and payment methods.				

[3] I only know one aspect of public charging; for example, only locations, speed, price, or payment methods. [4] I do not know anything about public charging.																																										
Q6 Would you agree or disagree that the number of public charging points available in your area is sufficient. [1] Strongly agree [2] Agree [3] Natural [4] Disagree [5] Strongly disagree [6] Not sure																																										
	EV user-specific section																																									
	Q7 How often do you use electric vehicle charging according to the following options? <table border="1"> <thead> <tr> <th></th> <th>Daily</th> <th>5-6 times per week</th> <th>3-4 times per week</th> <th>1-2 times per week</th> <th>1-2 times per month</th> <th>Less frequently</th> <th>Never</th> </tr> </thead> <tbody> <tr> <td>Home</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Work</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Public slow</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>Public fast</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> <td>☐</td> </tr> </tbody> </table>		Daily	5-6 times per week	3-4 times per week	1-2 times per week	1-2 times per month	Less frequently	Never	Home	☐	☐	☐	☐	☐	☐	☐	Work	☐	☐	☐	☐	☐	☐	☐	Public slow	☐	☐	☐	☐	☐	☐	☐	Public fast	☐	☐	☐	☐	☐	☐	☐	Ten Have et al. (2020); (Department for Transport 2022a); Anderson et al. (2018)
		Daily	5-6 times per week	3-4 times per week	1-2 times per week	1-2 times per month	Less frequently	Never																																		
Home	☐	☐	☐	☐	☐	☐	☐																																			
Work	☐	☐	☐	☐	☐	☐	☐																																			
Public slow	☐	☐	☐	☐	☐	☐	☐																																			
Public fast	☐	☐	☐	☐	☐	☐	☐																																			
Q8 How satisfied are you with the current public charging service in your area? [1] Very satisfied [2] Satisfied [3] Neither satisfied nor dissatisfied [4] Dissatisfied [5] Very dissatisfied	Wang et al. (2021)																																									

Q9 How important are the following characteristics of public charging, even if you do not currently drive an electric vehicle?						Ten Have et al. (2020);
	Very important	Important	Neither	Low important	Not at all important	
Charging speed	☐	☐	☐	☐	☐	
Amenities (e.g., toilets, shops)	☐	☐	☐	☐	☐	
Pricing	☐	☐	☐	☐	☐	
Easy access (e.g., high density and visibility, enough parking space and quantity of chargers)	☐	☐	☐	☐	☐	
Convenient to pay (e.g., easy to pay, multiple payment methods, app for all operators)	☐	☐	☐	☐	☐	
Clear information (e.g., about location, availability, pricing, use clean energy)	☐	☐	☐	☐	☐	
Safety (e.g., personal, vehicle, personal information privacy)	☐	☐	☐	☐	☐	
Reliability (e.g., whether chargers are working or not)	☐	☐	☐	☐	☐	

On the other hand, most ambiguity issues mentioned in the choice experiment part were also addressed by add detailed descriptions of attributes and attribute levels (see, in Figure 4-10).

Next, we will present you with five choice cards, like the one below, and we will ask you to make a choice across: on street, surface-level car park, and multi-storey car park.

The "Description" column shows different characteristics of public charging for electric vehicles at these locations.

The following is a detailed description of these characteristics:

- **Fast charging available** - Indicates whether the public charging location offers fast charging (V) or slow charging (X).

- **Waiting time (minutes)** - This is the time you may need to wait for a charging location to become available.

- **Amenities** - The amenities likely to be available at the charging location can include: a waiting room, small shop or café, and nearby shopping centre.

- **Cost (p/kWh)** - This is the electricity rate in pence per kilowatt hour charged at the location.

- **Percentage of renewable sources (e.g. wind, solar)** - The proportion of clean energy sources utilised to generate the energy provided at the public charging location.

- **Authentication** - Electric vehicle users may be required to provide identification or credentials to start charging. These credentials may include a membership card (RFID card), smartphone app, or users may just simply to plug in the charger to automatically authenticate and start charging.

- **Number of charging points** - This is the total number of charging points available at the location.

- **Station rating** - The station rating by previous users.

Figure 4-10: Description of attributes and attribute levels

With referencing previous studies and syntheses findings from cognitive interviews, three attitudinal questions are generated (see, Table 4-13). Environmental cognition, risk aversion and pro-technology attitudes are assumed to have an effect on the public charging preferences of potential and existing EV users. Therefore, the following latent construct of the three attitudinal questions was adopted in the survey questionnaire.

Table 4-13: The attitudinal questions in previous public charging choice studies

Latent construct	Reference
[Environmental cognition] To what extent do you agree with the following statements? (Strongly agree 1 – Strongly disagree 5) [1] There are natural limits to growth that our industrialized world has reached long ago [2] For the environmental benefit, we should all be willing to restrict our current standard of living [3] We need more economic growth, even if it pollutes the environment [4] More environmental protection also means more quality of life and health for all	Gutjar and Kowald (2023)
[Risk aversion attitude] To what extent do you agree with the following statements? (Strongly agree 1 – Strongly disagree 5) [1] When I leave the car in the parking spot, I keep valuables secured out of sight [2] When I leave the car in the parking spot, I lock the doors [3] I avoid any situation that may cause danger [4] I do not care to leave the car in risky neighbourhood [5] I usually leave the car on high traffic roads	Soto et al. (2018)
[Technophillia] To what extent do you agree with the following statements? (Strongly agree 1 – Strongly disagree 5) [1] I am very interested in the latest technology developments [2] It doesn't take me long to learn to like new technology developments [3] I am always keen to use the latest technological devices	Globisch (2019)

Chapter 5 Public charging survey data collection and analysis

5.1 Survey implementation

Between September and October 2023, an online survey was launched on Qualtrics targeting full-driving license holders in Great Britain. [The study targeted to recruit 600 participants](#). Half of them were electric vehicle users, who drove plug-in hybrids or full battery electric vehicles. The other half were non-electric car users who either did not drive or drove internal combustion (gasoline or diesel) or hybrid vehicles.

As shown in Tables 5-1 to 5-3, the recruitment of respondents was guided by the allocation of quotas for age, gender, and region based on the population distribution from the UK Census. For example, the composition of the non-EV user group is consistent with the population distribution observed in the UK Census, considering factors such as age, gender and regional representation. However, the EV user group faces challenges in meeting specific quotas due to their relatively limited numbers. As a result, these quotas for the EV user group have been relaxed to obtain a sufficient sample.

Table 5-1: Age quota allocation and counts of participants

Age	Allocation	Quota counts (Reality/Target)
18-24	5.82%	42 / 37
25-34	15.12%	112 / 95
35-44	18.09%	130 / 114
45-54	18.95%	76 / 119
55-64	19.79%	130 / 124
65-74	13.48%	85 / 85
75+	8.74%	55 / 55

[Note: “Target” refers to the number of participants targeted for recruitment, “Reality” refers to the number of participants actually recruited.](#)

Table 5-2: Gender quota allocation and counts of participants

Gender	Allocation	Quota counts (Reality/Target)
Male	53.55%	338 / 337
Female	46.55%	291 / 293
Prefer not to say	1%	1 / 6

Note: “Target” refers to the number of participants targeted for recruitment, “Reality” refers to the number of participants actually recruited.

Table 5-3: Region quota allocation and counts of participants

Region	Allocation	Quota counts (Reality/Target)
London	16.74%	123 / 105
North East	2.68%	21 / 16
North West	8.43%	65 / 53
Yorkshire and The Humber	6.49%	42 / 40
East Midlands	6.83%	54 / 43
West Midlands	7.32%	52 / 46
East of England	11.29%	77 / 71
South East	19.96%	70 / 126
South West	9.52%	44 / 59
Scotland	7.57%	52 / 47
Wales	3.17%	29 / 19

Note: “Target” refers to the number of participants targeted for recruitment, “Reality” refers to the number of participants actually recruited.

Individuals were invited to participate through a designated survey link distributed in the Qualtrics panel. Prior to officially launching the survey, a soft-launch phase was conducted with 30 participants from the Qualtrics panel to evaluate and refine the functionality of the survey.

The pre-launch phase sent a message of possible speeding behaviour in completing the survey and low median time of completing the survey (4 minutes). A previous test of survey completion time with 14 university students yielded a result of 15 minutes, which is far from the average survey completion time of the 30 participants recruited from the Qualtrics panel.

To address this issue, 5 minutes of survey completion time was suggested to be set as the limit in Qualtrics of acceptable responses. This adjustment is intended to filter out hastily provided or poorly thought-out responses and ultimately improve the reliability of the data collected.

Due to commitment requests instead of attention checks for speed is a better approach to improve data quality (Geisen 2022), the survey added a new commitment question “We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you provide thoughtful answers to each question in this survey. Do you commit to providing thoughtful answers to the questions in the survey?” at the beginning of the survey questionnaire. Only participants who selected “Yes, I will” were considered valid responses and could continue to answer additional survey questions.

After the survey was officially launched, a total of 909 responses were received, of which 365 were from non-EV users and 331 were from EV users. Of the 909 responses, (1) 184 were excluded based on the following screening questions:

- (a) From the soft-launch phase with 30 participants, we found that people tended to speed up to complete the survey. Therefore, we considered adding attention-checking questions to avoid speeders. As a result, we added a commitment question, which proved to be more useful than the attention-checking question (<https://www.qualtrics.com/blog/attention-checks-and-data-quality/>) to achieve this aim. Thus, the survey began by asking participants if they were committed to providing thoughtful responses to the questions in the survey, and we excluded participants (85) who chose “No, I won’t” and “I can’t promise”.
- (b) Participants (93) who did not have a full driving license (who selected “No” for the question “Q2 Do you have a full driving license?”)
- (c) Participants (6) who were under the age of 18 (who selected “Under 18” for the question “Q3 What is your age group?”)

In addition, (2) 95 participants did not complete the entire survey. (3) At the same time, a minimum of 300 seconds (5 minutes) was used as a criterion to detect speeders (245) during the official launch phase. Participants who met one of the above data exclusion criteria were ineligible for our study. This data exclusion criteria were set as a program in Qualtrics, which automatically excluded the ineligible responses.

5.2 Data screening procedures

After the automated data exclusion process, a total of 630 responses were eventually recorded for the public charging preference experiment. The first step in processing survey data was performing an initial screening of the data and cleansing unqualified survey data.

5.2.1 Survey and SPDCE completion time

Table 5-4 summarises the distribution of time spent completing the survey and the Stated Preference Discrete Choice Experiment (SPDCE) tasks. Table 4 shows that almost two-thirds of the participants (68.73%) completed the survey for up to ten minutes. 87.46% of the participants took the survey under 15 minutes. 52.22% of participants used one and a half minutes to complete the five choice cards. The mean times to complete the choice cards and the survey were 1.939 and 10.452 minutes.

Table 5-4: Completion times of the survey questionnaire including the SPDCE tasks

Total response time				SPDCE response time			
Time	n	%	Cumulative	Time	n	%	Cumulative
< 3 mins	1	0.16	0.16	< 0.25 min	4	0.63	0.63
3-4 mins	6	0.95	1.11	0.25-0.5 mins	96	15.24	15.87
4-5 mins	5	0.79	1.90	0.5-0.75 mins	53	8.41	24.29
5-6 mins	131	20.79	22.70	0.75-1 mins	59	9.37	33.65
6-7 mins	103	16.35	39.05	1-1.5 mins	117	18.57	52.22
7-8 mins	78	12.38	51.43	1.5-2 mins	108	17.14	69.37
8-9 mins	55	8.73	60.16	2-2.5 mins	71	11.27	80.63
9-10 mins	54	8.57	68.73	2.5-3 mins	51	8.10	88.73
10-15 mins	118	18.73	87.46	3-3.5 mins	20	3.17	91.90
15-20 mins	39	6.19	93.65	3.5-4 mins	11	1.75	93.65
20-25 mins	14	2.22	95.87	4-4.5 mins	9	1.43	95.08
25-30 mins	10	1.59	97.46	4.5-5 mins	5	0.79	95.87
>=30 mins	16	2.54	100.00	5-10 mins	17	2.70	98.57
				>=10 mins	9	1.43	100.00
Mean	Median		Std. Dev.	Mean	Median		Std. Dev.
10.452	7.792		10.072	1.939	1.4333		2.815

To avoid excessively long responses, all responses within three standard deviations of the mean time to complete the survey and the SPDCE were deemed eligible responses, which were 40.668 and 10.384 minutes respectively. Therefore 17 responses were removed due to this criteria.

In keeping with the data exclusion criteria for the ‘soft launch’ data collection phase, five minutes was the minimum acceptable response time for the entire survey. Therefore, 12 responses were excluded.

Since Qualtrics suggested that normally participants need at least “3 seconds time to transition between pages” (Qualtrics 2023), thus the total time to complete the five choice cards would be at least no less than 15 seconds, or 0.25 minutes. This was used as an additional data deletion criterion for further data analysis. As a result, four responses were deleted.

5.2.2 Diagnostic questions

Diagnostic questions in a survey are a specific type of question designed to gather information that will help diagnose or assess a particular aspect of a respondent’s knowledge, experience, perspective, or behaviour (SurveyMonkey 2023). For example, asking respondents to detail the reasons behind their ratings or choices, thus providing valuable insights into specific areas of improvement.

Three diagnostic questions were included at the end of each choice experiment block in the questionnaire to allow respondents to report whether they understood the set of choice cards presented to them. In terms of the question “Did you understand the choices we presented in the previous five cards” (see Figure 5-1), most participants selected “Yes” (436) and “Only a few” (20). However, there were still 168 participants selected “most part” and 6 selected “No”.

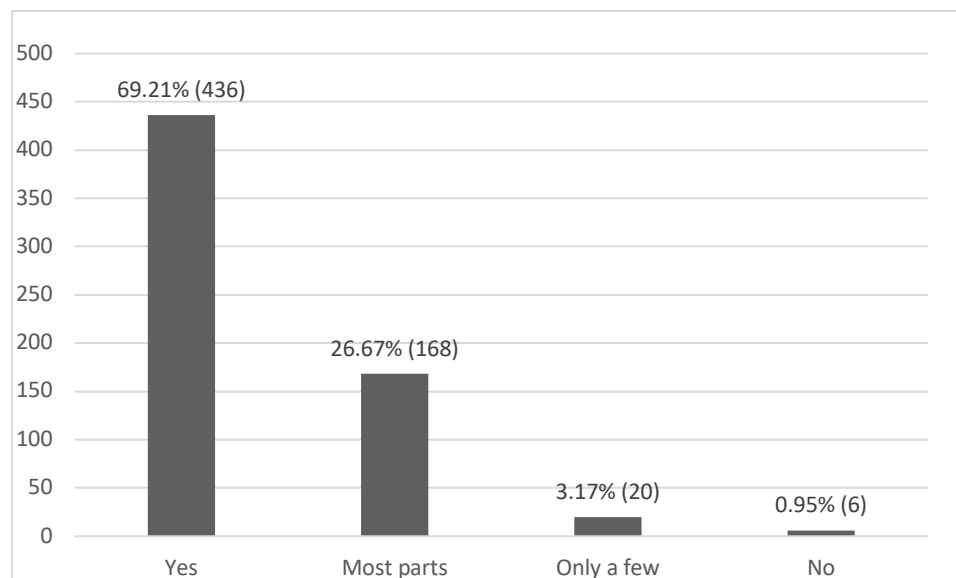


Figure 5-1: Responses on the difficulty level of comprehending the choice cards

Table 5-5 lists further explanations from these six participants for their lack of understanding of the choice experiment. In order to maintain the validity of the sample, participants who indicated that they did not understand the choice experiment were excluded from this study.

Table 5-5: Reasons selected “No” for the first diagnostic question

Observation ID	Reason stated	Stated unclear attributes
118	“All of it as I am totally disinterested in electric cars. I don’t like them and I don’t want one. And why we should have to give up parking spaces for electric cars is beyond belief. If you can charge an electric car on the street, street level, multi-story, then why can’t I get petrol for my car in the same places? Why do I have to go to a petrol station? Why can’t electric cars also go to recharging stations like internal combustion engine cars? it is completely unfair and discriminative and all this pampering to electric cars should be stopped at once.”	All attributes were unclear
150	“Too small to read and too poorly presented bother going through it all”	All
184	“All”	Cost (p/kWh)
190	“No”	All
301	“NA”	All
345	“I don’t understand at all, how to use it”	Fast charging availability, waiting time, cost (p/kWh), station rating

Table 5-6 summarises participants’ discontinuous responses to these diagnostic questions. For example, some participants may have selected that they understood only “only a few” or “most parts” of the choice experiment when they indicated that they did not actually understand the entire choice experiment at all. In addition, this study eliminated some odd answers that did not make sense in the reasons listed, as well as answers that selected that they understood most parts, but then chose many attributes (equal or over six items) they did not understand in later diagnostic question.

Table 5-6: Discontinuous responses for diagnostic questions

Observation ID	Whether understand	Reason stated	Stated unclear attributes
Participants stated totally did not understand the choice cards			
248	Only a few	"I have no idea I don't own one."	1,7,9
274	Only a few	"What exactly I needed to do to charge my vehicle"	2,5,6,7,8,9
280	Understand most parts	"All"	6
515	Only a few	"All of it if I'm honest"	1,3,5,8
Strange answers for "Which, if any, aspects of the choice cards did you find difficult to understand?"			
290	Understand most parts	"The sigh ones when u drive a car"	3,5
528	Understand most parts	"Tit juo"	4,5
Participants who said understand most parts, but then selected many attributes (equal or over 6 items)			
418	Understand most parts	"Nothing much"	1,2,3,4,5,8
615	Understand most parts	"Nope"	1,2,3,5,6,8,9

Note: The numbers in the "Stated unclear attributes" column from 1 to 9 refer to "Fast charging availability", "Method of Payment", "Waiting time", "Amenities at the charging station", "cost(p/kWh)", "% of renewable sources", "Authentication", "Number of charging points", and "Station rating" attribute respectively.

5.2.3 Non-trading behaviour

In choice experiments, non-trading behaviour refers to the situations where participants in the experiment do not make a trade or choose not to make a choice among the given alternatives (Hensher et al. 2015).

Table 5-7: Participants who showed non-trading behaviour

Non-trading behaviour	EV	Non-EV	Total
On street	9	22	31
Surface car park	12	19	31
Multi-storey car park	7	2	9
Total	28	43	71

As shown in Table 5-7 and Figure 5-2, a total of 71 participants consistently chose the same

option across the five choice cards, including 28 EV users and 43 non-EV users. Of these, 31 always chose street, 31 chose surface, and 9 chose multi-story car parks.

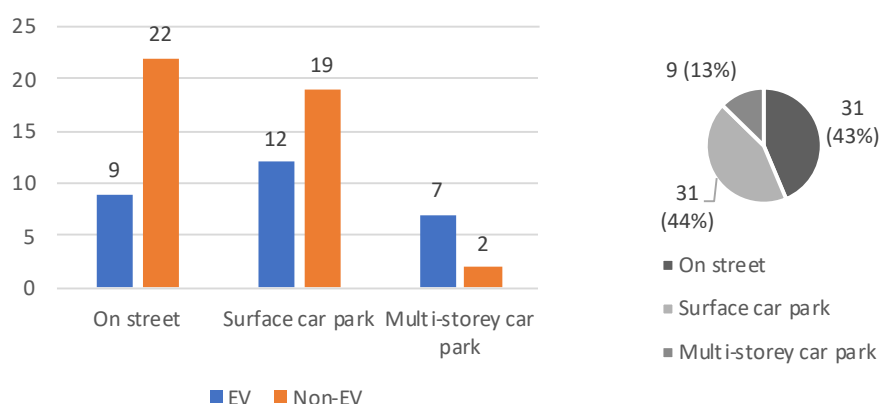


Figure 5-2: Participants who showed non-trading behaviour

5.2.4 Summary

In summary, a total of eight criteria were used for data cleaning in Table 5-8 below. However, for criteria eight, this study did not remove all participants who exhibited non-trading behaviour in the choice experiment, but only those overlapping responses (in blue) that also met the other criteria. After sorting out duplicate respondents in more than one criterion, 42 participants were removed from the main dataset. Therefore, a total of 588 observations were available for further data analysis.

Table 5-8: Criteria for data cleaning

Criteria	Explanation	Count	IDs
1	Exclude extreme long responses: three standard deviations of the mean of survey completion time (40.668 minute)	8	127, 133, 215, 216, 345, 416, 473, 485
2	Exclude extreme long responses: three standard deviations of the mean of SPDCE completion time (10.384 minute)	9	145, 151, 216, 271, 345, 465, 483, 593, 603
3	5 minutes as the minimum acceptable time for completing the survey	12	1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 14
4	Total SPDCE completion time is not less than 15 seconds (0.25 minute)	4	305, 346, 460, 599
5	Diagnostic questions - who stated they did not understand the choice card	6	118, 150, 184, 190, 301, 345
6	Diagnostic questions - who selected “understand mostly” or “only a few”, but stated totally did not understand the choice cards	4	248, 274, 280, 515
7	Diagnostic questions - who said understand most parts, but then selected many attributes (equal or over 6 items)	2	418, 615
8 *	Non-trading behaviour (on street)	31	11, 25, 30, 57, 81, 118, 151, 153, 160, 167, 182, 184, 199, 208, 212, 214, 224, 241, 251, 280, 282, 336, 344, 348, 428, 469, 503, 532, 557, 558, 610
	Non-trading behaviour (surface)	31	12, 18, 19, 36, 84, 98, 123, 149, 150, 178, 190, 191, 215, 219, 265, 268, 299, 314, 316, 319, 456, 462, 466, 467, 473, 548, 554, 564, 567, 575, 620
	Non-trading behaviour (multi-storey)	9	40, 193, 213, 343, 349, 446, 483, 495, 615
Total (after sorting out duplicate respondents in more than one criterion)		42	1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 14, 118, 127, 133, 145, 150, 151, 184, 190, 215, 216, 248, 271, 274, 280, 301, 305, 345, 346, 416, 418, 460, 465, 473, 483, 485, 515, 593, 599, 603, 615

Note: The blue marking of IDs means that a participant who meets criterion 8* is the same as one who meets any of criteria 1 to 7 (duplicate respondents).

5.3 Analysis framework

The quantitative analysis framework shown in Figure 5-3 consists of two main parts in examining the entire sample: exploratory analysis and discrete choice modelling. The first part is the descriptive analysis, which provided a comparative assessment of multiple aspects of EV users and non-EV users. These included socio-demographic characteristics, perceptions of public charging infrastructure, usage patterns, satisfaction levels, and attitudinal characteristics.

The second part are choice models, as seen in Figure 5-3, various types of choice models were employed on the sample for different analysis purposes. The pooled MNL model was firstly adopted for testing whether there were significantly different preferences towards public charging choices among EV and non-EV users. If no, then the EV and non-EV data should be pooled together, and following MXL and LCL models can be used for testing the individual level and group level heterogeneity for the pooled sample. If yes, then MNL models should be applied separately for EV and non-EV users data. Following this, the subsequent steps involving MXL and LCL models remain consistent, enabling the examination of individual and group-level preference differences within each group of the sample.

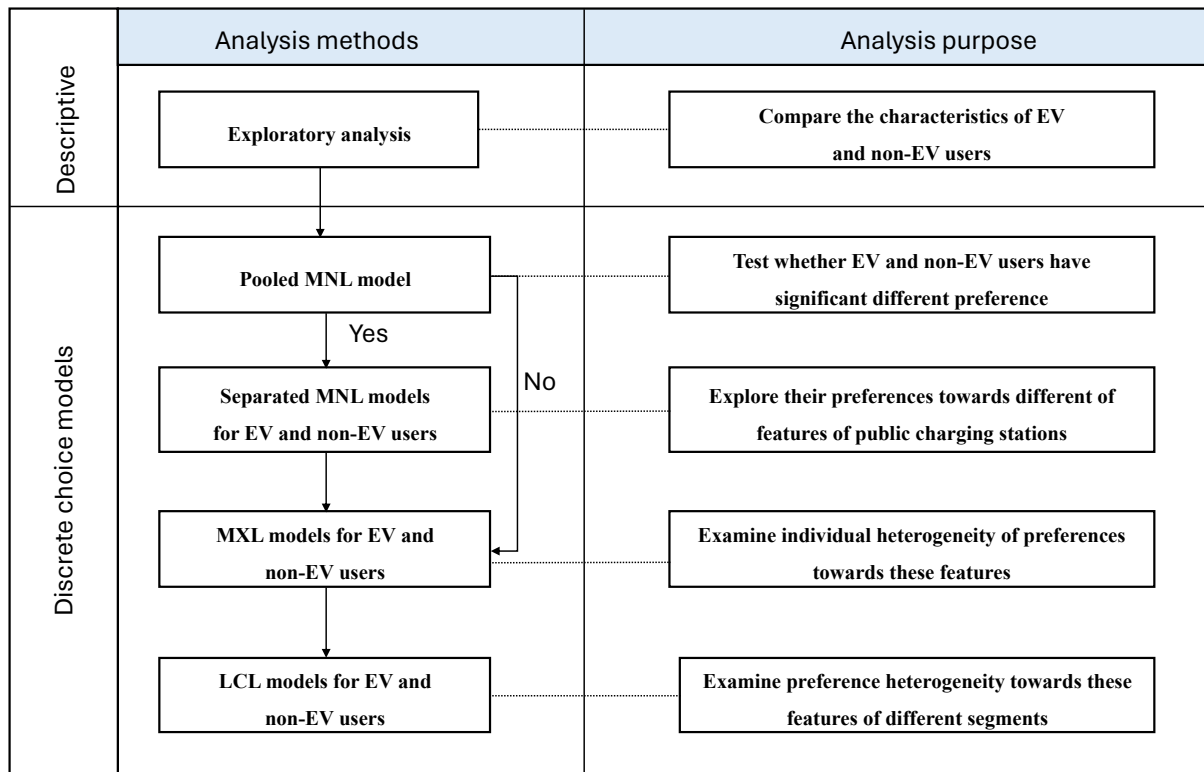


Figure 5-3: Quantitative analysis framework

5.4 Analysis methods

5.4.1 Exploratory analysis

Based on participants' responses to the question "Q4 Do you drive a car and what type of car do you drive most often?", participants were categorised into two groups: EV users and non-EV users. Participants who drove an internal combustion engine (ICE) car, a hybrid car, or did not drive a car currently were categorised as non-EV users, while participants who drove a plug-in hybrid car or a full battery electric car were categorised as EV users. The results showed that there were 288 non-EV users, and 300 EV users in the whole dataset. The frequencies and percentages for each group are presented in Table 5-9.

Table 5-9: Summary of data by car type

EV users	Frequency	Percentage	Non-EV users	Frequency	Percentage
PHEV	55	9.35%	ICEV	239	40.65%
BEV	245	41.67%	Hybrid	29	4.93%
			Do not drive	20	3.40%
Total	300	51.02%	Total	288	48.98%

5.4.2 Analysis of the public charging choice data

Discrete choice models are specifically designed to analyse the decision-making process of an individual choosing from a set of different alternatives. Unlike scenarios involving continuous outcomes that are typically regressed using ordinary least squares (OLS), discrete choice models rely on maximum likelihood (ML) techniques commonly used in logit models (Hensher et al. 2015). These models estimate the probability of selecting each alternative based on various attributes or characteristics associated with the available options and are particularly well suited for understanding and predicting choices in discrete scenarios.

In the context of decision-making, a decision maker can be presented as n who faces J available alternatives. When the decision maker makes a choice for a certain alternative, this person would get a certain level of utility from alternative J . The utility that decision maker n obtains from alternative j is U_{nj} , $j = 1, \dots, J$. The assumption is that the decision-maker will always choose the alternative with the highest utility, which is alternative i if $U_{ni} > U_{nj} \forall j \neq i$.

The utility can be divided into two parts, one is systematic utility (V_{nj}) which captures the observable attributes of the alternatives and the preferences of the decision maker, while random utility (ε_{nj}) accounts for unobserved factors or captures the factors that affect utility but are not included in V_{nj} . Therefore, the function is as follows:

$$U_{nj} = V_{nj} + \varepsilon_{nj}$$

5.4.2.1 Multinomial logit model (MNL)

The most commonly employed discrete choice model is the logit model, primarily due to its simplicity and interpretability of choice probabilities (Train 2009). In the baseline models, the observed utility V of an alternative j for individual i in the choice exercise t is typically specified as follows:

$$V_{ijt} = \alpha_j + \sum_k \beta_{kj} * X_{kjt}$$

where: α_j denotes an alternative-specific constant representing the baseline utility of alternative j ; β_{kj} denotes the coefficients associated with explanatory variables X_{kjt}

representing the attributes of alternative j ; X_{kjt} contains the various characteristics of alternative j that are relevant to the decision-making process.

Despite its widespread use, MNL models have several notable limitations (Hensher et al. 2015):

- (1) taste variation: MNL models can accommodate systematic taste variation, i.e., preferences vary according to the observed characteristics of the decision maker. However, they cannot capture stochastic taste variation, i.e., differences in tastes that are unrelated to observable characteristics.
- (2) substitution patterns: logit models assume that there is a proportional substitution relationship between alternatives based on the researcher's description of representative utility. To consider more flexible substitution patterns, it is often necessary to use alternative models.
- (3) repeated choices over time: In cases involving repeated choices over time, MNL models can effectively capture dynamic changes, such as state dependence, if the unobserved factors are independent across time. However, they cannot handle cases where unobserved factors show a correlation over time.

These limitations highlight the need for more advanced choice models, such as mixed logit, or latent class models, which offer greater flexibility in addressing complex decision-making scenarios and capturing a wider range of preference heterogeneity.

5.4.2.2 Mixed logit model

The mixed logit model is an extension of the MNL model, offering increased flexibility and realism in modelling decision-making behaviour (Train 2009). Unlike the MNL model, which assumes constant preference parameters across decision makers, the mixed logit model allows for heterogeneity in preferences by treating the coefficients associated with explanatory variables as random variables. Meanwhile, it obviates the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time.

In the mixed logit model, the coefficients of the explanatory variables are assumed to follow a distribution across decision-makers, allowing for variation in preferences within the population. This enables the model to capture individual-specific preferences and account for unobserved heterogeneity among decision-makers.

The function of mixed logit models can be written as follows:

$$V_{ijt} = \alpha_j + \beta'_{random} * Attribute\ 1_{jt} + \sum_k \beta_{kj} * X_{kjt} + \varepsilon_{jnt}$$

with:

$$\beta'_{random} = \beta + \eta_n$$

where η_n denotes the standard deviation around the mean of the coefficient, reflecting the extent of variation in respondents' tastes compared to the average taste observed in the sample (Train 2009).

5.4.2.3 Latent class logit model

Unlike traditional choice models that assume homogeneity of preferences across the population, latent class logit models allow for the identification of distinct subgroups or categories within the population, each with unique preferences and decision patterns.

The main goal of the latent class logit model is to estimate the probability of choosing a particular alternative for each class based on the attributes of the alternatives and the characteristics of the decision-makers in each class (Hensher et al. 2015). This approach allows for a more nuanced understanding of choice behaviour, which can lead to targeted interventions and policy recommendations for specific populations.

The choice probability is:

$$P_{ni} = \sum_{m=1}^M s_m \left(\frac{e^{b'_m x_{ni}}}{\sum_j e^{b'_m x_{nj}}} \right).$$

This approach is useful when dealing with populations consisting of multiple segments M , each of which has its own unique choice behaviours or preferences. Within these segmented populations, denoted by m , there exists a proportion of the population, denoted by s_m , which can be accurately estimated by the researcher in the model. In addition, the model can determine the specific coefficients (b 's) for each segment of the population, thus contributing to a more nuanced analysis of the population's behaviour and preferences.

Chapter 6 Findings

6.1 Sample characteristics

6.1.1 Participants' socio-demographic characteristics

Table 6-1 shows the breakdown of EV adoption based on gender. There is a slightly higher percentage of males in EV use at 54.6% compared to 45.2% of females. Notably, 61% of male drivers use EVs and 47.9% use non-EVs. In contrast, among female license holders, there is a larger percentage of non-EV users (52.1%) and a lower percentage of EV users (38.7%).

The age range of the sample respondents was wide, ranging from 18 to over 75 years old. Of those who do not use EVs, the majority fall into the 55-64 age group (36.8%), followed by the 65-74 age group (25.0%). In contrast, EV users are concentrated in the 25-34 age group (31.7%) and the 35-44 age group (34.3%), with an additional 17.3% in 45-54 age group. This distribution provides a nuanced view of the age composition of EV and non-EV users.

Of the survey sample, 58.7% of participants had a university degree or higher, while the remaining 41.3% had less than a university-level education. It is important to note that the distribution of education levels varies greatly between EV users and non-EV users. Among EV users, the vast majority (75.7%) had a college or university degree or higher, while only 24.3% had less than a university degree. Conversely, a slight majority (59%) of non-EV users had less than a university degree, while 41% had a university degree or higher.

Of the sample participants, 74.5% indicated that they had children in the household and 24.5% indicated that they did not have children in the household. In terms of the race of the participants, the majority were white (86.9%). These trends were consistent across both the EV and the non-EV user samples.

In examining the urban context of the participant's place of residence, the study categorised them into four tiers based on increasing degrees of rurality: city/urban, small town/suburban, village/fringe of town, and isolated rural areas. The data showed that the majority of participants lived in either cities/urban areas (39.5%) or small towns/suburbs (40.5%). Interestingly, a higher percentage of electric vehicle (EV) users (52.0%) lived in cities/urban areas compared to those living in small towns/suburbs (33%). Conversely, a higher percentage

of non-EV users were found in small towns/suburbs (48.3%) compared to a lower percentage in cities/urban areas (26.4%).

In the surveyed population, the majority of participants resided in detached houses (46.4%) or attached houses (36.1%), with only 15.8% living in apartments. Notably, among EV users, a higher proportion (55.7%) were found to inhabit detached houses, whereas 29.3% lived in attached houses. In contrast, non-EV users showed a slightly higher prevalence of residing in attached houses (43.1%) compared to those in detached houses (36.8%). Interestingly, in each sample, apartment dwellers consistently comprise less than 20% of both groups.

The composition of participants in this study was diverse, with a strong concentration in London (19.2%) and the rest of England excluding London (67.4%). Interestingly, only 8% of non-EV users lived in London, while the majority (71.9%) lived in the rest of England. In comparison, 30% of EV users live in London and 63% live in the rest of England. This geographical distribution illustrates the regional differences in EV use.

Table 6-1: Individual characteristics

Characteristics	EV users (%)	Non-EV users (%)	In total (%)
Gender			
Males	183 (61.0)	138 (47.9)	321(54.6)
Females	116 (38.7)	150 (52.1)	266 (45.2)
Prefer not to say	1 (0.3)	0	1 (0.2)
Age group			
18-24	19 (6.3)	22 (7.6)	41 (7.0)
25-34	95 (31.7)	7 (2.4)	102 (17.4)
35-44	103 (34.3)	19 (6.6)	122 (20.8)
45-54	52 (17.3)	17 (5.9)	69 (11.7)
55-64	11 (3.7)	106 (36.8)	117 (19.9)
65-74	12 (4.0)	72 (25.0)	84 (14.3)
75+	8 (2.7)	45 (15.6)	53 (9.0)
Education			
University and higher	227 (75.7)	118 (41.0)	345 (58.7)
Only have qualification	73 (24.3)	170 (59.0)	243 (41.3)
Whether having children			
Yes	238 (79.3)	200 (69.4)	438 (74.5)
No	58 (19.3)	86 (29.9)	144 (24.5)
Prefer not say	4 (1.3)	2 (0.7)	6 (1.0)
Residence			
City/urban	156 (52.0)	76 (26.4)	232 (39.5)
Small town/suburban area	99 (33.0)	139 (48.3)	238 (40.5)
Village/fringe of town	39 (13.0)	58 (20.1)	97 (16.5)
Isolated rural area	6 (2.0)	15 (5.2)	21 (3.6)
Type of housing			
Detached House	167 (55.7)	106 (36.8)	273 (46.4)
Attached House (e.g. townhouse, duplex, etc.)	88 (29.3)	124 (43.1)	212 (36.1)
Apartment	38 (12.7)	55 (19.1)	93 (15.8)
Mobile Home	7 (2.3)	3 (1.0)	10 (1.7)
Ethnicity			
White	244 (81.3)	267 (92.7)	511 (86.9)
Non-white	54 (18.0)	20 (6.9)	74 (12.6)
Prefer not to say	2 (0.7)	1 (0.4)	3 (0.5)
Region			
London	90 (30.0)	23 (8.0)	113 (19.2)

England (except London)	189 (63.0)	207 (71.9)	396 (67.4)
Wales	9 (3.0)	19 (6.6)	28 (4.8)
Scotland	12 (4.0)	39 (13.5)	51 (8.7)
Total observation	300	288	

Figure 6-1 shows the annual pre-tax household incomes of the participants, from which a clear trend can be seen - EV users generally have higher levels of income compared to non-EV users. The vast majority of EV users (73.36%) had household incomes over £45,001. In contrast, the majority of non-EV users (72.2%) have a household income of less than £45,001. This difference highlights the correlation between EV adoption and higher household incomes, suggesting potential economic factors influencing EV ownership.

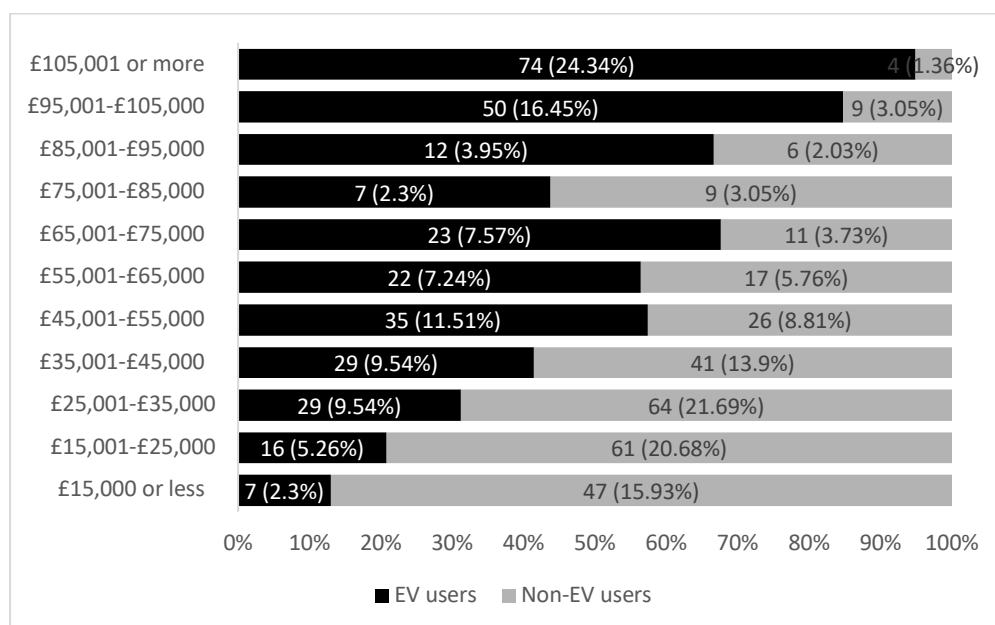


Figure 6-1: Annual household income (before tax) for EV and non-EV users

Figure 6-2 shows the distribution of EV users and non-EV users in the Great Britain survey sample. The colour gradient from light to dark green represents an increase in the proportion of EV users, while the orange gradient represents an increase in the proportion of non-EV users.

In terms of the distribution of EV users, London is the most dominant region, accounting for 30 per cent of the sample. This is closely followed by the East of England (15.33%), the North West (10.33%) and the East Midlands (9.67%). In contrast, regions such as Wales (3%), the South West (4%) and Scotland (4%) had the lowest proportions of EV users.

In terms of the distribution of non-EV users, the top three regions with the highest numbers are the South East (14.58%), Scotland (13.54%) and the South West (10.42%). Interestingly, two of these regions coincide with the regions with the lowest proportion of EV users. Notably, London, which initially had the highest proportion of EV users (30%), has seen a dramatic drop in the proportion of non-EV users to 7.99%. This contrast of the distribution of EV and non-EV users across the different regions of Great Britain suggests different rates of EV adoption.

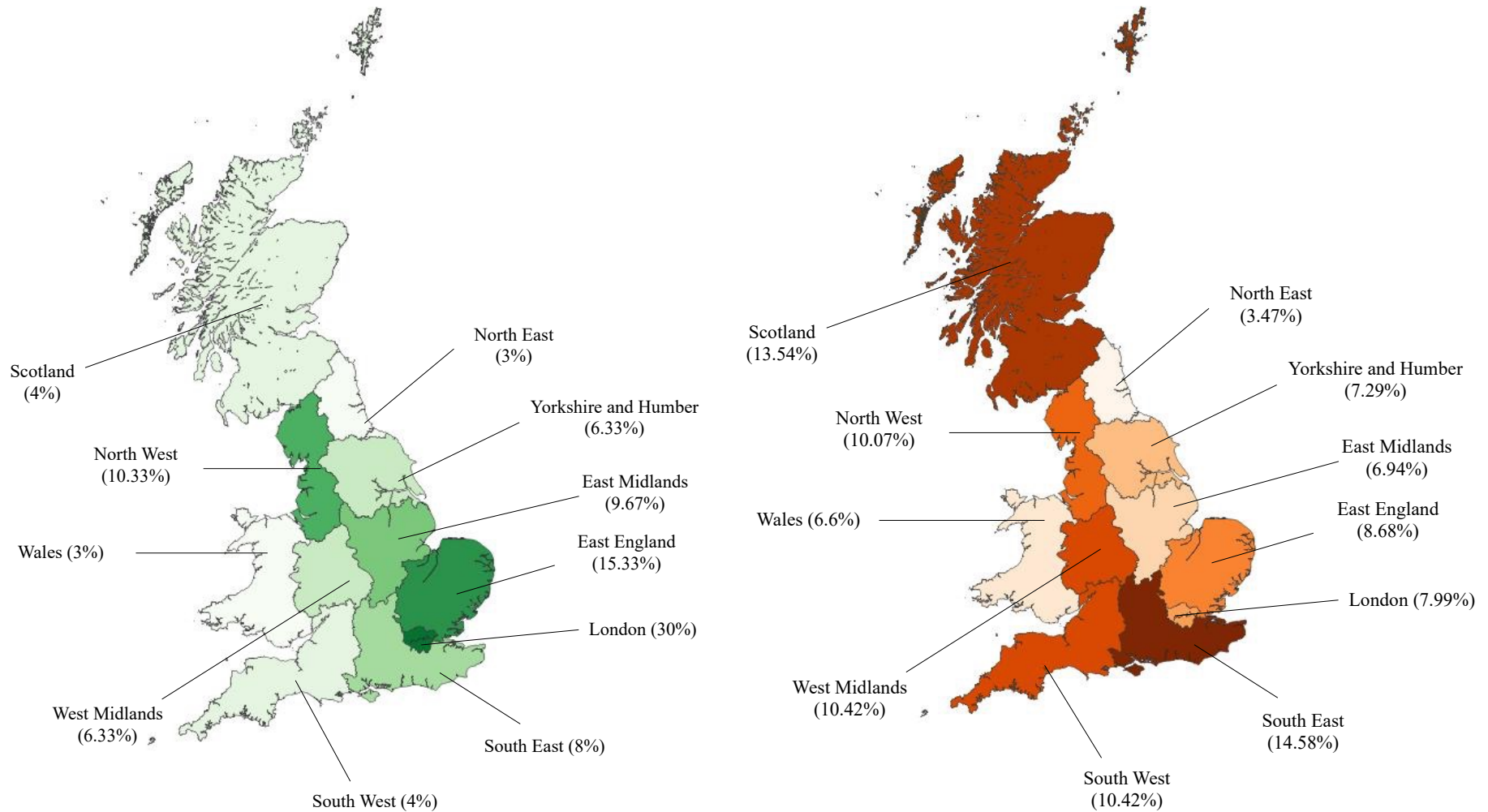


Figure 6-2: Regional distribution of EV users (in green) and non-EV users (in orange)

As shown in Figure 6-3, of the sample, 96.67% of EV users indicated that their driving experience lasted only 5 years or less. Broken down further, 40.33% of EV users reported using EVs for less than 1 year, and 56.33% reported using them for between 1 and 5 years. In contrast, the majority of non-EV users tended to drive conventional vehicles or hybrid vehicles for long periods of time. Specifically, 47.39% of non-EV users indicated that they had driven their vehicle for between one and five years, and 39.93% indicated that their overall driving experience was more than five years.

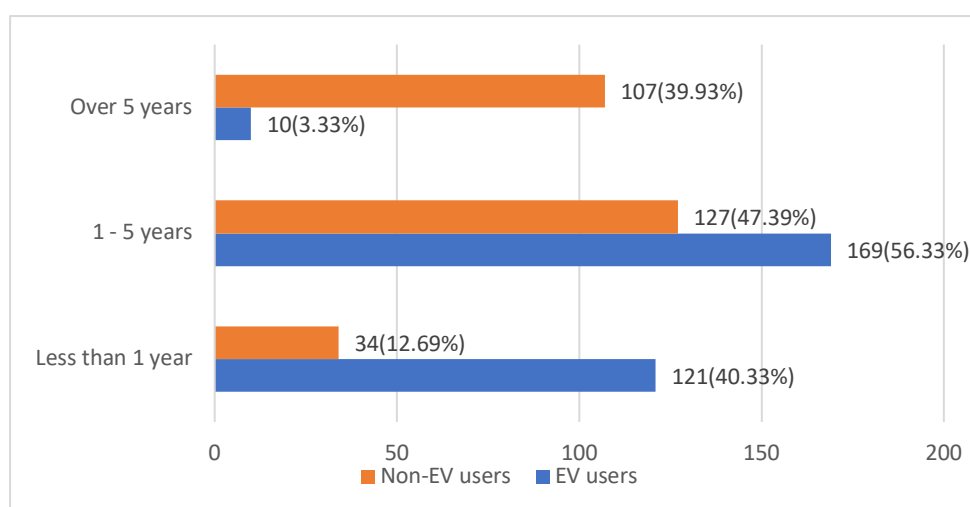


Figure 6-3: Driving experience for EV and non-EV users

6.1.2 Participants' knowledge and perception of public charging infrastructure

- Levels of knowledge on public charging

In order to understand participants' understanding of public charging for electric vehicles, the question "Q6 What is your understanding of public charging for electric vehicles?" was asked in the survey questionnaire. It is crucial to understand the level of knowledge of the participants as this could potentially influence their willingness to choose a public charging solution. The questionnaire contained a scale from 1 to 4 where respondents could indicate their increasing level of familiarity with public charging through options ranging from "I do not know anything" to "very familiar".

Figure 6-4 shows the distribution of EV and non-EV users' knowledge of public charging. The data shows that a big portion of non-EV users, specifically 41.3%, have no knowledge of public charging, while another 24.7% have only limited knowledge. In contrast, among EV users, the

majority showed a high level of familiarity with public charging, with 37.3% stating they were familiar and 53.7% believed they were very familiar with public charging.

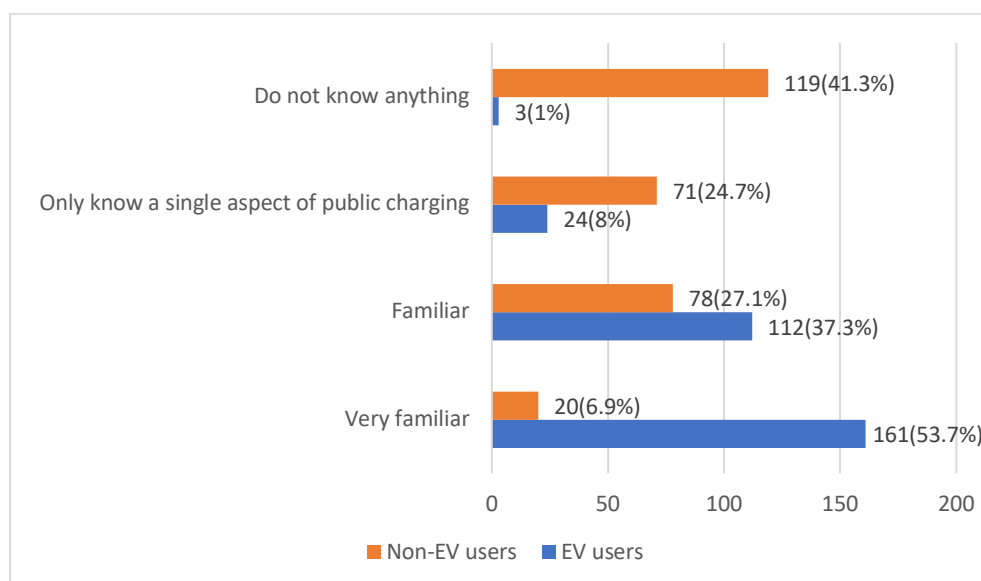


Figure 6-4: EV and non-EV users' understanding of public charging for electric vehicles

A t-test of the level of public charging knowledge between EV users and non-EV users revealed that the mean score for EV users was 3.44 (SD = 0.04), while the mean score for non-EV users was 2.00 (SD = 0.06). Meanwhile, the difference in public charging knowledge levels between the two groups of users was statistically significant ($t(586) = 20.70, p = 0.000$). This suggests that there is a significant difference in the level of knowledge of public charging infrastructure between EV users compared to non-EV users, with EV users having significantly higher levels of knowledge than non-EV users.

- The adequacy of public charging points in participants' residential areas

The survey included the following question “Q7 Would you agree or disagree that the number of public charging points available in your area is sufficient”. Participants were asked to indicate their agreement on a scale of 1 to 5, with 1 indicating “strongly disagree”, 5 indicating “strongly agree”, and 6 indicating “not sure” on the adequacy of public charging piles in their area.

Figure 6-5 shows the perceptions of EV users and non-EV users regarding the adequacy of public charging points in their residential areas. The data shows that slightly more than half of EV users either agreed (21.33%) or strongly agreed (31%) that the number of existing public

charging points in their residential area is sufficient. In contrast, slightly more than half of non-EV users said they strongly disagreed (36.81%) or disagreed (30.56%) that the number of public charging points around their residence was sufficient. This difference highlights the different perceptions of the adequacy of public charging infrastructure between EV and non-EV users.

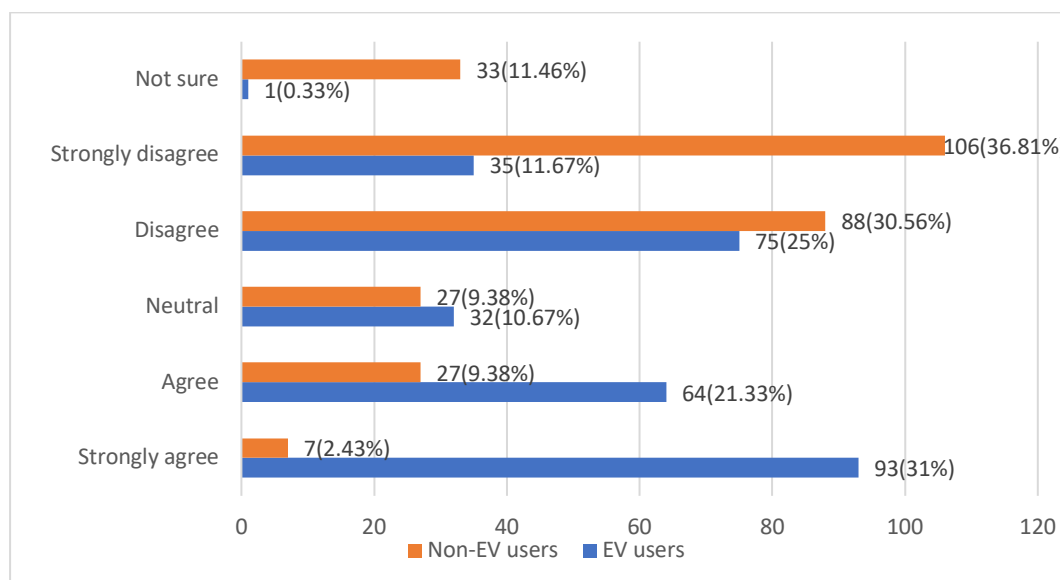


Figure 6-5: EV and non-EV users' perception of the sufficiency of the number of public charging points available in participants' living area

A t-test of the perception of the number of public charging points between EV users and non-EV users revealed that the mean score for EV users was 3.35 (SD = 0.08), while the mean score for non-EV users was 1.98 (SD = 0.07). Meanwhile, the difference in perception between the two groups of users was statistically significant ($t(552) = 12.43$, $p = 0.000$). This statistic suggests that there is a significant difference in the perceived adequacy of public charging points between EV users and non-EV users. Specifically, EV users are significantly more satisfied with the amount of public charging infrastructure available than non-EV users.

6.1.3 EV users' charging availability and public charging satisfaction

This study focused on EV users, specifically investigating their use of charging facilities and their satisfaction with public charging infrastructure. Figure 6-6 illustrates the key findings, showing that the majority of EV users (88.67%) charge their vehicles at home once a week, with a big proportion (40%) choosing to charge at home every day. At the workplace, 63.67%

of EV users charge their vehicles weekly, while 20% use workplace charging facilities daily. In addition, 38.33% of participants reported using public charging facilities on a weekly basis, while 49.67% preferred to use slow public charging facilities on a weekly basis. Notably, 60.67% of EV users use fast public charging services on a weekly basis. These insights reveal the diverse charging habits of EV users, emphasising the prevalence of home charging and the varying reliance on workplace and public charging options.

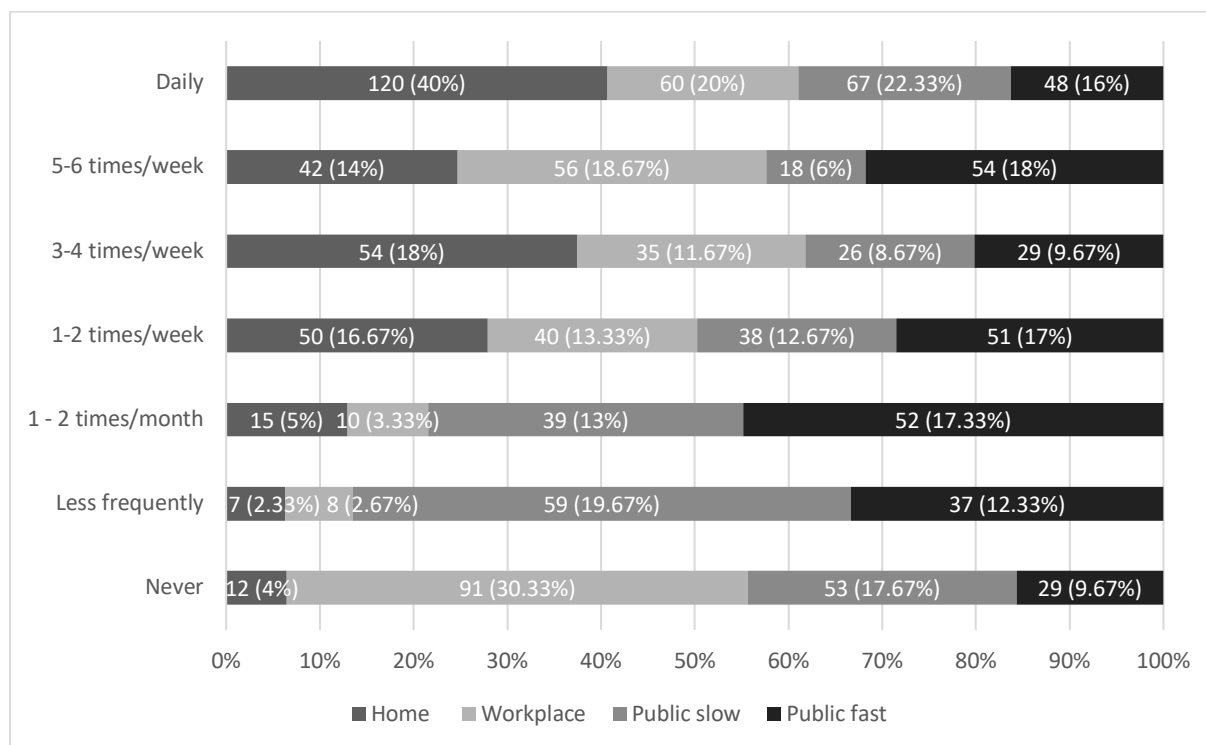


Figure 6-6: Charging availability of EV users

As shown in Figure 6-7, the majority of EV users (60%) are satisfied with the public charging infrastructure, with 24.33% being satisfied and another 35.67% being very satisfied. In contrast, 14.33% were neutral, while 25.66% were dissatisfied with the existing public charging facilities.

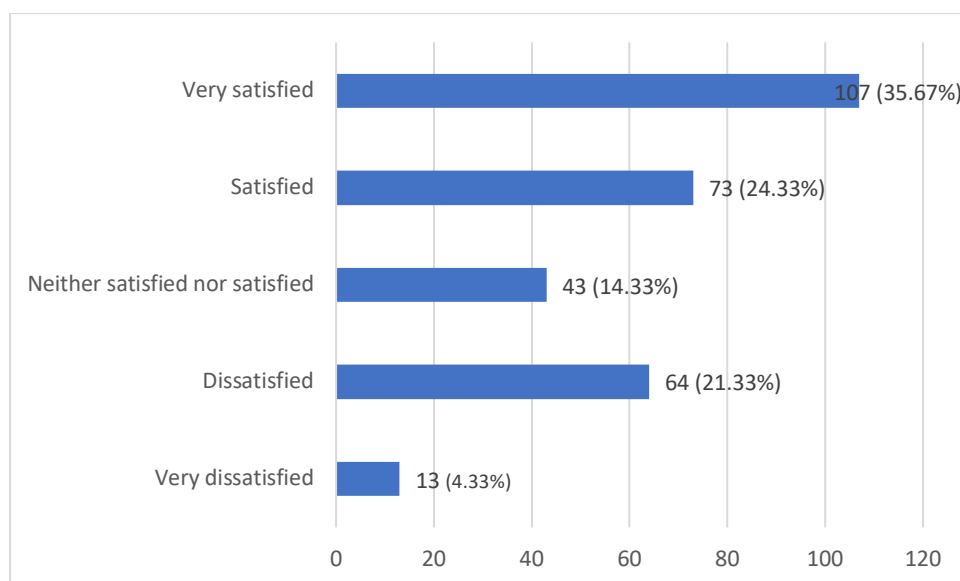


Figure 6-7: Satisfaction with public charging infrastructure for EV users

6.1.4 Attitudinal characteristics

In the questionnaire, participants answered a total of 12 questions (as shown in Table 6-2) aimed at understanding their attitudes toward environmental perceptions, risk aversion, and technology fandom. The variables labelled “envir1” to “envir4” reflected the participants’ attitudes toward environmental perceptions, while “risk1” to “risk5” represented their attitudes toward risk aversion. In addition, “tech1” through “tech3” indicated participants’ pro-technology attitudes. All variables were rated on a scale of 1 to 5, with 1 indicating strong disagreement with the statement and 5 indicating strong agreement.

It is important to note that the scale was reversed for three specific variables, “environment3”, “risk4”, and “risk5”. In these cases, a score of 1 indicates strong agreement with the statement and a score of 5 indicates strong disagreement. This reverse scaling was used to ensure consistency while maintaining the interpretation that higher scores on all items indicate higher levels of environmental perceptions and risk-averse attitudes, ranging from 1 to 5.

Table 6-2: Summarise the attitudinal variables

Variables	Description	EV users		Non-EV users		t-test	P
		Mean	SD	Mean	SD		
Envir1	There are natural limits to growth that our industrialised world has reached long ago (1 - strongly disagree, 5 - strongly agree)	3.95	0.06	3.25	0.06	t (586) = 7.73	0.000
Envir2	For the environmental benefit, we should all be willing to restrict our current standard of living (1 - strongly disagree, 5 - strongly agree)	3.97	0.05	3.52	0.07	t (586) = 5.06	0.000
Envir3_reversed	We need more economic growth, even if it pollutes the environment (1- strongly agree, 5 - strongly disagree)	2.59	0.08	3.29	0.07	t (586) = -6.41	0.000
Envir4	More environmental protection also means more quality of life and health for all (1 - strongly disagree, 5 - strongly agree)	4.29	0.05	4.12	0.05	t (586) = 2.43	0.016
Risk 1	When I leave the car in the parking spot, I keep valuables secured out of sight (1 - strongly disagree, 5 - strongly agree)	4.65	0.04	4.64	0.05	t (586) = 0.07	0.946
Risk 2	When I leave the car in the parking spot, I lock the doors (1 - strongly disagree, 5 - strongly agree)	4.71	0.03	4.89	0.03	t (586) = -4.46	0.000
Risk 3	I avoid any situation that may cause danger (1 - strongly disagree, 5 - strongly agree)	4.51	0.04	4.65	0.04	t (586) = -2.47	0.014
Risk 4_reversed	I do not care to leave the car in risky neighbourhood (1- strongly agree, 5 - strongly disagree)	2.34	0.08	2.01	0.08	t (586) = 2.81	0.005
Risk 5_reversed	I usually leave the car on high traffic roads (1- strongly agree, 5 - strongly disagree)	3	0.09	3.57	0.07	t (586) = -5.01	0.000
Tech1	I am very interested in the latest technology developments (1 - strongly disagree, 5 - strongly agree)	4.41	0.05	3.25	0.07	t (586) = 13.69	0.000

Tech2	It doesn't take me long to learn to like new technology developments (1 - strongly disagree, 5 - strongly agree)	4.18	0.05	3.30	0.07	t (586) = 10.63	0.000
Tech3	I am always keen to use the latest technological devices (1 - strongly disagree, 5 - strongly agree)	4.29	0.05	3.07	0.07	t (586) = 13.49	0.000

The mean scores and standard deviations of the attitudes of EV users and non-EV users are presented in Table 6-2. In order to assess the significance of the differences in the attitudes of the two groups of users, t-tests were conducted on various attitudinal variables. The results of these t-tests indicate that all attitudinal variables except statement 1 related to risk aversion attitudes, are significantly different between EV users and non-EV users. This indicates that there is a significant difference between the two groups of users in terms of their attitudes towards environmental perceptions, risk aversion and supportive technologies. In summary, EV and non-EV users appear to hold significantly different views on these attitudinal dimensions.

6.2 MNL-model estimates from pooled EV and non-EV user data

This dataset contains information about a choice experiment in which each row corresponds to a participant. In this experiment, each participant was asked to make five different choices. Overall, the dataset consisted of 588 participants, of which 300 were electric vehicle (EV) users and 288 were non-EV users.

In order to facilitate a comprehensive analysis of the choice experiment, the data was converted to a long format based on participants' responses to 60 choice scenarios previously identified in the experimental design chapter, with each participant contributing five rows representing their five choice observations. Thus, the dataset expanded to a total of 2,940 observations (588 participants * 5 choices).

Subsequently, attribute levels were incorporated into each choice scenario to provide contextual information for the participant's decision-making process. This included the scenarios outlining the circumstances under which particular choices were made. Together, these steps formed the final dataset, which was used to deeply analyse participants' choices in the choice experiments.

The study used the stated choice data to conduct a series of choice models. First, differences in the variance between EV users and non-EV users were assessed. As shown in Figure 6-8, this involved pooling data of EV users and non-EV users to assess unobserved variance (errors) between the two datasets (Hensher and Bradley 1993).

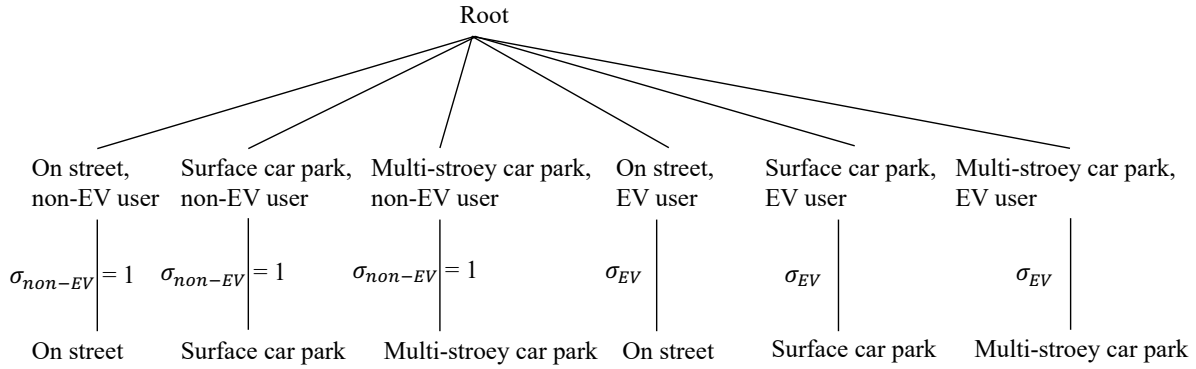


Figure 6-8: Estimation structure of the pooled EV and non-EV data

Within a single model, the non-EV data had an error variance equal to one (1) and the EV data had variance equal to σ_{EV} , a scale parameter to be estimated. The utility of the alternatives for EV users was then specified as (Bradley and Daly 1994):

$$V'_{ijt}^{EV} = \sigma_{EV} * V_{ijt}^{EV}$$

Table 6-3 displays the results from the pooled MNL model applied to EV and non-EV data. Notably, the scale parameter for EV users is significantly different from the value of one (1), which was pre-set for non-EV users. This difference highlights the different preferences of EV and non-EV users towards various choices. Therefore, their preferences must be independently assessed and analysed due to the apparent differences in their choice patterns.

Table 6-3: Results from the pooled MNL model

Parameter	Value	Rob. Std err	Rob. t-test
Constant: On street (EV)	Reference		
Constant: Surface car park (EV)	0.289*	0.167	1.73
Constant: Multi-storey car park (EV)	-1.31***	0.32	-4.08
Constant: On street (non-EV)	Reference		
Constant: Surface car park (non-EV)	-0.0851	0.0642	-1.33
Constant: Multi-storey car park (non-EV)	-0.481***	0.0701	-6.86
Authentication			
Via the operator's app	Reference		
An operator's card with RFID chip	-0.0147	0.0652	-0.226
Automatic via Plug and Charge	0.182***	0.063	2.88
Fast charging availability			
Fast charging not available	Reference		
Fast charging available	0.414***	0.131	3.15
Percentage of renewable energy (%)	0.501***	0.0742	6.75
Number of charging points	0.0223*	0.0121	1.85
Cost (£/KWh)	-2.85***	0.419	-6.8
Waiting time (minutes)	-0.0352***	0.00716	-4.91
Methods of payment			
Card or contactless	Reference		
Card, contactless, or via operator's app	0.0163	0.0765	0.213
Card, contactless, or via an app for all operators	-0.0167	0.0781	-0.214
Card, contactless, or an operator's card with RFID chip	-0.0833	0.0793	-1.05
Amenities at the charging station			
No amenities	Reference		
Waiting room	0.0911	0.0819	1.11

Small shop or café	0.281***	0.0789	3.56
Shopping centre	0.239***	0.0778	3.07
Station rating			
3 stars	Reference		
4 stars	0.1	0.0664	1.51
5 stars	0.4***	0.0648	6.18
Scale_EV	0.375***	0.0745	5.03
Number of observations	2940		
Initial log likelihood	-3229.92		
Log-likelihood at convergence	-3028.377		
d.f.	20		

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

6.3 MNL model estimates from EV and non-EV user choice data

As explained in Section 6.2, the MNL modelling should be carried out separately for EV user and non-EV user data specifically. However, before examining the impact of all attributes on public charging preferences of electric vehicle and non-electric vehicle users, it is necessary to assess the impact of charging prices. Models in Table 6-4 and Table 6-5 present the results of how EV and non-EV users weigh their choices among the three alternatives when considering the variable of charging price.

6.3.1 Nonlinearity of continuous variables

- Charging prices

Table 6-4: MNL models for EV users to test the effects of charging prices

Model parameter	Model 1 (Only price)	t-ratio	Model 2 (Price levels)	t-ratio
Surface car park	0.107*	1.81	0.107*	1.82
Multi-storey car park	-0.479***	-6.94	-0.480***	-6.95
Charging price (pence/kWh)	-0.303*	-1.78		
Charging price = 45 pence/kWh			Reference level	
Charging price = 55 pence/kWh			-0.085	-0.78
Charging price = 60 pence/kWh			-0.109	-1.05
Charging price = 75 pence/kWh			-0.014	-0.12
Charging price = 85 pence/kWh			-0.144	-1.50
Charging price = 90 pence/kWh			-0.194*	-1.94
Number of observations	4,500		4,500	
Pseudo R ²	0.0269		0.0279	
Null-loglikelihood	-1648		-1648	
Final loglikelihood	-1604		-1602	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

As shown in Table 6-4, with the charging prices to be equal, EV users had a slight more preference for charging at surface car parks (coeff: 0.107; $p < 0.10$) and a strong aversion to charging at multi-story car parks (coeff: -0.479; $p < 0.01$), relative to on-street charging, which was the reference. The negative effect of charging prices on EV users' public charging choices is marginally significant (coeff: -0.303; $p < 0.10$). In order to see if there is nonlinearity of price sensitivity (Hensher et al. 2015), Model 2 was estimated to see the effects of the six charging price levels. Still, Model 2 shows that the marginal effect is only significant (coeff: -0.194; $p < 0.10$) when the charging price is equal to 90p/kWh. This means that if all charging locations are equal, EV users are indifferent between 45, 55, 60, 75 or 85 p/kWh, and start to become sensitive when the charging price rises to 90 p/kWh. The fact that EV users did not trade-off between different charging prices (45 to 85 pence/kWh) suggests that the charging price levels in the choice experiment should probably be set higher for EV users, with a starting price of 90 pence/kWh. At the same time, they may have higher incomes than non-EV users and care less about charging prices than other characteristics.

Table 6-5: MNL models for non-EV users to test the effects of charging prices

Model parameter	Model 1 (Only price)	t-ratio	Model 2 (Price levels)	t-ratio
Surface car park	-0.075	-1.20	-0.079	-1.26
Multi-storey car park	-0.461***	-6.67	-0.466***	-6.72
Charging price (pence/kWh)	-1.805***	-10.17		
Charging price = 45 pence/kWh			Reference level	
Charging price = 55 pence/kWh			-0.047	-0.45
Charging price = 60 pence/kWh			-0.624***	-5.88
Charging price = 75 pence/kWh			-0.477***	-4.19
Charging price = 85 pence/kWh			-0.690***	-7.04
Charging price = 90 pence/kWh			-0.862***	-7.93
Number of observations	4,320		4,320	
Pseudo R ²	0.0498		0.0584	
Null log-likelihood	-1582		-1582	
Final log-likelihood	-1503		-1490	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-5 presents the effects of charging prices on non-EV users' preference for public charging. Similarly, non-EV users have a strong aversion to charging in multi-storey car parks compared to on-street charging. However, there is no difference in their preference for charging on-street or at surface car parks. Unlike EV users, non-EV users were strongly sensitive to the different levels of charging prices as the coefficients are significant at all levels except for charging prices equal to 55p/kWh. This means that non-EV users do not prefer higher charging prices (60, 75, 85, 90 p/kWh) than the base price of 45 p/kWh when the charging alternatives provided are the same, but they do not see much of a difference between 45 p/kWh and 55 p/kWh.

- The percentage of renewable resources

Tables 6-6 and 6-7 highlight the significant positive impacts of renewable resources on public charging preferences for EV and non-EV users. Models 3 and 4 were conducted in order to explore the potential non-linear effects of different levels of renewable resources on user preferences. The results show a clear upward trend in the positive impact on both EV and non-EV users' preferences as the level of utilisation of renewable resources at public charging locations increases, compared to the scenario where a zero percentage of clean resources are used. For non-EV users, it is worth noting that this positive impact remains significant except renewable energy utilisation reaches 75%.

Table 6-6: MNL models for EV users to test the effects of renewable sources

Model parameter	Model 3 (Only renewable sources)	t-ratio	Model 4 (Renewable sources levels)	t-ratio
Surface car park	0.108*	1.84	0.108*	1.84
Multi-storey car park	-0.480***	-6.94	-0.481***	-6.95
% of renewable sources (e.g. wind, solar)	0.300***	4.02		
Renewable sources = 0%			Reference level	
Renewable sources = 25%			0.196*	1.69
Renewable sources = 50%			0.198**	2.07
Renewable sources = 75%			0.241**	2.43
Renewable sources = 100%			0.355***	3.77
Number of observations	4,500		4,500	
Pseudo R ²	0.0308		0.0312	
Null-loglikelihood	-1648		-1648	
Final loglikelihood	-1597		-1596	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-7: MNL models for non-EV users to test the effects of renewable sources

Model parameter	Model 3	t-ratio	Model 4	t-ratio
	(Only renewable sources)		(Renewable sources levels)	
Surface car park	-0.084	-1.36	-0.081	-1.33
Multi-storey car park	-0.457***	-6.72	-0.457***	-6.71
% of renewable sources (e.g. wind, solar)	0.411***	5.37		
Renewable sources = 0%			Reference level	
Renewable sources = 25%			0.248**	2.12
Renewable sources = 50%			0.117	1.18
Renewable sources = 75%			0.260**	2.50
Renewable sources = 100%			0.496***	5.25
Number of observations	4,320		4,320	
Pseudo R ²	0.0252		0.0271	
Null-loglikelihood	-1582		-1582	
Final loglikelihood	-1542		-1539	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

- Waiting time

Tables 6-8 and 6-9 show a significant negative effect of waiting time on public charging preferences for both EV and non-EV users, which suggests that as waiting time increases, the likelihood of choosing these public charging locations over the reference category (on the street) decreases. Models 5 and 6 were conducted in order to explore the potential non-linear effects of different levels of waiting time. The results show that a significant effect only occurs when both groups of respondents have a waiting time of 10 minutes. This means that they tend to avoid longer waiting times (10 minutes) compared to no wait when the charging alternatives provided are the same. However, they did not see much of a difference between no wait and waiting for 2 or 5 minutes.

Table 6-8: MNL models for EV users to test the effects of waiting time

Model parameter	Model 5 (Only waiting time)	t-ratio	Model 6 (Waiting time levels)	t-ratio
Surface car park	0.106*	1.80	0.106*	1.80
Multi-storey car park	-0.482***	-6.98	-0.483***	-6.98
Waiting time (minutes)	-0.017**	-2.39		
Available right away			Reference level	
Waiting time = 2 min			0.005	0.06
Waiting time = 5 min			-0.043	-0.46
Waiting time = 10 min			-0.162**	-2.16
Number of observations	4,500		4,500	
Pseudo R ²	0.0277		0.0278	
Null-loglikelihood	-1648		-1648	
Final loglikelihood	-1602		-1602	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-9: MNL models for non-EV users to test the effects of waiting time

Model parameter	Model 5 (Only waiting time)	t-ratio	Model 6 (Waiting time levels)	t-ratio
Surface car park	-0.081	-1.33	-0.080	-1.31
Multi-storey car park	-0.454***	-6.70	-0.455***	-6.70
Waiting time (minutes)	-0.031***	-4.30		
Available right away			Reference level	
Waiting time = 2 min			0.065	0.84
Waiting time = 5 min			-0.065	-0.71
Waiting time = 10 min			-0.284***	-3.68
Number of observations	4,320		4,320	
Pseudo R ²	0.0219		0.0229	
Null-loglikelihood	-1582		-1582	
Final loglikelihood	-1547		-1546	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

- Number of charging points

Tables 6-10 and 6-11 show the different effects of the number of charging points on public charging preferences for EV and non-EV users. For EV users, the effect of the number of charging points was positive and marginally significant (coefficient: 0.022; $p < 0.10$). When the non-linearity of the attribute was taken into account, the effect was significant only when the number of public charging points was equal to eight (coefficient: 0.154; $p < 0.05$). This suggests that EV users preferred public charging stations with eight charging points to those with only two charging points when trading off different public charging locations. However, they did not see any difference between locations with four and six charging points compared to locations with only two charging points.

The effect of the number of charging points was not significant for non-EV users. However, when testing the non-linear effect of this attribute, surprisingly, only the positive effect of the number of public charging points equal to six was significant, meaning that non-EV users preferred public charging stations with six charging points to four or eight charging points, compared to two charging points.

Table 6-10: MNL models for EV users to test the effects of number of charging points

Model parameter	Model 7 (Only number of charging points)	t-ratio	Model 8 (Number of charging points levels)	t-ratio
Surface car park	0.107*	1.82	0.107*	1.81
Multi-storey car park	-0.481***	-6.96	-0.481***	-6.96
Number of charging points	0.022*	1.88		
No. charging points = 2			Reference level	
No. charging points = 4			0.112	1.26
No. charging points = 6			0.098	1.16
No. charging points = 8			0.154**	1.99
Number of observations	4,500		4,500	
Pseudo R ²	0.0270		0.0272	
Null-loglikelihood	-1648		-1648	
Final loglikelihood	-1603		-1603	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-11: MNL models for non-EV users to test the effects of number of charging points

Model parameter	Model 7 (Only number of charging points)	t-ratio	Model 8 (Number of charging points levels)	t-ratio
Surface car park	-0.077	-1.27	-0.082	-1.35
Multi-storey car park	-0.450***	-6.66	-0.452***	-6.68
Number of charging points	0.007	0.61		
No. charging points = 2			Reference level	
No. charging points = 4			0.120	1.34
No. charging points = 6			0.165**	1.96
No. charging points = 8			0.035	0.45
Number of observations	4,320		4,320	
Pseudo R ²	0.0161		0.0175	
Null-loglikelihood	-1582		-1582	
Final loglikelihood	-1557		-1554	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-12 presents the results of the likelihood ratio tests comparing the two models on continuous attributes in the choice experiment. The analysis shows that only Model 2, which incorporates multiple charging price levels into the model of multidirectional mobility of EV users, shows stronger explanatory power compared to the use of a single continuous price variable ($\chi^2(4) = 27.46$, $p = 0.000$). This suggests that integrating the price attributes of multiple charging levels into the model will improve its validity.

Table 6-12: Likelihood ratio-test for continuous variables

Model good of fit comparison	EV users		Non-EV users	
	Likelihood ratio-test	P value	Likelihood ratio-test	P value
Charging price (model 1 and 2)	$\chi^2 (4) = 3.39$	P = 0.495	$\chi^2 (4) = 27.46$	P = 0.000
Renewable energy (model 3 and 4)	$\chi^2 (3) = 1.18$	P = 0.758	$\chi^2 (3) = 6.06$	P = 0.109
Waiting time (model 5 and 6)	$\chi^2 (3) = 0.34$	P = 0.845	$\chi^2 (2) = 2.94$	P = 0.229
Number of charging point (model 7 and 8)	$\chi^2 (2) = 0.63$	P = 0.730	$\chi^2 (2) = 4.42$	P = 0.110

However, it is important to consider the experimental design outlined in Chapter 3, which establishes the conditions for linking availability to charging price. Specifically, slow charging falls into charging price levels 1, 2, and 3, while fast charging corresponds to levels 4, 5, and 6. Therefore, incorporating charging price levels into the MNL model introduces a correlation with fast charging attributes. This correlation may distort the MNL results for fast charging, causing it to be omitted. Therefore, in subsequent iterations of the MNL model, we decided to keep charging price as a single continuous variable to avoid such correlation issues and to ensure the completeness of the analysis.

6.3.2 Fully-specified MNL estimates for EV and non-EV users

Table 6-13 presents the MNL model coefficients and t-ratio for EV and non-EV users. For EV users, all else being equal, their preference for charging in surface car parks (coefficient: 0.106; $p < 0.1$) was slightly higher than charging on the street, while their aversion to charging in multi-storey car parks (coefficient: -0.478; $p < 0.01$) was strong. Non-EV users had a similarly strong aversion to charging in multi-storey car parks (coefficient: -0.474; $p < 0.01$). However, their preference for charging in surface car parks was not significant. These results were similar to what in the pooled MNL model in Section 5.6.

Charging prices, waiting times, the number of charging points at public charging locations, and the proportion of charging points using renewable energy all showed the expected signs, similar to the results from the MNL models which only include one continuous attribute in Section 5.7.1. Among these four attributes, charging price (EV users: coefficient: -0.891; $p < 0.05$; non-

EV users: coefficient: -2.910; $p < 0.01$) and waiting time (EV users: coefficient: -0.018; $p < 0.05$; non-EV users: coefficient: -0.033; $p < 0.01$) had a negative effect on public charging choices for both groups of users, whilst the proportion of renewable energy (EV users: coefficient: 0.300; $p < 0.01$; non-EV users: coefficient: 0.453; $p < 0.01$) had a positive effect. The number of charging points at public charging locations, on the other hand, had a positive effect on EV users (coefficient: 0.026; $p < 0.05$), while it had an insignificant effect on non-EV users.

EV users and non-EV users show different preferences for fast charging. Table 5-21 shows that the availability of fast charging did not have a significant effect on EV users' preferences towards public charging choices compared to slow charging, but for non-EV users, fast charging (coefficient: 0.393; $p < 0.01$) was important to them and contributed positively to their public charging choices.

Surprisingly, both groups perceived that the four payment methods provided: (1) Card, contactless; (2) Card, contactless, or via operator's app; (3) Card, contactless, or via an app for all operators; (4) Card, contactless, or an operator's card with RFID chip) were the same, and were insignificant to their public charging choices. Similar results appear in the pooled MNL model.

In terms of the method of authentication for the start of vehicle charging, both EV users (coefficient: 0.139; $p < 0.05$) and non-EV users (coefficient: 0.155; $p < 0.05$) showed a preference for automatic authentication by plugging in for charging compared to authentication via the operator's app. However, they did not see any difference between authentication via an operator card with an RFID chip and authentication via the operator app.

As for the amenities at the public charging points, EV users perceived that they prefer various types of amenities such as waiting rooms (coefficient: 0.166; $p < 0.05$), small shop or café (coefficient: 0.189; $p < 0.05$), or shopping centre (coefficient: 0.191; $p < 0.05$) compared to places had no amenities. Meanwhile this level of preference for amenities increases according to the order of amenities mentioned. However, non-EV users had the strongest preference towards small shops or café (coefficient: 0.249; $p < 0.01$) and then shopping centres (coefficient: 0.197; $p < 0.05$), but did not see any difference between waiting rooms, compared to those with no amenities.

The five-star rating of public charging points had a significant positive effect on the public charging choice preference of both EV users (coefficient: 0.146; $p < 0.05$) and non-EV users (coefficient: 0.402; $p < 0.01$) compared to the three-star rating. However, they had no preference towards a four-star rating charging point as they perceived it was no different to a three-star rating charging point.

Although the model fit statistics, such as the Pseudo R-squared, indicate values of 0.04 for the MNL model for EV users and 0.09 for non-EV users, both are relatively low. Typically, a Pseudo R-squared value from 0.10 to 0.20 is considered a reasonable model fit, suggesting that these models might not explain a substantial portion of the variance in the data. However, in our model, only the value for non-EV users (0.09) is close to this threshold (0.10), it's important to note that the Pseudo R-squared value for non-EV users (0.09) is more than twice that of the EV user sample (0.04).

This discrepancy in model performance could be attributed to differences in the sample collection methods. The non-EV user sample was collected using quotas based on age, gender, and region according to UK census data, ensuring a more representative and balanced sample. In contrast, the EV user sample was gathered from a naturally occurring population without constraints to meet specific quotas, largely due to the limited number of EV users in the UK. This lack of quota-based sampling might have resulted in a less representative sample for EV users, potentially explaining the lower Pseudo R-squared value.

Although the Pseudo R-squared value in our model is relatively low, this does not diminish the model's value. The sample of EV users in our study reflects the natural distribution of current EV users, who are likely early adopters according to Rogers' Diffusion of Innovation theory. Early adopters are critical to understanding because their behaviours and preferences often set the stage for broader adoption trends. By exploring the public charging preferences of these early adopters, we can gain valuable insights that are essential for tailoring better quality services, ultimately supporting the expansion and adoption of electric vehicles in the future.

Table 6-13: MNL models for EV and non-EV users (Model 9)

Model parameter	EV users		Non-EV users	
	Coefficient	t-ratio	Coefficient	t-ratio
Surface car park	0.106*	1.79	-0.080	-1.24
Multi-storey car park	-0.498***	-7.13	-0.474***	-6.65
Charging price (pence/kWh)	-0.891**	-2.09	-2.910***	-6.58
Fast Charging Available	0.201	1.44	0.393***	2.73
Waiting time (minutes)	-0.018**	-2.43	-0.033***	-4.36
Number of charging points	0.026**	2.11	0.015	1.18
% of renewable sources (e.g. wind, solar)	0.300***	4.01	0.453***	5.68
Method of payment				
Card or contactless	Reference level			
Card, contactless, or via operator's app	0.032	0.40	0.006	0.08
Card, contactless, or via an app for all operators	-0.082	-1.02	0.012	0.14
Card, contactless, or an operator's card with RFID chip	0.009	0.11	-0.100	-1.18
Authentication methods				
Via the operator's app	Reference level			
An operator's card with RFID chip	0.087	1.32	-0.050	-0.72
Automatic via Plug and Charge	0.139**	2.14	0.155**	2.29
Amenities at the charging station				
No amenities	Reference level			
Waiting room	0.166**	2.03	0.036	0.41
Small shop or café	0.189**	2.34	0.249***	2.94
Shopping centre	0.191**	2.38	0.197**	2.37
Station rating				
3 Star	Reference level			
4 Star	0.060	0.91	0.093	1.30
5 Star	0.146**	2.24	0.402***	5.86
Number of observations	4,500		4,320	
Pseudo R ²	0.04		0.09	
Null-loglikelihood	-1648		-1582	

Final loglikelihood	-1579	-1440
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Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

6.3.3 Willingness to pay estimates

Additionally, we converted the significant parameter estimates into marginal WTP by dividing the marginal utility of each attribute by the marginal utility of the public charging price. Each of the WTP for the attributes is presented in Table 6-14, for EV and non-EV users.

Table 6-14: Willingness to pay (WTP) for marginal attribute increase for EV and non-EV users (pence/kWh)

Model parameter	EV users	Non-EV users
Surface car park	12	
Multi-storey car park	-56	-16
Fast Charging Available		14
Waiting time (minutes)	-2	-1
Number of charging points	3	
% of renewable sources (e.g. wind, solar)	34	16
Authentication methods		
Automatic via Plug and Charge	16	5
Amenities at the charging station		
Waiting room	19	
Small shop or café	21	9
Shopping centre	21	7
Station rating		
5 Star	16	14

Note: Italicised WTP values were computed for statistically significant parameters with a 95% confidence level.

Interestingly, it is clear from Table 6-14 that both EV and non-EV users show a strong willingness to pay the highest amount for increased renewable energy utilisation at public charging points- specifically 34p/kWh for EV users and 16p/kWh for non-EV users. It is worth noting that both user groups indicated a willingness to compensate for longer waiting times - 2p/kWh for EV users and 1p/kWh for non-EV users, and EV users showed a stronger aversion to long waiting times than non-EV users.

The second highest priority for EV users was to allocate additional funds to various amenities. This is closely followed by a preference for five-star charging station ratings (16 p/kWh) and automatic vehicle authentication via plugging in the charger (16 p/kWh). Surprisingly, their willingness to pay for an increase in the number of charging points was low at 3 p/kWh.

In contrast, non-EV users expressed the second highest willingness to pay for fast charging (14 p/kWh) and five-star charging stations (14 p/kWh), in addition to prioritising the proportion of renewable energy at public charging stations. Their preference for amenities such as small shops or café (9 p/kWh) and shopping centres (7 p/kWh) came third. Interestingly, they were least willing to pay for plug-in automatic authentication, perceiving it to be worth 7 p/kWh.

6.3.4 The interaction between charging price and income categories

In Section 6.1, when examining participant characteristics, it was found that those who use EVs generally have higher income levels compared to those who do not. Specifically, over half of EV users (54.67%) reported a household income of over £85,000. Conversely, the majority of non-EV users (72.2%) reported household incomes below £85,001. Therefore, the income variable for EV and non-EV users was divided into two categories specifically: below £85,001/£45,001 and above £85,000/£45,000.

Table 6-15 shows the interaction effect between the charging price attribute and the income variable, with the aim of exploring whether individuals at different income levels show different preferences for charging prices when choosing a public charging option.

Table 6-15 revealed some interesting patterns. Among EV users, those with incomes below £85,001 tended to believe that the price of charging would have a negative impact on their public charging decisions (coefficient = -1.086, $0.01 < p < 0.05$). In contrast, individuals with incomes over £85,000 (over half of the sample) appear to be indifferent to charging prices. This may explain the MNL results in Table 13, which shows that EV users were indifferent to different charging price levels from 45p/kWh to 85p/kWh. This lack of response to different prices may be due to the effects of different income levels of EV users.

For non-EV users, both income groups show a clear preference for lower public charging prices. Notably, the low-income group (70%+) was more sensitive to public charging prices

(coefficient = -2.949, $p < 0.01$) compared to the high-income group (coefficient = -2.772, $p < 0.01$). This suggests that affordability plays a critical role in shaping charging preferences in non-EV user groups, especially for individuals with higher incomes.

Table 6-15: MNL models for EV and non-EV users with interaction effects (Model 10)

Model parameter	EV users		Non-EV users	
	Coefficient	t-ratio	Coefficient	t-ratio
Surface car park	0.107*	1.80	-0.079	-1.24
Multi-storey car park	-0.498***	-7.13	-0.474***	-6.65
Charging price				
Charging price $\times$ income higher than A	-0.678	-1.47	-2.772***	-5.08
Charging price $\times$ income equal and lower than A	-1.086**	-2.38	-2.949***	-6.53
Fast Charging Available	0.204	1.46	0.391***	2.71
Waiting time (minutes)	-0.018**	-2.43	-0.033***	-4.36
Number of charging points	0.025**	2.06	0.015	1.18
% of renewable sources (e.g. wind, solar)	0.297***	3.97	0.453***	5.68
Method of payment				
Card or contactless	Reference level			
Card, contactless, or via operator's app	0.028	0.36	0.006	0.07
Card, contactless, or via an app for all operators	-0.080	-0.99	0.011	0.13
Card, contactless, or an operator's card with RFID chip	0.008	0.10	-0.100	-1.18
Authentication methods				
Via the operator's app	Reference level			
An operator's card with RFID chip	0.086	1.31	-0.049	-0.71
Automatic via Plug and Charge	0.138**	2.12	0.155**	2.30
Amenities at the charging station				
No amenities	Reference level			
Waiting room	0.166**	2.04	0.035	0.40
Small shop or café	0.188**	2.33	0.248***	2.93
Shopping centre	0.193**	2.40	0.198**	2.37
Station rating				
3 Star	Reference level			
4 Star	0.060	0.90	0.093	1.29
5 Star	0.145**	2.23	0.402***	5.85

Number of observations	4,500	4,320
Pseudo R ²	0.04	0.09
Null-loglikelihood	-1648	-1582
Final loglikelihood	-1578	-1440

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level. A presents for £85,000 for EV users, £45,000 for non-EV users;

Table 6-16 shows the goodness-of-fit statistics for the model evaluations. The results show that Model 9, designed for both EV and non-EV users, outperforms Model 10 considering the interaction of participant income levels, and this superiority is reflected in the lower AIC and BIC estimates.

Table 6-16: MNL model characteristics and fit measures for EV and non-EV users sample

Sample	Model	N	LL(null)	LL(model)	df	AIC	BIC
EV users	Model 9	4,500	-1647.918	-1579.136	17	3192.272	3301.274
	Model 10	4,500	-1647.918	-1578.422	18	3192.844	3308.257
No-EV users	Model 9	4,320	-1582.002	-1440.021	17	2914.043	3022.35
	Model 10	4,320	-1582.002	-1439.929	18	2915.858	3030.536

6.4 The results of mixed logit models

In Section 6.2, the pooled MNL model to the entire dataset revealed that there is a significant difference in public charging preferences between EV and non-EV users. This finding prompted a more in-depth investigation, where different MNL models were applied to EV users and non-EV users respectively. These subsequent MNL model analyses further confirmed and validated the observed differences in charging preferences between these two user groups.

6.4.1 Heterogeneity of preferences towards attributes and alternatives

However, for further investigating whether there is a significant difference in public charging preferences across individual of EV users and non-EV users, this section employs mixed logit models to capture the individual level of preference heterogeneity of these two groups, respectively. Table 6-18 to Table 6-20 are the results from mixed logit models for EV and non-EV users.

The modelling approach is divided into three stages:

- (1) In Model 1, all alternative-specific constants were set as random parameters;
- (2) In Model 2, all attributes except the charging price were set as random parameters.
- (3) In Model 3, all constants specific to the alternatives and all attributes except the charging price were set as random parameters.

This step-by-step inclusion of attributes as random attributes allows for a comparison of estimated coefficients and their standard errors across different models, facilitating the observation of changes in the magnitude and significance of coefficients.

These models assumed that all random parameters were following a normal distribution with 5,000 Halton draws used to estimate their standard deviations. Overall, compared to the MNL models, the increase in rho squared from 0.0417 to 0.0754, and the Likelihood ratio test indicates a significant improvement in the model. Meanwhile, MXL models have lower AIC and BIC values (see in Table 6-17 and Table 6-16).

Table 6-17: MXL model characteristics and fit measures for EV and non-EV users sample

Sample	Model		LL start	LL final	Rho-squared vs equal shares	Observations	Estimated parameters	AIC	BIC
EV users	Model 1 (constants)	1	-1579.14	-1559.41	0.0537	1500	19	3156.82	3257.77
	Model 2 (attributes)	2	-1579.14	-1549.12	0.06	1500	31	3160.24	3324.95
	Model 3 (all)	3	-1579.14	-1523.61	0.0754	1500	33	3113.21	3288.55
No-EV users	Model 1 (constants)	1	-1506.93	-1391.53	0.1204	1440	19	2821.06	2921.23
	Model 2 (attributes)	2	-1506.93	-1354.75	0.1436	1440	31	2771.5	2934.95
	Model 3 (all)	3	-1506.93	-1287.36	0.1862	1440	33	2640.72	2814.71

6.4.1.1 Mixed logit models with random alternative-specific constants

Table 6-18 presents the results of the mixed logit model with random alternative-specific constants, where only the alternative-specific constants are considered as random parameters in the model. The results in Table 6-18 show that the sign and significance level of the attributes are very similar to the results of the MNL model shown in Table 6-13.

One noteworthy point in Table 6-18 is that, when all else were equal, EV users tended to have a clear preference for charging in multi-storey car parks over charging on the street. Meanwhile, their aversions to multi-storey car parks were significant, suggesting that this group had varying levels of aversion to multi-storey car parks.

In contrast, non-EV users expressed significant aversion to charging in surface or multi-storey car parks. In addition, they showed greater aversion to multi-storey car parks compared to surface car parks. It is worth noting that these aversions varied considerably within the non-EV user group.

Table 6-18: Mixed logit models for EV and non-EV users with random alternative specific constants (Model 1)

	EV users		Non-EV users	
	Coefficient	t-ratio	Coefficient	t-ratio
Mean				
Surface car park	0.103*	1.67	-0.214**	-2.02
Multi-storey car park	-0.715***	-6.73	-0.586***	-5.94
Charging price (pence/kWh)	-0.838*	-1.76	-3.371***	-6.76
Waiting time (minutes)	-0.017**	-2.15	-0.038***	-4.38
Number of charging points	0.024*	1.85	0.021	1.34
% of renewable sources (e.g. wind, solar)	0.341***	4.29	0.550***	4.87
Fast Charging Available	0.181	1.15	0.492***	3.08
Method of payment ('Card or contactless' as the reference)				
Card, contactless, or via operator's app	0.037	0.47	-0.013	-0.15
Card, contactless, or via an app for all operators	-0.073	-0.81	0.003	0.04
Card, contactless, or an operator's card with RFID chip	0.021	0.25	-0.128	-1.44
0812 Authentication methods ('Via the operator's app' as the reference)				
An operator's card with RFID chip	0.084	1.15	-0.072	-0.92
Automatic via Plug and Charge	0.145**	2.07	0.177**	2.31
Amenities at the charging station ('No amenities' as the reference)				
Waiting room	0.186**	2.15	0.095	0.93
Small shop or café	0.202**	2.38	0.332***	3.48
Shopping centre	0.188**	2.11	0.270***	2.60
Station rating ('3 Star' as the reference)				
4 Star	0.038	0.58	0.076	0.89
5 Star	0.134*	1.94	0.458***	5.27
Standard deviation				
Surface car park	0.217	0.87	1.187***	9.13
Multi-storey car park	0.963***	7.28	0.778***	5.77
Observations	4,500		4,320	
Null-loglikelihood	-1648		-1582	
Final-loglikelihood	-1559		-1392	
Pseudo R ²	0.05		0.12	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

6.4.1.2 Mixed logit models with random attributes

Table 6-19 presents the results of the mixed logit model, in which all attributes except the price charged are treated as random parameters. The decision to fix the price attributes was made to simplify the model and improve interpretability.

Compared to the MNL results in Table 6-13, the importance of certain attributes changed in this mixed logit model. Specifically, the effect of the number of public charging points at charging stations is no longer significant, although its positive effect on EV users' public charging preferences was previously observed in the MNL model. Similarly, the availability of fast charging remained insignificant in the mixed logit model. However, there was a significant difference in the preference of EV users for this attribute, as evidenced by a significant standard deviation ($SD=0.991$, $p<0.01$). In addition, the negative effect of waiting time was marginally significant among EV users in the mixed logit model ($SD=0.045$, $0.01<p<0.05$). This suggests that although the overall effect may not be significant, there are significant differences in inter-individual preferences for waiting time. Interestingly, the overall impact of authentication via operator card with RFID chip versus authentication via operator app on user preference remains insignificant, which is consistent with the results of the MNL model (Table 6-13). However, there is significant variation in the preferences of EV users for these authentication methods.

For non-EV users, the attributes showed similar sign and significance levels compared to the Multinomial Logit (MNL) model results. However, there is one noteworthy finding: they show a significant aversion to the "carded, contactless, or operator card with RFID chip" authentication method compared to the "carded or contactless" authentication method (coefficient = -0.215 , $0.01<p<0.05$). Similarly, while the number of charging points did not have a significant effect on the choice of public charging method by non-EV users, there was a significant difference in preference for this attribute within this group ($SD = 0.129$, $p<0.01$). This suggests that while some non-EV users strongly preferred charging stations with more public charging points, others may have different preferences or may not prioritise this attribute. In addition, non-EV users had significant standard deviations for other attributes: percentage of green resources used in the public charging point ($SD=1.187$, $p<0.01$), fast charging availability ($SD=1.650$, $p<0.01$), shopping centres as the charging station amenity ($SD=0.862$, $p<0.01$), and five-star charging station ratings ($SD=0.593$, $p<0.01$). These results indicate considerable heterogeneity in non-EV users' preferences for these attributes,

suggesting that further exploration is needed to better understand the underlying factors that contribute to these differences.

Overall, the significant differences in preferences for various attributes among EV and non-EV users highlights the importance of considering individual-level heterogeneity when analysing the choice behaviour among these groups. This information can provide valuable insights beyond the aggregate-level effects observed in traditional models such as MNL.

Table 6-19: Mixed logit models for EV and non-EV users with random attributes except charging price (Model 2)

	EV users		Non-EV users	
	Coefficient	t-ratio	Coefficient	t-ratio
Mean				
Surface car park	0.138*	1.95	-0.075	-0.63
Multi-storey car park	-0.551***	-5.63	-0.654***	-5.53
Charging price (pence/kWh)	-1.126**	-2.22	-4.356***	-6.47
Waiting time (minutes)	-0.022**	-2.46	-0.045***	-4.17
Number of charging points	0.021	1.50	0.010	0.55
% of renewable sources (e.g. wind, solar)	0.319***	3.54	0.541***	3.97
Fast Charging Available	0.266	1.57	0.594***	2.86
Method of payment ('Card or contactless' as the reference)				
Card, contactless, or via operator's app	0.004	0.05	-0.088	-0.81
Card, contactless, or via an app for all operators	-0.094	-0.95	0.026	0.25
Card, contactless, or an operator's card with RFID chip	0.002	0.02	-0.215**	-2.00
Authentication methods ('Via the operator's app' as the reference)				
An operator's card with RFID chip	0.070	0.84	-0.121	-1.22
Automatic via Plug and Charge	0.155**	2.13	0.156*	1.79
Amenities at the charging station ('No amenities' as the reference)				
Waiting room	0.192**	2.12	0.062	0.49
Small shop or café	0.233**	2.50	0.346***	2.98
Shopping centre	0.197**	2.02	0.233*	1.73
Station rating ('3 Star' as the reference)				
4 Star	0.088	1.24	0.129	1.20
5 Star	0.171**	2.37	0.564***	5.23
Standard deviation				
Waiting time (minutes)	0.045**	2.11	-0.019	-0.35
Number of charging points	0.061	1.34	0.129***	3.73
% of renewable sources (e.g. wind, solar)	-0.270	-0.73	1.187***	5.84
Fast Charging Available	0.991***	8.89	1.650***	9.02
Method of payment ('Card or contactless' as the reference)				
Card, contactless, or via operator's app	-0.002	-0.54	-0.007	-0.44
Card, contactless, or via an app for all operators	0.211	0.58	0.007	0.49
Card, contactless, or an operator's card with RFID chip	-0.002	-0.32	0.065	0.21

Authentication methods ('Via the operator's app' as the reference)				
An operator's card with RFID chip	0.434***	2.96	0.394	1.62
Automatic via Plug and Charge	-0.001	-0.18	-0.021	-0.67
Amenities at the charging station ('No amenities' as the reference)				
Waiting room	0.005	0.18	-0.390	-1.27
Small shop or café	0.017	0.45	0.027	0.40
Shopping centre	0.347	1.46	0.862***	4.79
Station rating ('3 Star' as the reference)				
4 Star	-0.004	-0.49	-0.273	-0.80
5 Star	0.244	0.86	0.593***	3.27
Observations	4,500		4,320	
Null-loglikelihood	-1648		-1582	
Final-loglikelihood	-1549		-1355	
Pseudo R ²	0.06		0.14	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

6.4.1.3 Mixed logit models with random alternative-specific constants and attributes

Table 6-20 presents the combined results for Models 1 and 2 in a mixed logit framework. The table illustrates the results of the mixed logit model in which alternative-specific constants and all attributes are treated as random parameters except for the charging price. It is worth noting that there was significant heterogeneity in the preferences of EV users for multi-story and surface car parks. This contrasts with the previous model (Table 6-19), where only EV users' preferences for multi-story car parks were significantly different. In contrast, among non-EV users, there was significant heterogeneity in preferences for both multi-story and surface car parks. However, unlike the results of Model 1 (Table 6-18), where only non-EV users showed significant aversion to multi-story car parks, here both multi-story and surface car parks showed significant heterogeneity in the preferences of non-EV users.

Comparing Table 6-18 with Model 2 of the mixed logit model (Table 6-19), it can be seen that the significant change in EV users' preferences for waiting time observed in Model 2 was no longer significant in Model 3. Interestingly, EV users viewed all payment methods the same way and perceived them as having little impact on their public charging choices. This result was consistent with the results of the MNL and model 1 and 2 of the mixed logit models. However, the standard deviation of EV users paying via "Card, contactless, or via an app for all operators" compared to "card or contactless" was marginally significant in Model 3, but not

in Model 2. In addition, unlike in Model 2, the heterogeneity of EV users' preferences for five-star station ratings was marginally significant in Model 3.

Similar to the results of Model 2 (Table 6-19), the standard deviations for several attributes in Model 3 remain significant for non-EV users. These attributes include the number of public charging points within the charging station, the percentage of renewable energy used at public charging points, the availability of fast charging, the availability of a shopping center as an amenity for the charging station, and the rating of the five-star charging station. However, while the effect of waiting rooms on non-EV users' preferences for public charging options was not significant, there were significant differences in non-EV users' preferences for waiting rooms.

Table 6-20: Mixed logit models for EV and non-EV users (Model 3)

	EV users		Non-EV users	
	Coefficient	t-ratio	Coefficient	t-ratio
Mean				
Surface car park	0.130*	1.74	-0.251	-1.41
Multi-storey car park	-0.831***	-6.56	-0.981***	-5.33
Charging price (pence/kWh)	-1.095*	-1.94	-6.125***	-5.76
Waiting time (minutes)	-0.021**	-2.23	-0.065***	-4.22
Number of charging points	0.020	1.33	0.019	0.74
% of renewable sources (e.g. wind, solar)	0.378***	3.94	0.763***	3.74
Fast Charging Available	0.243	1.30	0.847***	2.84
Method of payment ('Card or contactless' as the reference)				
Card, contactless, or via operator's app	0.012	0.13	-0.183	-1.15
Card, contactless, or via an app for all operators	-0.086	-0.79	0.020	0.14
Card, contactless, or an operator's card with RFID chip	0.021	0.22	-0.353**	-2.32
Authentication methods ('Via the operator's app' as the reference)				
An operator's card with RFID chip	0.068	0.75	-0.117	-0.88
Automatic via Plug and Charge	0.182**	2.25	0.234*	1.88
Amenities at the charging station ('No amenities' as the reference)				
Waiting room	0.233**	2.32	0.234	1.37
Small shop or café	0.271***	2.61	0.680***	3.97
Shopping centre	0.219**	2.10	0.499***	2.71
Station rating ('3 Star' as the reference)				
4 Star	0.067	0.87	0.113	0.83
5 Star	0.163**	2.02	0.763***	4.62
Standard deviation				
Surface car park	0.411**	2.07	2.017***	6.89
Multi-storey car park	1.193***	7.56	1.523***	5.50
Waiting time (minutes)	0.041	1.52	0.004	0.35
Number of charging points	0.034	0.34	0.182***	3.70
% of renewable sources (e.g. wind, solar)	-0.026	-0.16	1.816***	5.12
Fast Charging Available	1.151***	9.14	2.486***	7.14
Method of payment ('Card or contactless' as the reference)				
Card, contactless, or via operator's app	0.002	0.16	0.219	0.60
Card, contactless, or via an app for all operators	0.411*	1.66	-0.017	-0.09

Card, contactless, or an operator's card with RFID				
chip	0.012	0.54	0.154	0.32
Authentication methods ('Via the operator's app' as the reference)				
An operator's card with RFID chip	0.513***	3.35	-0.286	-0.49
Automatic via Plug and Charge	0.006	0.27	0.293	0.62
Amenities at the charging station ('No amenities' as the reference)				
Waiting room	-0.078	-0.32	-0.635*	-1.75
Small shop or café	0.045	0.49	-0.112	-0.44
Shopping centre	-0.041	-0.35	-0.929***	-2.86
Station rating ('3 Star' as the reference)				
4 Star	-0.001	-0.09	-0.211	-0.64
5 Star	0.368*	1.65	1.039***	4.32
Observations	4,500		4,320	
Null-loglikelihood	-1648		-1582	
Final-loglikelihood	-1523		-1288	
Pseudo R ²	0.08		0.19	

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

As mixed logit Models 1, 2, and 3 are nested within each other, the likelihood ratio test is appropriate for identifying superior models. Based on the results presented in Table 6-21, Model 3 outperforms Models 2 and 1 on both the EV and non-EV datasets. It is worth noting that Model 3 includes more variables as random parameters, which may enhance its ability to capture the heterogeneity of EV user preferences.

Table 6-21: MXL model characteristics and fit measures for EV and non-EV users sample

Sample	Models	Likelihood-ratio test	p
EV users	Model 2 vs Model 1	LR chi2(12) = 20.51	Prob > chi2 = 0.0581
	Model 3 vs Model 2	LR chi2(2) = 51.33	Prob > chi2 = 0.0000
	Model 3 vs Model 1	LR chi2(14) = 71.84	Prob > chi2 = 0.0000
No EV users	Model 2 vs Model 1	LR chi2(12) = 72.70	Prob > chi2 = 0.0000
	Model 3 vs Model 2	LR chi2(2) = 134.74	Prob > chi2 = 0.0000
	Model 3 vs Model 1	LR chi2(14) = 207.44	Prob > chi2 = 0.0000

6.4.2 Willingness to pay estimates and variations for attributes

Table 6-22 presents the results of estimating the attribute willingness to pay (WTP) based on the statistically significant coefficients in the mixed logit model. The average WTP estimates are very close to those from the MNL model, with the exception of the number of charging points at public charging stations, which was not estimated because the factor was not significant in the mixed logit model.

Table 6-22: Willingness to pay estimates for EV users and non-EV users

Model parameter	EV users	Non-EV users
Fast Charging Available		14 (7:21)
Waiting time (minutes)	-2 (-5:1)	-1 (-2:1)
% of renewable sources (e.g. wind, solar)	35 (-6:75)	12 (5:20)
Payment methods		
Card, contactless, or an operator's card with RFID chip		-6 (-11:-1)
Authentication methods		
Automatic via Plug and Charge	17 (-6:39)	4 (0:8)
Amenities at the charging station		
Waiting room	21 (-4:47)	
Small shop or café	25 (-6:55)	11 (5:17)
Shopping centre	20 (-8:48)	8 (2:14)
Station rating		
5 Star	15 (-6:36)	12 (6:18)

Note: All values are in pence/kWh; confidence intervals are in brackets. Italicised WTP values were computed for statistically significant parameters with a 95% confidence level.

EV users expressed a strong willingness to pay for greener energy used at public charging stations, with an estimated value of 35 pence/kWh. In contrast, non-EV users prioritised fast charging, indicating a willingness to pay 14 pence/kWh for this feature, followed by 12 pence/kWh for greener energy.

Amenities around public charging stations are also important factors influencing WTP. EV users valued amenities such as waiting rooms, small shops or cafés, and shopping centres, and were willing to pay 21, 25, and 20 p/kWh for these amenities, respectively. In contrast, non-

EV users were willing to pay 11 p/kWh or 8 p/kWh for small shops or cafés and shopping centres, respectively.

Automatic authentication was particularly important to EV users, who were willing to pay 17 pence/kWh for this feature, while non-EV users were assigned a lower value of 4 pence/kWh. Both groups expressed a high WTP for a five-star station rating, with EV and non-EV users willing to pay 15 and 12 pence/kWh, respectively.

In addition, both EV and non-EV users perceived longer waiting times and were willing to pay either 2 pence or 1 pence per kWh in compensation for each additional minute of waiting time. Non-EV users also indicated a preference for card or contactless payments over the inconvenience of using the charging operator's RFID card, and indicated a willingness to pay 6 pence per kWh compensation to offset this inconvenience.

6.5 Latent class logit models for EV users and non-EV users

In the initial phase of the analysis, an iterative model estimation was conducted to determine the optimal number of categories that would effectively capture the unobserved heterogeneity of EV and non-EV users' public charging preferences. A latent class Logit model (LCM) with 2-4 categories was used, and its fit was evaluated using Akaike Information Criterion (AIC), Rho-Square, and Bayesian Information Criterion (BIC) metrics. Two-class models were chosen for their lowest BIC scores.

Tables 6-23 and Table 6-34 present the estimated coefficients for the two types of LCMs, as well as coefficients reflecting the socio-demographic characteristics of EV and non-EV users, in order to illustrate their impact on the probability of category membership.

It was found that there are significant differences in the decision-making processes of electric and non-EV users, and that continuous distribution models such as mixed logit models do not adequately capture this complexity. Instead, it was found that latent class methods better generalise these differences by classifying different classes associated with unique parameter estimates reflecting the utility functions of different public charging location choices (e.g., street, surface parking, multi-story parking). Most importantly, the latent class Logit model was able to relate taste heterogeneity to respondents' socio-economic characteristics as well as

the detailed psychosocial scales. This is a significant advantage over the mixed logit model. In a mixed Logit model, sensitivity to choice is simply assumed to be randomly distributed without the nuanced understanding provided by latent class analysis.

6.5.1 Segmentation of EV users and non-EV users

6.5.1.1 Segmentation with the effect of socio-economic characteristics

- **EV users**

As shown in Table 6-23, in Class 1 of EV users, there was a significant aversion towards charging at multi-storey car parks compared to street charging, whereas Class 2 displayed a preference for this particular type of charging location. When considering preferences regarding various aspects of public charging stations, Class 1 preferred lower charging prices, higher utilisation of renewable energy sources, and an increased number of charging points—although the significance of the last was marginal at the 90% confidence level. Additionally, Class 1 showed a significant inclination towards using the charging operator’s RFID card for vehicle authentication as opposed to utilising apps. However, for Class 2, there was a clear preference for fast charging and shorter waiting times, which suggests that they may prioritise the time efficiency. It was also noted that Class 2 exhibited a dislike for payment methods involving cards, contactless payment, and universal apps (marginally significant), or cards, contactless payment, and the operator’s RFID card, compared to simpler card and contactless payment methods—possibly due to its convenience. This group also strongly favoured convenient automatic authentication via plug-in chargers over alternative methods such as apps or charging operators’ RFID cards. Additionally, Class 2 expressed a preference for various amenities such as waiting rooms, small shops or cafés, or even shopping centres, compared to locations with no such facilities around. Furthermore, they displayed a preference for higher-rated stations, such as those with 4-star or 5-star ratings, over those with 3-star ratings.

- **Non-EV users**

For non-EV users, two distinct classes were identified, each exhibiting unique characteristics. Concerning preferences for charging locations, Class 1 displayed a dislike for both surface and multi-storey car parks relative to street charging. In contrast, Class 2 showed a preference for surface car parks. Regarding the features of public charging stations, both classes shared a dislike for high charging prices. Additionally, Class 1 displayed a dislike for longer waiting times and card/contactless/operator’s RFID cards over card/contactless payment, and a preference for 5-star station ratings. Conversely, Class 2 showed a significant preference for fast charging and a higher percentage of renewable resources at charging stations. They

favoured the presence of small shops or cafes, or even shopping centres adjacent to charging stations, along with a preference for stations with five-star ratings. Interestingly, the number of charging points and various authentication methods appeared to be indifferent to both classes. Examining their socio-economic characteristics (as shown in Table 6-24), EV users in Class 1 were more likely to be male, to have a university or higher education, and to live in a city or urban area compared to those in Class 2. It is worth noting that 69.7% of EV users belonging to Class 1 were while those belonging to Class 2 were only 30.3%. Class 1 (43.2%) non-EV users were also more likely to be male, older in age, lived in attached houses/apartments/mobile homes, and had lower income compared to Class 2.

Table 6-23: Latent class logit model for EV and non-EV users (Model 1)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park	0.048	(0.076)	0.243	(0.181)	-1.000***	(0.237)	0.424***	(0.117)
Multi-storey car park	-1.013***	(0.120)	0.498**	(0.215)	-1.121***	(0.287)	-0.221	(0.138)
Charging price (pence/kWh)	-1.472**	(0.603)	-0.188	(1.184)	-7.522***	(1.396)	-1.408**	(0.664)
Fast Charging Available	-0.110	(0.202)	1.238***	(0.384)	0.279	(0.321)	0.720***	(0.224)
Waiting time (minutes)	-0.010	(0.010)	-0.073***	(0.021)	-0.064***	(0.018)	-0.018	(0.012)
% of renewable sources (e.g. wind, solar)	0.297***	(0.105)	0.155	(0.216)	0.145	(0.211)	0.541***	(0.131)
Number of charging points	0.028*	(0.017)	0.045	(0.031)	0.028	(0.036)	0.009	(0.021)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.097	(0.113)	-0.150	(0.194)	-0.162	(0.222)	-0.055	(0.129)
Card, contactless, or via an app for all operators	0.043	(0.115)	-0.386*	(0.230)	-0.109	(0.199)	0.126	(0.122)
Card, contactless, or an operator's card with RFID chip	0.150	(0.114)	-0.413*	(0.226)	-0.481***	(0.187)	0.015	(0.123)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.261***	(0.091)	-0.248	(0.171)	0.220	(0.176)	-0.111	(0.104)
Automatic via Plug and Charge	0.142	(0.091)	0.317**	(0.155)	0.213	(0.164)	0.140	(0.100)
Amenities at the charging station								
No amenities	Reference level							

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Waiting room	0.163	(0.111)	0.406*	(0.223)	-0.149	(0.208)	0.137	(0.135)
Small shop or café	0.123	(0.112)	0.514**	(0.239)	0.198	(0.193)	0.286**	(0.129)
Shopping centre	0.000	(0.117)	0.777***	(0.277)	0.146	(0.216)	0.330***	(0.125)
Station rating								
3 Star	Reference level							
4 Star	-0.040	(0.088)	0.547***	(0.180)	0.089	(0.166)	0.048	(0.110)
5 Star	-0.086	(0.094)	0.794***	(0.185)	0.293*	(0.174)	0.501***	(0.102)

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-24: Class membership model estimates with socio-demographic variables (Model 1)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Female	-0.621*	(0.368)	-1.271***	(0.331)
Age	-0.000	(0.146)	0.394***	(0.127)
Education	1.166***	(0.426)	0.427	(0.356)
Number of children	-0.206	(0.199)	0.391	(0.374)
City	0.724*	(0.408)	-0.552	(0.415)
Detached	0.269	(0.399)	-0.675*	(0.366)
White	0.372	(0.468)	0.009	(0.696)
London	0.126	(0.487)	1.109*	(0.665)
Income	-0.024	(0.068)	-0.131*	(0.076)
Constant	-0.164	(1.069)	-1.553	(1.030)
Membership probability	0.697		0.432	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1499		-1340	
Pseudo R ²	0.08		0.15	

Note: $\pm$ Class 2 is the reference class for the class membership model

6.5.1.2 Segmentation with the effect of socio-economic and attitudinal characteristics

- EV users

Twelve variables were used to consider the impact of attitudinal characteristics and grouped into three categories: environmental cognition, risk aversion, and technophilia. These variables were aggregated to produce three new attitude variables representing each of these attitudes. As shown in Table 6-25, the inclusion of these variables in the class membership model resulted in some changes in the significance of the latent class logit model estimates.

For EV users, the previously significant factor of charging price for Class 1, as shown in Table 32, no longer retained significance (as shown in Table 6-25), indicating that neither class perceived charging prices as crucial in their public charging decisions. The marginal significance of the number of charging points for Class 1 was no longer significant for Class 1. Moreover, aversions towards level 3 and level 4 payment methods were no longer significant for Class 2. Additionally, when considering station ratings, only a five-star rating was preferred over a three-star rating for Class 2. The loss of significance implies that the attitudes captured by the newly added attitudinal variables may have a stronger influence on the preferences of EV users in Class 2. This was confirmed by the coefficients of attitudinal variables which exhibited lower levels of risk aversion compared to Class 2.

In terms of socio-economic characteristics, Class 1 remained more likely to possess a university degree or higher education and live in cities or urban areas. However, the significance of the gender variable changed and became insignificant after incorporating attitudinal variables, indicating that attitudes may mediate the relationship between socio-economic characteristics and class membership.

- Non-EV users

In the initial Model 1, prior to accounting for attitudinal variables, Class 1 demonstrated a preference against both surface and multi-storey car parks, favouring street charging instead. Conversely, Class 2 displayed a preference for surface car parks and seemed indifferent towards multi-storey options. However, in the subsequent Model 2, Class 2 exhibited a preference towards surface car parks and disliked multi-storey car parks compared to street charging.

In terms of socio-economic and attitudinal characteristics, Class 1 was more likely to be male, older in age, live in an attached house/apartment/mobile home, and reside in London. However, the inclusion of attitudinal variables in the model revealed that these attitudes did not have a significant impact on non-EV users' preferences for the choices of alternatives and different features of public charging stations.

Table 6-25: Latent class logit model for EV and non-EV users with socio-demographic and attitudinal variables (Model 2)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park	0.062	(0.079)	0.146	(0.157)	-1.059***	(0.251)	0.402***	(0.119)
Multi-storey car park	-1.104***	(0.153)	0.337*	(0.182)	-1.216***	(0.294)	-0.213*	(0.125)
Charging price (pence/kWh)	-1.156	(0.743)	-1.091	(1.237)	-8.029***	(1.569)	-1.463**	(0.656)
Fast Charging Available	-0.217	(0.249)	1.218***	(0.333)	0.331	(0.341)	0.694***	(0.217)
Waiting time (minutes)	-0.005	(0.011)	-0.069***	(0.019)	-0.064***	(0.019)	-0.019*	(0.011)
% of renewable sources (e.g. wind, solar)	0.239**	(0.108)	0.341*	(0.193)	0.088	(0.228)	0.545***	(0.128)
Number of charging points	0.021	(0.018)	0.050*	(0.028)	0.033	(0.039)	0.009	(0.020)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.110	(0.113)	-0.072	(0.165)	-0.209	(0.243)	-0.040	(0.125)
Card, contactless, or via an app for all operators	0.015	(0.120)	-0.185	(0.196)	-0.108	(0.208)	0.124	(0.119)
Card, contactless, or an operator's card with RFID chip	0.175	(0.121)	-0.309	(0.203)	-0.515***	(0.200)	0.012	(0.121)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.280***	(0.096)	-0.187	(0.155)	0.244	(0.186)	-0.110	(0.100)
Automatic via Plug and Charge	0.132	(0.095)	0.268*	(0.142)	0.195	(0.174)	0.146	(0.098)
Amenities at the charging station								
No amenities	Reference level							

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Waiting room	0.105	(0.120)	0.483**	(0.192)	-0.188	(0.230)	0.138	(0.132)
Small shop or café	0.019	(0.131)	0.680***	(0.199)	0.171	(0.204)	0.290**	(0.125)
Shopping centre	-0.051	(0.118)	0.735***	(0.256)	0.091	(0.245)	0.339***	(0.122)
Station rating								
3 Star	Reference level							
4 Star	-0.005	(0.095)	0.329*	(0.188)	0.087	(0.174)	0.045	(0.107)
5 Star	-0.102	(0.096)	0.643***	(0.201)	0.277	(0.183)	0.498***	(0.098)

Note: *** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level.

Table 6-26: Class membership model estimates with socio-demographic variables (Model 2)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Female	-0.317	(0.420)	-1.434***	(0.358)
Age	0.074	(0.156)	0.353***	(0.130)
Education	1.204**	(0.476)	0.373	(0.377)
Number of children	-0.183	(0.217)	0.404	(0.429)
City	0.894*	(0.516)	-0.577	(0.424)
Detached house	0.433	(0.506)	-0.716*	(0.383)
White	0.152	(0.580)	-0.246	(0.738)
London	0.160	(0.551)	1.408*	(0.719)
Income	-0.092	(0.082)	-0.131	(0.080)
Environmental cognition	-0.263	(0.341)	-0.253	(0.221)
Risk aversion	-1.964***	(0.548)	-0.129	(0.345)
Technophilia	-0.209	(0.314)	0.200	(0.177)
Constant	8.657***	(2.852)	-0.219	(2.014)
Membership probability	0.647		0.413	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1486		-1339	
Pseudo R ²	0.09		0.15	

6.5.1.3 Segmentation by considering the interaction effects

As shown in Table 6-25, household income had a significant impact on the preferences of EV users. Subsequently, when attitudinal factors were included in the model (as shown in Table 6-25), it was found that charging price no longer had a significant impact on both types of users.

This finding prompted further research into whether household income would have a significant impact on EV users' public charging preferences. Tables 6-27 and 6-29 explored the interaction effects between public charging attributes and individual household income levels. Similar to the MNL model discussed in Section 6.3, thresholds of £85,000 and £45,000 were specifically tailored in the model for EV and non-EV users.

The results in Tables 6-23 and 6-25 show that household income does have an interaction effect on charging price preferences for EV and non-EV users. For example, both categories of EV users with higher incomes (£85,000 and above) showed indifference to charging prices, while only the first category of users with lower incomes (£85,000 and below) showed concern about charging prices.

The results of Table 6-23 (Model 1) and Table 6-25 (Model 2), both showed that gender is an important factor that would influence each EV and non-EV segments' public charging preferences, therefore, Table 6-31 (Model 5) and Table 6-33 (Model 6) which discovered the interaction effects among gender and charging locations (alternatives) were conducted. The results from these two LCL models further confirm that gender differences have a significant impact on public charging location preferences for both EV and non-EV segments.

Table 6-27: Latent class logit model with socio-demographic variables accounting charging price and income interactions (Model 3)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park	0.040	(0.080)	0.272	(0.172)	-1.116***	(0.237)	0.445***	(0.114)
Multi-storey car park	-1.044***	(0.122)	0.405**	(0.197)	-1.286***	(0.254)	-0.165	(0.123)
Charging price × income higher than A	-0.785	(0.647)	0.733	(1.317)	-6.001***	(1.431)	-1.790**	(0.840)
Charging price × income equal and lower than A	-2.568***	(0.732)	-0.599	(1.083)	-8.160***	(1.417)	-1.540**	(0.667)
Fast Charging Available	-0.118	(0.202)	1.142***	(0.365)	0.234	(0.331)	0.742***	(0.216)
Waiting time (minutes)	-0.008	(0.010)	-0.068***	(0.019)	-0.058***	(0.018)	-0.022**	(0.011)
% of renewable sources (e.g. wind, solar)	0.267**	(0.107)	0.205	(0.201)	0.179	(0.214)	0.511***	(0.123)
Number of charging points	0.024	(0.017)	0.040	(0.029)	0.043	(0.037)	0.006	(0.020)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.093	(0.115)	-0.161	(0.181)	-0.173	(0.217)	-0.055	(0.124)
Card, contactless, or via an app for all operators	0.021	(0.118)	-0.283	(0.205)	-0.096	(0.206)	0.116	(0.119)
Card, contactless, or an operator's card with RFID chip	0.122	(0.117)	-0.305	(0.203)	-0.474**	(0.189)	0.012	(0.121)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.293***	(0.094)	-0.262*	(0.159)	0.216	(0.173)	-0.109	(0.100)
Automatic via Plug and Charge	0.124	(0.093)	0.318**	(0.142)	0.224	(0.171)	0.139	(0.098)
Amenities at the charging station								
No amenities	Reference level							

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Waiting room	0.169	(0.113)	0.358*	(0.203)	-0.197	(0.208)	0.132	(0.132)
Small shop or café	0.114	(0.116)	0.485**	(0.216)	0.170	(0.199)	0.278**	(0.126)
Shopping centre	0.012	(0.118)	0.671***	(0.235)	0.053	(0.211)	0.346***	(0.121)
Station rating								
3 Star	Reference level							
4 Star	-0.046	(0.090)	0.507***	(0.168)	0.039	(0.179)	0.049	(0.108)
5 Star	-0.105	(0.097)	0.743***	(0.170)	0.259	(0.189)	0.495***	(0.099)

Table 6-28: Class membership model estimates with socio-demographic variables accounting charging price and income interaction (Model 3)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Female	-0.680*	(0.359)	-1.168***	(0.325)
Age	0.013	(0.138)	0.409***	(0.124)
Education	1.231***	(0.402)	0.238	(0.348)
Number of children	-0.161	(0.189)	0.192	(0.446)
City	0.687*	(0.396)	-0.559	(0.426)
Detached house	0.264	(0.377)	-0.714*	(0.366)
White	0.614	(0.475)	-0.232	(0.705)
London	0.233	(0.465)	1.105*	(0.666)
Constant	-0.795	(0.961)	-1.860*	(1.030)
Membership probability	0.671		0.420	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1491		-1340	
Pseudo R ²	0.09		0.15	

Note: $\pm$ Class 2 is the reference class for the class membership model

Table 6-29: Latent class logit model with socio-demographic and attitudinal variables accounting charging price and income interactions (Model 4)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park	-0.050	(0.092)	0.307***	(0.111)	-1.159***	(0.253)	0.416***	(0.117)
Multi-storey car park	-1.157***	(0.145)	0.038	(0.123)	-1.336***	(0.257)	-0.182	(0.122)
Charging price × income higher than A	-0.038	(0.731)	-1.088	(0.868)	-6.513***	(1.604)	-1.805**	(0.820)
Charging price × income equal and lower than A	-3.509***	(0.918)	-0.902	(0.715)	-8.644***	(1.531)	-1.550**	(0.653)
Fast Charging Available	-0.199	(0.234)	0.705***	(0.231)	0.296	(0.349)	0.713***	(0.212)
Waiting time (minutes)	0.008	(0.012)	-0.055***	(0.012)	-0.059***	(0.019)	-0.022**	(0.011)
% of renewable sources (e.g. wind, solar)	0.147	(0.120)	0.414***	(0.129)	0.113	(0.232)	0.519***	(0.121)
Number of charging points	0.018	(0.020)	0.030	(0.021)	0.044	(0.039)	0.007	(0.020)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.106	(0.126)	-0.058	(0.128)	-0.198	(0.231)	-0.046	(0.122)
Card, contactless, or via an app for all operators	-0.006	(0.131)	-0.155	(0.134)	-0.091	(0.214)	0.117	(0.117)
Card, contactless, or an operator's card with RFID chip	0.098	(0.132)	-0.035	(0.128)	-0.500**	(0.199)	0.009	(0.119)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.358***	(0.103)	-0.161	(0.112)	0.236	(0.181)	-0.109	(0.098)
Automatic via Plug and Charge	0.100	(0.107)	0.221**	(0.103)	0.213	(0.180)	0.141	(0.096)
Amenities at the charging station								
No amenities	Reference level							

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Waiting room	0.086	(0.123)	0.315**	(0.143)	-0.233	(0.223)	0.134	(0.129)
Small shop or café	-0.156	(0.127)	0.587***	(0.138)	0.148	(0.208)	0.284**	(0.123)
Shopping centre	-0.162	(0.130)	0.549***	(0.142)	0.019	(0.225)	0.351***	(0.119)
Station rating								
3 Star	Reference level							
4 Star	0.028	(0.104)	0.117	(0.111)	0.042	(0.188)	0.046	(0.105)
5 Star	-0.116	(0.108)	0.391***	(0.106)	0.246	(0.196)	0.493***	(0.097)

Table 6-30: Class membership model estimates with socio-demographic and attitudinal variables accounting charging price and income interaction (Model 4)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Female	-0.976	(0.756)	-1.351***	(0.357)
Age	0.027	(0.197)	0.357***	(0.128)
Education	1.307**	(0.650)	0.167	(0.362)
Number of children	-0.446	(0.295)	0.225	(0.480)
City	1.202*	(0.710)	-0.590	(0.433)
Detached house	0.703	(0.568)	-0.774**	(0.384)
White	2.285*	(1.201)	-0.452	(0.745)
London	0.639	(0.706)	1.363*	(0.708)
Environmental cognition	-0.799**	(0.389)	-0.199	(0.222)
Risk aversion	-3.753***	(1.030)	-0.033	(0.340)
Technophilia	-1.372**	(0.609)	0.229	(0.172)
Constant	16.616***	(4.642)	-1.110	(2.033)
Membership probability	0.520		0.404	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1474		-1339	
Pseudo R ²	0.10		0.15	

Note: $\pm$ Class 2 is the reference class for the class membership model

Table 6-31: Latent class logit model with socio-demographic and attitudinal variables accounting charging price and income interactions (Model 5)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park × female	0.087	(0.157)	-0.036	(0.217)	0.045	(0.223)	0.021	(0.204)
Surface car park × male	-0.025	(0.112)	0.674***	(0.237)	-0.718***	(0.190)	0.708***	(0.233)
Multi-storey car park × female	-1.117***	(0.232)	0.215	(0.237)	-0.635**	(0.260)	-0.522**	(0.218)
Multi-storey car park × male	-1.083***	(0.158)	0.512*	(0.291)	-0.931***	(0.197)	0.286	(0.238)
Charging price × income higher than A	-0.542	(0.716)	0.093	(1.344)	-4.606***	(1.010)	-1.151	(1.023)
Charging price × income equal and lower than A	-2.505***	(0.793)	-1.155	(1.036)	-5.569***	(0.998)	-1.148	(0.842)
Fast Charging Available	-0.229	(0.230)	1.230***	(0.351)	0.022	(0.242)	1.026***	(0.277)
Waiting time (minutes)	-0.006	(0.011)	-0.064***	(0.017)	-0.067***	(0.014)	-0.005	(0.016)
% of renewable sources (e.g. wind, solar)	0.259**	(0.111)	0.249	(0.187)	0.390**	(0.159)	0.543***	(0.172)
Number of charging points	0.020	(0.019)	0.041	(0.027)	0.001	(0.024)	0.030	(0.026)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.116	(0.120)	-0.179	(0.172)	0.049	(0.144)	-0.158	(0.161)
Card, contactless, or via an app for all operators	0.025	(0.124)	-0.234	(0.200)	0.045	(0.150)	0.084	(0.152)
Card, contactless, or an operator's card with RFID chip	0.131	(0.122)	-0.260	(0.208)	-0.381**	(0.154)	0.073	(0.148)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.296***	(0.100)	-0.185	(0.156)	-0.104	(0.131)	0.048	(0.141)
Automatic via Plug and Charge	0.112	(0.099)	0.309**	(0.135)	0.053	(0.121)	0.199	(0.133)

Amenities at the charging station								
No amenities	Reference level							
Waiting room	0.153	(0.119)	0.358*	(0.191)	-0.160	(0.155)	0.293*	(0.164)
Small shop or café	0.103	(0.124)	0.452**	(0.199)	0.098	(0.154)	0.425***	(0.159)
Shopping centre	0.030	(0.122)	0.544**	(0.219)	0.082	(0.148)	0.409***	(0.158)
Station rating								
3 Star	Reference level							
4 Star	-0.058	(0.096)	0.461***	(0.164)	0.185	(0.128)	-0.061	(0.144)
5 Star	-0.108	(0.101)	0.675***	(0.175)	0.438***	(0.141)	0.457***	(0.138)

Table 6-32: Class membership model estimates with socio-demographic and attitudinal variables accounting charging price and income interaction (Model 5)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Age	0.048	(0.136)	0.307***	(0.114)
Education	1.066***	(0.409)	0.332	(0.327)
Number of children	-0.144	(0.187)	0.512*	(0.290)
City	0.905**	(0.403)	-0.269	(0.419)
Detached house	0.364	(0.364)	-0.642*	(0.337)
White	0.806	(0.513)	0.859	(0.667)
London	0.379	(0.445)	-0.004	(0.644)
Constant	-1.639	(1.022)	-2.257**	(0.943)
Membership probability	0.636		0.577	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1491		-1342	
Pseudo R ²	0.09		0.15	

Note: $\pm$ Class 2 is the reference class for the class membership model

Table 6-33: Latent class logit model with socio-demographic and attitudinal variables accounting charging price and income interactions (Model 6)

Variables	EV users				Non-EV users			
	Class 1		Class 2		Class 1		Class 2	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Surface car park × female	0.223	(0.184)	-0.087	(0.169)	0.027	(0.210)	0.042	(0.192)
Surface car park × male	-0.092	(0.106)	0.651***	(0.175)	-0.712***	(0.185)	0.683***	(0.236)
Multi-storey car park × female	-1.604***	(0.302)	-0.002	(0.153)	-0.665***	(0.251)	-0.497**	(0.210)
Multi-storey car park × male	-1.175***	(0.183)	0.321*	(0.191)	-0.945***	(0.201)	0.298	(0.240)
Charging price × income higher than A	0.280	(0.750)	-1.431	(0.903)	-4.641***	(1.030)	-1.194	(1.014)
Charging price × income equal and lower than A	-2.985***	(0.914)	-1.271*	(0.764)	-5.546***	(1.001)	-1.154	(0.841)
Fast Charging Available	-0.337	(0.235)	0.889***	(0.252)	0.015	(0.244)	1.025***	(0.277)
Waiting time (minutes)	0.004	(0.012)	-0.058***	(0.014)	-0.067***	(0.014)	-0.005	(0.016)
% of renewable sources (e.g. wind, solar)	0.179	(0.126)	0.405***	(0.140)	0.364**	(0.164)	0.573***	(0.174)
Number of charging points	0.016	(0.020)	0.036*	(0.021)	-0.001	(0.024)	0.031	(0.026)
Method of payment								
Card or contactless	Reference level							
Card, contactless, or via operator's app	0.123	(0.126)	-0.073	(0.133)	0.040	(0.144)	-0.151	(0.159)
Card, contactless, or via an app for all operators	0.006	(0.133)	-0.139	(0.144)	0.033	(0.150)	0.098	(0.153)
Card, contactless, or an operator's card with RFID chip	0.141	(0.132)	-0.106	(0.135)	-0.397**	(0.156)	0.080	(0.148)
Authentication methods								
Via the operator's app	Reference level							
An operator's card with RFID chip	0.355***	(0.107)	-0.126	(0.118)	-0.084	(0.134)	0.037	(0.142)
Automatic via Plug and Charge	0.081	(0.106)	0.252**	(0.110)	0.047	(0.121)	0.203	(0.134)

Amenities at the charging station								
No amenities	Reference level							
Waiting room	0.083	(0.125)	0.362**	(0.148)	-0.159	(0.155)	0.288*	(0.164)
Small shop or café	-0.137	(0.128)	0.565***	(0.147)	0.090	(0.154)	0.431***	(0.158)
Shopping centre	-0.108	(0.129)	0.514***	(0.156)	0.086	(0.149)	0.399**	(0.158)
Station rating								
3 Star	Reference level							
4 Star	-0.002	(0.110)	0.210*	(0.123)	0.185	(0.127)	-0.053	(0.144)
5 Star	-0.130	(0.112)	0.467***	(0.115)	0.429***	(0.141)	0.470***	(0.137)

Table 6-34: Class membership model estimates with socio-demographic and attitudinal variables accounting charging price and income interaction (Model 6)

Classes $\pm$	EV users		Non-EV users	
	Class 1		Class 1	
	Coefficient	Std. error	Coefficient	Std. error
Age	0.105	(0.165)	0.299**	(0.118)
Education	0.812	(0.517)	0.345	(0.328)
Number of children	-0.285	(0.246)	0.576*	(0.304)
City	1.083**	(0.524)	-0.290	(0.417)
Detached house	0.669	(0.481)	-0.669**	(0.339)
White	1.400**	(0.652)	0.702	(0.688)
London	0.410	(0.557)	0.071	(0.652)
Environmental cognition	-0.861**	(0.359)	-0.158	(0.214)
Risk aversion	-2.693***	(0.597)	-0.195	(0.347)
Technophilia	-0.724**	(0.344)	0.021	(0.155)
Constant	12.119***	(3.151)	-0.810	(1.970)
Membership probability	0.539		0.575	
Observations	4,455		4,305	
Initial-loglikelihood	-1631		-1577	
Final - loglikelihood	-1469		-1342	
Pseudo R ²	0.10		0.15	

Note: $\pm$ Class 2 is the reference class for the class membership model

Table 6-35: AIC and BIC estimation for latent class logit models

Sample	Model	Observation	LL (model)	df	AIC	BIC
EV users	Model 1	4,455	-1498.634	44	3085.268	3247.7922
	Model 2	4,455	-1485.516	47	3065.033	3238.6384
	Model 3	4,455	-1491.405	45	3072.8093	3239.0272
	Model 4	4,455	-1474.131	48	3044.2629	3221.5621
	Model 5	4,455	-1490.735	48	3077.4705	3254.7696
	Model 6	4,455	-1468.749	51	3039.4977	3227.878
Non-EV users	Model 1	4,305	-1340.302	44	2768.6035	2929.6207
	Model 2	4,305	-1339.005	47	2772.01	2944.0056
	Model 3	4,305	-1340.031	45	2770.0617	2934.7384
	Model 4	4,305	-1338.756	48	2773.5127	2949.1679
	Model 5	4,305	-1342.481	48	2780.9624	2956.6176
	Model 6	4,305	-1342.071	51	2786.1413	2972.7749

Tables 6-35 and 6-36 list the estimated goodness-of-fit statistics, including the AIC, BIC, and Likelihood-ratio tests. Since these LCL models are nested within each other, the results of the Likelihood-ratio test were referenced in the comparative analysis. The results show that among the six LCL models, Model 6 for EV users, proved to be the most effective. On the contrary, for non-EV users, Model 1 is better compared to the other five LCL models.

Table 6-36: Likelihood-ratio test for latent class logit models (Model 1 as the base model)

EV users			Non-EV users		
Model	Likelihood-ratio	P value	Model	Likelihood-ratio	P value
Model 2 vs Model 1	$\chi^2(3) = 26.24$	0.0000	Model 2 vs Model 1	$\chi^2(3) = 2.59$	0.4586
Model 3 vs Model 1	$\chi^2(1) = 14.46$	0.0001	Model 3 vs Model 1	$\chi^2(1) = 0.54$	0.4617
Model 4 vs Model 3	$\chi^2(3) = 34.55$	0.0000	Model 4 vs Model 1	$\chi^2(4) = 3.09$	0.5428
Model 5 vs Model 3	$\chi^2(3) = 1.34$	0.7199	Model 5 vs Model 1	$\chi^2(4) = -4.36$	1.0000
Model 6 vs Model 4	$\chi^2(3) = 10.77$	0.0131	Model 6 vs Model 1	$\chi^2(7) = -3.54$	1.0000
Model 6 vs Model 3	$\chi^2(6) = 45.31$	0.0000			

6.5.2 Willingness to pay for different segments

Table 6-37 presents the results of the willingness-to-pay estimates for LCL Model 1, segmented by EV and non-EV users. Within the EV user category, individuals classified under Class 1, characterised as males with higher levels of education residing in urban areas, exhibited the highest willingness to pay (69 pence/kWh) to avoid charging at multi-storey car parks. This suggests a strong aversion towards this particular charging location among this demographic. Additionally, they showed a willingness to pay 20 pence/kWh for accessing a higher level of renewable resources and 18 pence/kWh for authentication via the operator's RFID card compared to mobile apps.

For Class 1 of non-EV users, characterised by a higher likelihood of being males, older individuals residing in attached houses/apartments/mobile homes, living in London, and having lower incomes, the aversion towards charging at multi-storey car parks is evident, as they exhibited the highest willingness to pay (15 pence/kWh) to avoid such locations. Similarly, they expressed a dislike for charging at surface car parks, indicating a willingness to pay 13 pence/kWh to avoid them. This indicates that street charging emerges as the most suitable option for this demographic. Moreover, this group expressed a dislike for longer waiting times, showing a willingness to pay 1 pence/kWh to avoid each additional minute of waiting. They also preferred simpler payment methods over complex ones, being willing to pay 6 pence/kWh to avoid payment via card/contactless/an operator's RFID card. Comparably, the other group of non-EV users (Class 2) demonstrated different preferences. They displayed a higher willingness to pay for fast charging (51 pence/kWh), followed by a preference for higher renewable resources (38 pence/kWh), five-star station ratings (36 pence/kWh), charging at surface car parks (30 pence/kWh), and having shopping centres as amenities around public charging stations (23 pence/kWh).

Table 6-37: WTP estimates for EV and non-EV users (based on LCL Model 1 results)

	EV users		Non-EV users	
	Class 1	Class 2	Class 1	Class 2
Surface car parks			-13	30
Multi-storey car parks	-69	-	-15	-
% of renewable sources (e.g. wind, solar)	20	-	-	38
Waiting time (minutes)	-	-	-1	-
Fast Charging Available (reference: fast charging not available)	-	-	-	51
An operator's card with RFID chip (reference: Authentication via the operator's app)	18	-	-	-
Card, contactless, or an operator's card with RFID chip (reference: Card or contactless payment)	-	-	-6	-
5 Star (reference: 3 star station rating)	-	-		36
Shopping centre (reference: no amenities)	-	-		23

Note: All values are in pence/kWh; confidence intervals are in brackets. Italicised WTP values were computed for statistically significant parameters with a 90% confidence level.

Table 6-38: Summary of findings

Models	EV users	Non-EV users
MNL	- Compared to street charging, prefer to charge at surface car parks and dislike to charge at multi-storey car parks; - Prefer lower charging price, shorter waiting time, higher number of public charging points, greener sources, automatic authentication, all levels of amenities (waiting room, small shop or café, shopping centre), 5-star station rating; - Indifferent to fast charging availability and different payment methods;	- Dislike to charge at multi-storey car parks compared to street charging; - Prefer lower charging price, shorter waiting time, greener sources, fast charging, automatic authentication, small shop and café or shopping centre as amenities, 5-star station rating; - Indifferent to the number of public charging points and different payment methods;
WTP (MNL)	- Ordered from high to low: Green resources, small shop or café/shopping centre, waiting room, automatic authentication, 5-star station rating, number of charging points, waiting time (negative) - All these features EV users were willing to pay more compared to non-EV users, they also required more compensation for longer waiting time compared to non-EV users	Ordered from high to low: Green resources, fast charging/5-star station rating, small shop or café, shopping centre, automatic authentication, waiting time (negative)
MXL	- Preference towards higher number of charging points became insignificant; - Significant differences of preferences in individuals for charging at surface car parks, multi-storey car parks, fast charging, card/contactless/universal app payment, RFID authentication, 5-star station rating	- Indifferent towards different payment methods in this model was negatively significant for card/contactless/RFID card payment; - Significant differences of preferences in individuals for charging at surface car parks, multi-storey car parks, number of charging points, green resources, fast charging, waiting room and shopping centre as the amenity, 5-star station rating

WTP (MXL)	Ordered from high to low: Green resources, small shop or café, shopping centre, waiting room, automatic authentication, 5-star station rating, waiting time (negative)		Ordered from high to low: Fast charging, green resources/5-star station rating, small shop or café, shopping centre, automatic authentication, waiting time (negative), RFID card payment (negative)	
LCL (Class preference)	Class 1 (69.7%):	Class 2:	Class 1 (43.2%):	Class 2:
	- Disliked to charge at multi-storey car parks - Disliked higher charging price - Preferred greener resources - Preferred higher number of public charging - Indifferent to waiting time - Preferred RFID card authentication - Indifferent to different payment methods - Indifferent to various amenities - Indifferent to station ratings	- Preferred to charge at multi-storey car parks - Preferred to have fast charging available - Indifferent to greener resources - Indifferent to the number of public charging - Disliked long waiting time - Preferred automatic authentication - Disliked card/contactless/universal app, and card/contactless/RFID card - Preferred all types of amenities - Preferred 4 and 5-star station ratings	- Disliked surface car parks and multi-storey car parks - Disliked higher charging price - Indifferent to fast charging - Disliked longer waiting time - Indifferent to greener resources - Indifferent to the number of charging points - Indifferent to different types of authentication methods - Disliked card/contactless/RFID card payment - Indifferent to various amenities - Preferred 5-star station rating	- Preferred surface car parks - Disliked higher charging price - Preferred fast charging - Indifferent to waiting time - Preferred greener resources - Indifferent to the number of charging points - Indifferent to different types of authentication methods - Indifferent to different payment methods - Preferred small shop or café and shopping centre as amenities - Preferred 5-star station rating

LCL (Class members)	• More likely to be male • Had university and higher education level • Live in cities/urban areas	Reference class • More likely to be female • Had under university level of education • Live in rural areas	• More likely to be male • Older • Live in attached house/apartment/mobile home • Live in London • Had lower income	Reference class • More likely to be female • Younger • Live in detached house • Not live in London • Had higher income
WTP (LCL)	• Ordered from high to low: Avoid multi-storey car parks, green resources, operator's RFID card to authenticate	-	• Ordered from high to low: avoid multi-storey car parks, avoid surface car parks, avoid card/contactless/RFID card payment, avoid longer waiting time	• Ordered from high to low: fast charging, renewable energy, five-star rating, surface car parks, shopping centre as amenity

Chapter 7 Discussions

7.1 Discussions for qualitative cognitive interviews

The primary insight gained from the cognitive interviews of the EV public charging choice experiment is that participants needed the choice experiment to clearly specify the travel destination, the timing of day for travel, travel purposes, the specific details of the vehicle (e.g., target charge level and car brand or size), and information about the public charging point (e.g., certainty of waiting time, number of charging points, parking price, idling fee). This is because all of these charging context-related factors could also have a significant impact on public charging choices (Potoglou et al. 2023). However, the complexity of these factors in public charging studies generally resulted in various designs of choice experiments. For example, some studies focused on public charging choices en route (e.g., Li et al. 2023), while some focused on destination charging (e.g., Wang et al. 2021). Also, some studies examined different travel purposes, such as commute travel (Chakraborty et al. 2019) and long-distance travel (Ge and MacKenzie 2022).

Another important finding from cognitive interviews for the choice experiment is that attribute non-attendance exists. Participants showed preferences for specific factors like charging location, price, waiting time, and distance from the charging point to their destination. Through participants' explanations of the reasons for prioritising these factors, this tendency may be related to their unobserved attitudinal characteristics, such as risk aversion (Pan et al. 2019), cost minimising (Ge et al. 2018), and charging service concerned attitudes (Wang et al. 2021). For example, risk-aversion attitudes might affect individuals' decisions about public charging locations, whether on-street, surface car parks, or multi-storey car parks. Their preferences for these locations are associated with varying levels of risk concern, including concerns about personal and vehicle safety, as well as concerns about potential cell phone signal loss. This is consistent with the study of Soto et al. (2018), which found that individuals' risk aversion attitudes towards personal and vehicle security had a significant impact on parking choices.

Terminology issues towards understanding payment methods were also identified in the cognitive interviews for this study. Participants showed various understandings of “supplier’s app” “universal app” and “payment taken automatically”, suggesting that a clear explanation

of terminology is needed. In addition, individuals hold contrasting views on new technologies, particularly considering privacy issues. Such different attitudes have been extensively explored in previous studies, and they have been further categorised into risk-seeking and risk-averse attitudes (Pan et al., 2019). Also, pro-technology attitudes may result in preferences towards specific payment methods, given that varying levels of technological sophistication of payment methods may be used in the future. This is in line with the study of Globisch (2019) which found that consumers with strong technophilia attitudes tended to give higher ratings to public charging points.

7.2 Discussions for quantitative analysis

7.2.1 Different public charging preferences for EV and non-EV users

The pooled MNL model analysis revealed a significant difference in public charging preferences between EV users and non-EV users. Subsequent MNL modelling for each group further confirmed this difference. However, there is a lack of research that has comparatively analysed EV users and non-EV users/potential future EV users.

Most studies did their analysis based on pooling the EV and non-EV data (Moon et al. 2018; Gutjar and Kowald 2023) or focusing only on segments such as EV users (Lee et al. 2020; Wang et al. 2021; Ge and MacKenzie 2022), BEV users (Visaria et al. 2022; Zhang et al. 2022; Li et al. 2023), PHEV users (Ge et al. 2018; Chakraborty et al. 2019), or non-EV users/potential EV users (Sheldon et al. 2019; Ma et al. 2022). Only two studies have specifically compared charging preferences between BEV and PHEV users (Chakraborty et al. 2019; Lee et al. 2020). For example, Lee et al. (2020) identified different patterns in public charging habits between BEV and PHEV users. BEV owners who relied exclusively on public charging were less likely to live in detached dwellings, were more likely to be male, tended to own a Tesla, and typically lacked access to a workplace or Level 2 home charging facilities. On the other hand, PHEV users who primarily use public charging facilities tend to own fewer family cars, have more experience driving plug-in electric vehicles (PEVs), and are less inclined to use free workplace or Level 2 home charging facilities. These findings emphasise the importance of a tailored approach to understanding and meeting the different charging needs of different user groups. This also indicates that there is an urgent need for better comparative studies of EV and non-EV users to gain insights into their charging preferences and behaviours.

7.2.2 Preferences towards different features of public charging points

After conducting multinomial Logit (MNL) models, mixed logit models (MXL), and latent class logit models (LCL) for EV users and non-EV users separately, it was found that the two types of users had similar preferences for most of the features of public charging stations, but there were still differences in their preferences for certain features. For example, both categories of respondents preferred lower charging prices, shorter waiting times, a higher percentage of renewable energy sources at public charging stations, automatic verification by just plugging in the charger, and nearby facilities such as small stores, cafes, or shopping centres to be built around the charging station and five-star charging stations. Meanwhile, both of them were indifferent towards varying types of payment methods and the number of charging points available at the public charging station. However, non-EV users specifically valued fast charging availability while EV users did not perceive this was an important factor.

These findings were compared with previous studies (as shown in Table 7-1), some of which had consistent results while others had conflicting results (e.g., studies in “[]”). In addition, Tables 7-2 and 7-3 summarise the willingness-to-pay estimates for different features of public charging infrastructure for EV and non-EV users in this study, respectively, and compare them with the existing literature. This comparison highlights the complexity and variability of public charging infrastructure preferences between EV and non-EV users/consumers and re-emphasises the need for tailored strategies in the design and management of public charging infrastructures to meet the different preferences of these two types of users.

Table 7-1 shows that there are no studies that specifically focus on non-EV users. Instead, studies related to the preferences of non-EV users have focused on general consumers (e.g., Moon et al. 2018; Sheldon et al. 2019; Wolff and Madlener 2019;), which contained both EV users and non-EV users. Therefore, this current study stands as the pioneering effort dedicated to identifying the distinct preferences towards public charging between EV and non-EV users. Understanding the preferences of non-EV users is important for facilitating EV adoption in the future and fostering the development of robust public charging networks.

Table 7-1: Findings that are consistent with previous studies

Non-EV users ...	Authors	EV users ...	Authors
• preferred surface car park * • disliked multi-storey car park *	-	• indifferent to surface car park * • disliked multi-storey car park *	-
• preferred lower charging price	Sheldon et al. (2019), Moon et al. (2018), Latinopoulos et al. (2017), Wolff and Madlener (2019), Ma et al. (2022)	• preferred lower charging price	Pan et al. (2019), Ten Have et al. (2020), Wang et al. (2021), Wen et al. (2016)
• preferred shorter waiting time	Wolff and Madlener (2019)	• preferred shorter waiting time	Wang et al. (2021), Ten Have et al. (2020)
• indifferent to the number of public charging points	-	• preferred higher number of public charging points *	Visaria et al. (2022)
• preferred fast charging *	Ma et al. (2022)	• indifferent to fast charging *	[Wen et al. (2016)]
• preferred higher percentage of renewable resources being used at the public charging station	Wolff and Madlener (2019), Gutjar and Kowald (2023)	• preferred higher percentage of renewable resources being used at the public charging station *	Nienhueser and Qiu (2016)
• preferred automatic authentication via plugging the charger (authentication method *)	Gutjar and Kowald (2023)	• preferred automatic authentication via plugging the charger	-
• indifferent to different types of payment methods *	[(Gutjar and Kowald (2023)]	• indifferent to different types of payment methods	-
• preferred small shop or café as the amenity	-	• preferred small shop or café as the amenity	[Visaria et al. (2022), Ge and MacKenzie (2022)]
• preferred shopping centres as the amenity	-	• preferred shopping centres as the amenity	-
• indifferent to waiting room as the amenity	-	• preferred waiting room as the amenity *	-
• preferred five-star station rating *	-	• preferred five-star station rating *	Wang et al. (2021)

Note: study that in the “[]” refers to the study that has conflict finding, * refers to there were significantly different preferences towards this attribute or attribute level among individuals

Table 7-2: Willingness to pay estimates compared with previous studies for EV users

Determinants	WTP	Denmark ^[1]	US ^{[2][7][8]}	China ^[4]
Less charging cost	-	5.59 min of detour or £1.04 (8.76 DKK) against 1 less DKK/kWh in charging cost;	-	-
Higher charging power	-	0.28 min of detour or £0.052 (0.44 DKK) for an extra km/min	-	-
Number of charger	-	7.87 mins of detour or £1.46 (12.32 DKK) for an available charger; 0.53 min of detour or £0.099 (0.83 DKK) for an occupied charger	-	-
Authentication methods	£0.17/kWh Automatic via Plug and Charge vs. authentication via the operator's app	-	-	-
Amenities	£0.25/kWh for small shop or café, £0.21/kWh for waiting room, £0.20/kWh for shopping centre vs. none	1.23 min of detour or £0.23 (1.93 DKK) for availability of restrooms vs. none ; 9.55 min of detour or £1.78 (14.97 DKK) for availability of restrooms, restaurants, supermarkets vs. none	£17.25 (\$21) for restroom, dining facilities and Wi-Fi vs. none ^[2]	-
Higher station rating	£0.15/kWh for five-star station rating vs. three-star rating	-	-	£0.049/ kWh (0.45 yuan/kWh) for higher satisfaction of the station
Shorter waiting time	£0.02/kWh for 1 minute short for waiting	-	£2.05 (\$2.5) ^[2]	-
Higher renewable energy	£0.35/kWh for higher renewable energy to be used in the public charging station	-	[£0.50 (\$0.61) per hour for Level 2 EVSE; £1.49 (\$1.82) per hour for Direct Current Fast Chargers (DCFC);] ^[8]	-
Charging locations		-	-	-

Note : [1] Visaria et al. (2022); [2] Ge and MacKenzie (2022); [4] Wang et al. (2021); [7] Wen et al. (2016); [8] Nienhueser and Qiu (2016)

Table 7-3: Willingness to pay estimates compared with previous studies for non-EV users

Determinants	WTP	US ^[6]	Germany ^[5]
Higher charging power	£0.14/kWh for fast charging vs. fast charging not available	£0.041 (\$0.05) for an extra mile from charging ^[6]	-
Authentication methods	£0.04/kWh Automatic via Plug and Charge vs. authentication via the operator's app	-	-
Amenities	£0.11/kWh for small shop or café, £0.08/kWh for shopping centre vs. none	-	-
Higher station rating	£0.12/kWh for five-star station rating vs. three-star rating	-	-
Shorter waiting time	£0.01/kWh for 1 minute less of waiting time	-	£0.72/month (€0.82/month)
Higher renewable energy	£0.12/kWh for higher renewable energy to be used in the public charging station	-	£0.37/month (€0.42/month)
Charging locations		[£2.31 (\$2.81) for grocery; £1.35 (\$1.65) for mall, £1.13 (\$1.38) for quick charge near home; £1.03 (\$1.26) for quick charge near freeway; £0.0082 (\$0.01) for at transit; - £0.78 (-\$0.95) for gym; - £1.01 (-\$1.23) for school] ^[6]	- £40.84/month (-€46.26/month) for en-route charging on the road vs. at home; -£31.46/month (-€35.64/month) for destination charging on the road vs. at home; -£19.70/month (-€22.31/month) for charging at work vs. at home;

Note : [5] Wolff and Madlener (2019) [car drivers, including a small portion (2%) of EV users]; [6] Sheldon et al. (2019) [California new car buyers];

- Charing prices

This study confirms previous findings (Sheldon et al. 2019; Wang et al. 2021) that both EV and non-EV users preferred lower public charging prices. However, an intriguing insight emerges from the sensitivity of EV users to charging prices based on income level. As the average household income of EV users is higher than that of non-EV users, all non-EV users were sensitive to the charging prices, whereas only EV users with incomes below £85,001 were sensitive to the charging prices. This suggests that EV users with incomes above £85,000 did not consider charging prices to be an important factor as these costs were totally affordable for them. Later latent class logit model also suggests that EV users who had university or higher education were white, lived in urban areas, were less environmental, were less risk averse, and were less pro-technology, with household income below £85,000 were more likely to prioritise charging price, while others with contrary demographic and attitudinal characteristics did not consider charging price to be an important factor when making public charging choices. This suggests that public charging pricing strategies may need to be tailored separately for EV and non-EV users. Meanwhile, future public charging choice experiments may need to incorporate a broader range of charging price levels to more accurately capture the preferences of higher-income EV users.

- Charging locations

Unlike previous studies, which either focused on non-EV users' location preferences to home, workplace, or public places (Sheldon et al. 2019), or focused on specific locations such as grocery stores, shopping malls, gyms, and schools (Wolff and Madlener 2019). As it is hard to explore people's preferences for exact locations, this study innovatively focused on the three common types of parking in all possible locations (e.g., on-street, surface car parks, multi-storey car parks).

The results of the study showed that when all else was equal, both EV and non-EV users disliked charging in multi-storey car parks compared to charging on the street. Both EV and non-EV users were willing to pay the most (£0.56 /kWh for EV users, £0.16 /kWh for non-EV users) to avoid charging at multi-storey car parks. However, compared with street charging, EV users had a slight preference for charging in surface car parks, and they were willing to pay £0.12 /kWh to charge at these locations.

Different preferences towards these charging locations were significant among individuals of these two groups. Latent class logit modelling (model 1) reveals subtle patterns within these groups. Class 1, more likely to be male EV users with higher levels of education and living in cities or urban areas, displayed a tendency to avoid charging at multi-storey car parks when all other factors kept the same. Conversely, Class 2, which were more likely female EV users with lower education levels living in rural areas, exhibited a preference for charging at multi-storey car parks over street charging. The effect of gender on charging location preferences was further explored in model 6. When all else being equal, both male and female EV users expressed a dislike of multi-story car parks over street charging, with females showing a stronger aversion to such locations. On the other hand, males preferred multi-storey and surface car parks over street charging, while females in Class 2 did not see any preferences in charging at these three locations.

Non-EV users are also comprised of two groups in model 1. Class 1 was characterised as male, older, lived in an attached house/apartment/mobile home, lived in London, had lower household income, and preferred neither surface nor multi-storey car parks to on-street charging when all other features of the public charging station were the same. In contrast, the Class 2, who were more likely to be female, younger, lived in detached houses, did not live in London, had higher household income, and preferred charging in surface car parks to on-street charging in the same situation.

All these findings suggest that the installation of public charging points should take into account the different preferences of EV and non-EV users for various types of car parks, as well as gender preferences. When attitudinal attributes were added to the latent class logit model of EV users (model 4), it was found that the gender variable was no longer significant for EV segments, while the risk aversion attitude was significant. This indicates that this attitude may have an impact on EV and non-EV users' preferences for charging locations via acting as mediators between socio-economic characteristics (e.g., gender) and attributes, leading to a deeper understanding of individuals' preferences and decision-making processes.

- Waiting time and the number of charging points

This study found that both EV and non-EV users disliked long waiting times, which is consistent with the studies by Wolff and Madlener (2019) and Wang et al. (2021). This study categorised the waiting time into four levels: no waiting, 2 minutes, 5 minutes, and 10 minutes.

The MNL models suggest that facing the same charging options for EV and non-EV users, waiting for 10 minutes is unacceptable when all other features are the same, however, they did not see any difference between waiting for 2 minutes or 5 minutes and not waiting at all. They were willing to pay £0.02 pence/kWh or £0.01 pence/kWh to avoid 1 minute more of waiting. Comparably, ten Have et al. (2020) reported that EV drivers in the Netherlands preferred a ‘certain’ waiting time of up to 5 minutes against charging stations with unknown or uncertain waiting times. Car drivers in Germany least preferred public charging points with 30-minute waiting times and they were willing to pay £0.72/month (€0.82/month) for every 1-minute reduction in waiting time (Wolff and Madlener 2019). Latent class logit models showed that one group (Class 2) of EV users, who were more likely to live in rural areas, be non-white, be more environmental, risk-averse, and pro-technology disliked longer waiting times. Similarly, non-EV users who were male and older lived in attached houses/apartments/mobile homes and lived in London with lower household incomes and disliked longer waiting times.

Without considering the individual level of differences in preferences, preliminary findings suggest that EV users typically preferred a higher number of charging points at the public charging station, while non-EV users did not show such preference. However, when mixed logit models were conducted to account for the heterogeneity of preferences towards various attributes, both EV and non-EV users believed that the number of charging points was not important for them. This diminishing significance for EV users might suggest that other attributes other than the number of charging points became more important when making decisions. However, this finding contradicts the study by Visaria et al. (2022), which reported the importance of the number of charging points at the station and estimated that Danish EV users were willing to make a 7.87-minute detour (valued at £1.46 or 12.32 DKK) to reach an available charger and 0.53 min detour or £0.099 (0.83 DKK) to reach an occupied charger, respectively. On the other hand, the mixed logit model also revealed that for non-EV users, there were significantly different preferences towards this attribute at the individual level. This means that while the number of public charging points itself might not significantly impact choices among non-EV users, the preference heterogeneity towards this attribute across alternatives still plays a significant role in their decision-making process.

- Renewable energy

This study found that both EV users and non-EV users expressed a preference for a higher percentage of renewable energy in public charging stations. This preference is consistent with

earlier studies by Wolff and Madlener (2019) and Nienhueser and Qiu (2016). EV users were willing to pay the highest amount of money for this feature (£0.35/kWh), and this is also the second highest willingness to pay for non-EV users (£0.12/kWh). Comparably, US EV users were willing to pay for greener resources with £0.50 (\$0.61) per hour using Level 2 charger and £1.49 (\$1.82) per hour using Direct Current Fast Chargers (DCFC) (Nienhueser and Qiu 2016). Germany car license holders were willing to pay £0.37/month (€0.42/month) for higher renewable energy (Wolff and Madlener 2019).

- Fast charging

This study also suggests that EV users did not consider fast charging to be important, while non-EV users preferred fast charging provided by public charging stations. This is inconsistent with previous studies showing that both EV users (Wen et al., 2016) and also potential EV users (Ma et al. 2022) preferred fast charging.

This study found that this feature was the most important one for non-EV users, as they were willing to pay the highest (£0.14/kWh) among various features. There is a lack of research on preferences for fast charging amongst non-EV users or wider consumers (EV and non-EV users). All WTP estimates studies were conducted for EV users. For example, Danish EV users were willing to pay £0.052 (0.44 DKK) the equivalent of making a 0.28 minute-detour to be able to drive an extra km/min (Visaria et al., 2022) whereas US users were willing to pay for an average £0.041 (\$0.05) for an extra mile per minute charging (Sheldon et al., 2019). Also, Wen et al. (2016) reported US users' average willingness to pay £1.58/hr (\$1.91/hr) in order to use Level 2 instead of Level 1 charging. Although fast charging was not perceived as important for EV users, the mixed logit models also revealed that there was significant individual heterogeneity of preferences towards this attribute among both EV and non-EV users.

- Authentication methods

This study found that both EV and non-EV users preferred automatic authentication compared to authentication through the operator's app, and EV and non-EV users were willing to pay an average of £0.17/kWh or £0.04/kWh for using automatic authentication compared to authentication via the operator's app. Comparably, Gutjar and Kowald (2023) examined German adults' (including EV and non-EV drivers) preferences towards the authentication methods of public charging for EVs, and the results show that German consumers with higher

intention to buy an EV perceived ‘plug and charge’ (i.e., automatic authentication and payment) as the most convenient method compared to app-based solutions, which might involve internet connection issues, low battery or cold weather, and disliked RFID-card (Radio Frequency Identity Card) because of incompatibility issues among different charging networks. However, people with low intention to buy an EV preferred RFID cards than plug and charge automatic authentication. The study also found that while both EV and non-EV users saw no difference in authentication via the charging operator’s RFID card or via their app, there were significant differences in EV users’ preferences for RFID card authentication methods at the individual level.

- Payment methods

This study found that all different types of payment methods seem the same for EV users. While for non-EV users, showed a strong aversion towards payment via card/contactless/an operator’s RFID card, and they were willing to pay £0.06/kWh to avoid using this type of payment. In comparison, Gutjar and Kowald (2023) found that German consumers preferred web-based (e.g., PayPal) and card-based (e.g. credit card) payment methods rather than automatic debit transfer for customers who have accepted a contract with a charging provider. When considering individual heterogeneity in preferences for various payment methods, significant differences were found in EV users’ preferences for payments via card/contactless/a universal app.

- Amenities

Amenities at the public charging station are also important for both EV and non-EV users. This study found that compared to no amenities around the public charging station, EV users preferred waiting rooms, small shops or cafés, and shopping malls, while non-EV users also preferred the last two types of facilities to be built near the public charging station. EV users were willing to pay the second highest amount of money for such amenities, for example, £0.25/kWh for small shops or cafés, £0.21/kWh for waiting rooms, and £0.20/kWh for shopping malls. In comparison, non-EV users were also willing to pay quite high for these facilities, such as £0.11/kWh for small shops or cafés and £0.08/kWh for shopping malls. It can be seen that small shops or cafés were the most popular facilities for both EV and non-EV users. This is in line with previous studies, which have also shown that both EV users and consumers prefer a variety of amenities over no amenities at all. For example, ten Have et al.

(ten Have et al. 2020) reported EV users in the Netherlands preferred shopping areas to be around slow public charging points. Visaria et al. (2022) estimated that relative to ‘no amenities nearby’, EV users in Denmark were willing to make a 1.23 minute-detour or an equivalent pay £0.23 (1.93 DKK) for the availability of restrooms, and make a 9.55 minute-detour or pay £1.78 (14.97 DKK) to have toilets, restaurants and supermarkets available at the charging station. EV users in the US were willing to pay on average £17.25 (\$21) for the availability of restrooms, dining facilities and Wi-Fi (Ge and MacKenzie 2022). The mixed logit model results also suggest that non-EV users’ preferences for shopping centres as the amenity significantly varied among individuals.

- Station rating

This study found that both EV and non-EV users preferred the highest level of charging stations (5-star) compared to 3-star charging stations. This feature of public charging stations was extremely important for non-EV users as it ranked second among all other characteristics in terms of willingness to pay (£0.12/kWh), the same value as they would be willing to pay for greener resources. EV users were also willing to pay £0.12/kWh for a five-star station rating. While there has been no dedicated research directly assessing the impact of this particular feature of public charging stations, however, Wang et al. (2021) conducted a study focusing on EV user satisfaction and its correlation with public charging choices. Their findings suggest that EV users’ satisfaction with public charging stations does have an impact on their decision to charge or not. The mixed logit models found that for both EV and non-EV users, there was individual heterogeneity of preferences for five-star station ratings.

7.2.3 Unobserved heterogeneity in public charging preferences

Unobserved heterogeneity in public charging preferences was explored by dividing the sample into different groups using latent class logit models. As shown in Tables 7-4 and 7-5, these analyses revealed two groups that exhibited significantly different characteristics. This segmentation allows for a more nuanced understanding of the various preferences and behaviours of the sample population and reveals the underlying factors that influence the public charging preferences of different groups.

- EV users

The latent class logit models suggest that for EV users, rurality of residence, ethnicity, environmental recognition, risk aversion, and technophilia attitudes are important socio-demographic and attitudinal characteristics to identify segments who had significantly different public charging preferences. Meanwhile, EV users with different income levels also exhibited significantly different preferences towards charging prices.

A little bit over half (53.9%) of EV users fall into the first class, who lived in cities or urban areas, and white were expected to be less environmental, risk-averse, and pro-technology. They disliked charging at multi-storey car parks but preferred to use authentication via the operator's RFID card compared to their apps. Their sensitivity to charging prices was different from their income levels. This group of EV users with lower household income (lower than £80,000) cared about charging prices. However, the other group of EV users (46.1%), who resided in rural areas, were non-white and were more environmental, risk-averse, and pro-technology. They disliked long waiting times but preferred fast charging and higher percentage of renewable resources, and a higher number of charging points at the public charging station. They also preferred automatic authentication compared to authenticating via the operator's app, various types of amenities compared to no amenities, and higher ratings of the station.

- Non-EV users

For non-EV users, gender, age, type of dwelling (detached house, attached house, apartment, mobile home), ethnicity, region of residence (whether living in London), and different income levels also revealed that these characteristics significantly influence their preferences towards different attributes and alternatives. The latent class logit models found that there are two classes among EV users and non-EV users who showed significantly different characteristics. EV users can be categorised into two groups, one group (Class 1) with lower income cared more about charging price, preferred RFID card authentication and disliked charging at multi-storey car parks, while Class 2 cared about more features, such as preferred to charge at surface car parks, fast charging, greener resources, automatic authentication, all types of amenities, five-star station rating, and disliked long waiting time.

For non-EV users, there were also two classes. One group (Class 1) disliked both surface car parks and disliked multi-storey car parks, and also disliked higher charging prices and longer waiting time, disliked card/contactless/RFID card payment compared to normal card/contactless payment, and had a five-star rating of the station. However, another group

(Class 2), significantly disliked either surface car parks compared to street charging. Also, Class 1 disliked higher charging prices, but less disliked waiting time compared with Class 1, and preferred fast charging and less waiting time, and preferred a five-star station rating. Compared to Class 1, Class 2 tended to have fewer children, live in attached houses, being white, did not live in London, and were more environmental and more risk averse. They preferred surface car parks, higher renewable resources and fast charging, different types of amenities, and five-star ratings.

Table 7-4: Unobserved heterogeneity in preferences and segmented groups of EV users

Subject	Authors	Segments	Personal characteristics
EV users	This study	Group 1 (53.9%): value charging locations, price, authentication methods	Live in city/urban areas, white, less environmental, less risk averse, less pro-technology
		Group 2 (46.1%): value charging locations, price, fast charging, waiting time, green energy, number of charging points, authentication methods, amenities, station rating	Live in rural areas, non-white, more environmental, more risk averse, more pro-technology
	Wang et al. (2021)	Group 1 Charging service concerned group (76.2%): value SOC, queueing time, and satisfaction	Younger, female, have richer driving experience, higher income, more risk averse
		Group 2 Pragmatic concerned group (23.8%): SOC, ER, parking time, charging fee	Senior, male, low income, less risk aversion
	Pan et al. (2019)	Group 1 Risk averse group (30%): value ER	Male, earning more than £600/month (5,000 yuan/month), purchased EVs more than a year
		Group 2 Risk seeking group (70%): SOC, charging price, and parking price	Female, with income less than £600/month (5,000 yuan/month), purchased their EV in the past year
PHEV users	Wen et al. (2016)	Group 1 (20.3%): value charging price, ER, if the vehicle has enough battery to reach the next EVSE	-
		Group 2 (58.7%): price, ER, charging point power, cost at home, and dwell time	Number of vehicles owned or leased
		Group 3 (21%): value cost at home	Higher income level
	Ge et al. (2018)	Gas anxiety group (66%): have higher willingness to charge at public places to avoid using petrol	Had a longer using experience, buy PHEVs not only by financial benefits
		Cost-minimizing group (34%): value recharge and refuel cost the same	Had a shorter using experience, buy PHEV because of financial benefits

Table 7-5: Unobserved heterogeneity in preferences and segmented groups of non-EV users/consumers

Subject	Reference	Segments	Personal characteristics
Non-EV users	This study	Group 1 (41.3%): value charging locations, price, waiting time, payment methods	Male, older, live in attached house/apartment/mobile home, live in London
		Group 2 (58.7%): value charging locations, price, waiting time, green energy, amenities, station rating	Female, younger, live in detached house, not live in London
Consumers	Latinopoulos et al. (2017)	Risk averse (pricing) group (67.9%)	Aged over 60, employed, not having children, lower education level, not owning or leasing an EV, have multiple trip chains, doing work-based tour, driving EV < 1 year, higher EV loyalty, EV daily mileage < 40 miles,
		Risk seeking group (32.1%)	Characteristics are in the opposite with risk averse group

7.2.4 Future research direction

In this study, an examination was made of how environmental awareness, risk aversion, and attitudes toward technology affect EV users' preferences for attributes and alternatives. The findings suggest that these attitudinal factors have a significant impact on EV users' preferences. Interestingly, for non-EV users, these attitudes did not play an important role in their public charging preferences.

In LCL model 1, it was found that factors such as gender, rural residence, and educational background had a significant impact on the public charging preferences of EV users. However, gender lost significance with the inclusion of attitudinal variables and risk-averse attitudes being significant, suggesting that the attitude variable may play a mediating role between the attributes and preferences of specific demographic groups. In other words, attitudes may act as a mediator because they help explain why certain socio-economic groups are more likely to belong to a particular class. For example, risk aversion attitudes may mediate the relationship between socio-economic characteristics (e.g., gender) and class membership by providing additional insights into individuals' preferences and decision-making processes.

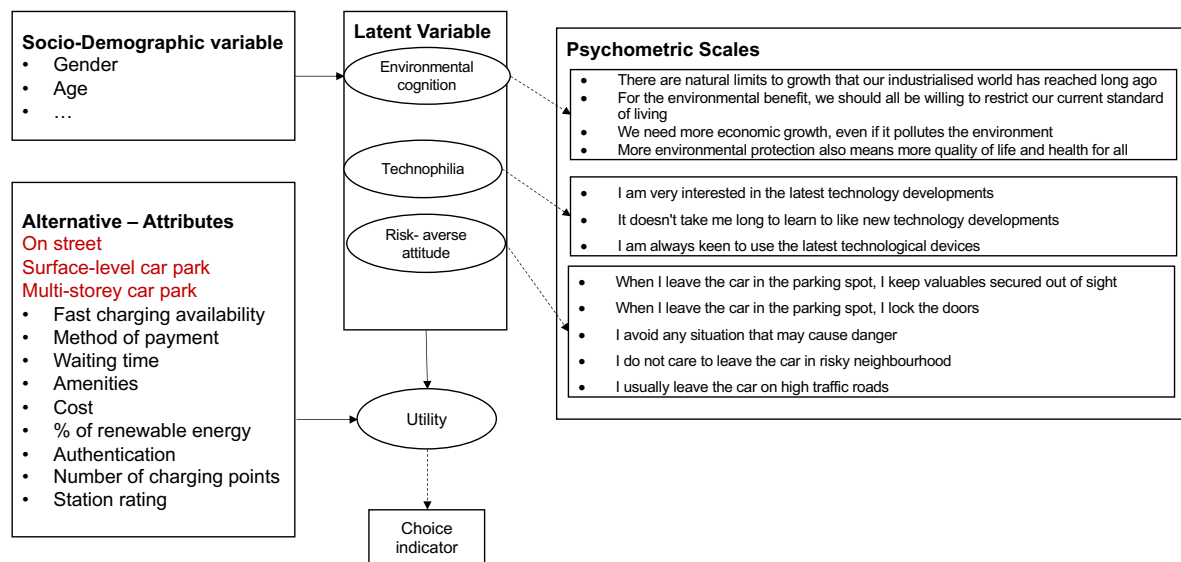


Figure 7-1: Conceptual framework of the quantitative analysis

Therefore, a conceptual framework for future analysis of how attitudinal variables influence EV users' public charging preferences was proposed in Figure 7-1. For example, this model can be used to test whether that latent variables (e.g. environmental cognition, risk aversion,

technophilia attitudes) affect public charging preferences/choices. It extends traditional choice models with latent variables that capture an individual's attitudes and perceptions. These latent variables are derived from respondents' socio-demographic characteristics and psychological indicators, which is a latent variable model. Then these latent variables together with attributes/characteristics of public charging points can form a choice model. In this way, a better understanding of public charging preferences will be made with the consideration of the latent attitudes of existing EV users.

7.2.5 Strengths and limitations

This is the first qualitative analysis using think-aloud and verbal probing techniques to uncover the challenges and nuances faced by potential and existing EV users in choosing public charging based on the choice tasks of a stated preference discrete choice experiment. It delves into the reasons and mindset behind their preferences and how they weigh various factors in the choice experiment. However, it is important to highlight that participants' emphasis on certain factors in the quotations does not necessarily imply statistical significance. It is only an indication of areas of possible concern for participants. The statistical importance of these factors should be thoroughly investigated through quantitative analysis.

This study conducted a rigorous quantitative analysis focusing on comparing the preferences of EV users and non-EV users. It is important to note that this study is the first of its kind to focus specifically on the public charging preferences of non-EV users. Previous studies have focused on EV users or pooled data covering all consumers. However, our survey reveals very different public charging preferences between EV and non-EV users in the UK, providing valuable insights for policymakers and public charging operators. These findings can help promote EV adoption for non-EV users in the future and the development of public charging infrastructure in Great Britain.

It is important to recognise the limitations of this study: the sample of EV users lacked representativeness in terms of gender and age of the whole research region. This limitation stems from the inherent challenges of recruiting different groups of EV users through data collection platforms as the number of EV users in Great Britain is limited. As a result, there may be bias in analysing the public charging preferences of EV users.

Chapter 8 Conclusion

This study provides valuable insights into understanding potential and existing EV users' preferences towards public charging in Great Britain. Firstly, a comprehensive literature review that carefully synthesises previous relevant studies was conducted, which identified key factors important for both EV and non-EV users' public charging preferences. This literature review laid the groundwork for further exploration of this topic.

Subsequently, a discrete choice experiment was carefully designed to incorporate a variety of influencing factors identified in the literature review. To mitigate researcher bias in factor selection and understand participants' choices and preferences, qualitative cognitive interviews ($n = 25$) were conducted on the stated choice experiment materials. These interviews revealed several important findings that potential and existing EV users in the public charging choice experiment: (a) required a clear charging context, (b) showed attribute non-attendance, and (c) had different understandings and attitudes towards various payment methods.

Based on feedback from the cognitive interviews, improvements were made to the choice experiment, including clarifying the choice context and addressing complexities caused by various charging-context factors. The choice experiment was made to focus on the attractiveness of the public charging station - the 'configurations' and 'locations' of public charging stations to avoid complexity caused by various charging-context factors. Also, participants' attribute non-attendance and diverse attitudes towards payment methods showed that attitudinal characteristics such as risk aversion, cost minimising, charging service concern, and technophilia attitudes needed to be further explored in future quantitative analysis.

This leads to the quantitative analysis of the choice experiment data ($n = 588$, with 300 EV users, and 288 non-EV users). In this section, choice modelling was employed for the data. For example, multinomial logit models have conducted to first test the effects of different characteristics of the public charging station on people's choices, mixed logit models were used to examine the individual level of preference heterogeneity for these characteristics, and latent class logit models were done to reveal the characteristics of different segments within the sample.

These choice models found that: (a) EV users and non-EV users exhibited significantly different preferences towards public charging choices, therefore the overall data should be treated separately; (b) EV users and non-EV users shared some similar preferences, such as lower charging prices, shorter waiting times, a higher percentage of renewable energy sources at public charging stations, automatic authentication by just plugging in the charger, and small stores, cafes, or shopping centres to be built around the charging station, and five-star charging stations; (c) They were also indifferent towards varying types of payment methods and the number of charging points available at the public charging station; (d) They also showed totally different trends, for example, non-EV users valued fast charging availability the most while EV users did not perceive this was an important factor; (e) The segmentations of EV and non-EV users were further identified in relation to different socio-demographic and attitudinal characteristics – attitudinal variables (e.g., environmental cognition, risk aversion, technophilia) were influential on EV users' public charging choices, while they did not have significant effects for non-EV users.

Our study also reveals a different willingness to pay for public charging services between EV users and non-EV users in the UK. EV users were particularly willing to pay a premium for charging stations with higher levels of renewable energy utilisation, reflecting their strong preference for environmentally sustainable practices. On the other hand, non-EV users valued fast charging capabilities the most, which may address their concerns about range anxiety and charging convenience. However, both groups expressed a willingness to pay extra for charging stations located near conveniences such as small stores, cafes, and shopping centres. Additionally, both EV and non-EV users valued the five-star ratings of charging stations, demonstrating the importance of reliable, high-quality service at these stations. These findings highlight key factors that public charging service providers should consider to meet the diverse needs of current and potential EV users.

Based on the findings from this study, several policy recommendations can be proposed to guide both policymakers and public charging service providers in the UK. For policymakers, it is crucial to establish comprehensive standards for public EV charging points, as the UK currently lacks a unified set of guidelines. These standards should ensure safety, interoperability, transparent pricing, and convenient access to charging stations. Additionally, the guidelines should address the need for accessible payment methods, particularly for older adults and people with disabilities, making EV charging user-friendly for all. Policymakers

should also consider introducing incentives to encourage public charging providers and businesses to expand the availability of EV charging infrastructure, particularly in high-traffic areas such as shopping centres, cafes, and other amenities. This would support the growing demand for EVs and make it easier for potential owners to charge their vehicles conveniently.

Public charging service providers, on the other hand, should focus on strategic investments to enhance their infrastructure offerings. A key priority should be the expansion of fast charging options, which are crucial for reducing range anxiety among potential EV users, especially those in the early majority who may still be hesitant to adopt EVs. Moreover, integrating a higher proportion of renewable energy into charging stations is essential to align with sustainability goals and attract environmentally conscious consumers. Providers should also consider expanding charging points in key locations such as small shops, cafes, and shopping centres, where potential EV users frequently visit, thereby integrating charging into their daily routines. Improving service reliability and maintaining high station ratings are vital for ensuring customer satisfaction and encouraging repeat use. Additionally, providers should use data insights to target specific user groups, such as younger women living in London, who may represent a significant future market for EVs and public charging services. Tailored marketing strategies and services that cater to the unique preferences of these groups could further accelerate EV adoption. For example, high-income EV users may prioritise factors other than charging price, such as convenience or environmental concerns. In contrast, providing affordable charging options could be crucial for encouraging adoption among lower-income non-EV users.

These findings provide insights to further explore the effect of attitudinal variables on EV users using an integrated choice and latent variable model (ICLV). These findings are valuable not only for operators to adopt different pricing strategies but also for building desirable facilities and services to attract existing and potential EV users. In addition, they are able to help policymakers develop specific policy interventions to promote EV adoption and help improve the development of public charging networks in Great Britain.

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Appendix

Table A1. Summary of EV policies in different countries

Country	Policy incentives	Categories	Source
Norway	No purchase/import taxes (1990-)	Tax benefits	Norsk elbilforening (2020)
	Exemption from 25% VAT on purchase (2001-)	Tax benefits	
	No annual road tax (1996-);	Tax benefits	
	Maximum 50% of the total amount on ferry fares for EVs (2018-)	Monetary benefits	
	Company car tax reduction reduced to 40% (2018-)	Tax benefits	
	Access to bus lanes (2005-)	Travel priority	
	Parking fee for EVs was introduced locally with an upper limit of a maximum 50% of the full price (2018-)	Parking benefits	
UK	Office for Low Emission Vehicles (OLEV): over £900 million to position the UK at the global forefront of ULEV development, manufacture and use	National plan	BALZHÄUSER (2019); Office for Low Emission Vehicles (2016)
	Road to Zero strategy (2018-): £290m budget dedicated to boosting the use of low-emission vehicles and ambition of 50% new cars to be ULEV by 2030	National plan	
	Plug-in Car Grant when purchase	Subsidies	
	BEVs owners are exempt from the annual road tax; Businesses with EVs or PHEVs have tax benefit	Tax benefits	
	EVs are PHEVs are exempt from London's Congestion Charge scheme until 2025	Local benefits	
	Free or discounted parking	Parking benefits	
	Electric Vehicle Home Charge Scheme (EVHS) (2016-)	Chargepoint installation subsidies	
	The Workplace Chargepoint Scheme (WCS) (2016-)	Chargepoint installation subsidies	
	On-Street Residential Charge Point Scheme (ORCS) (2016-)	Chargepoint installation subsidies	
	Businesses install charging infrastructure can access tax benefits through a 100% first-year free charging	Charging benefits	

EU	Clean vehicle Directive (2019-): National targets for public procurement	Regional plans	European Commission (2019)
	Energy Performance Buildings Directive (2019-)		
	Clean Power for Transport (2014-)		
	European Clean Bus Deployment Initiative (2016-)		
China	Energy-saving and new-energy vehicle (ENEV) industry development plan (2012-2020): ambition of production of 2 million EVs, and sales of over 5 million BEVs and PHEVs by 2020	National plan	Columbia University (2020)
	Zero emissions vehicle mandate (2016-): 12% NEV credit sales in passenger cars by 2020	National regulations	
	Subsidies for EV manufacturer	Subsidies	
	Levels of subsidies for EVs with different ranges and kinds	Subsidies	
	EVs exempt from consumption and sales taxes	Tax benefits	
	50% of new vehicles of China's central government should be new energy vehicles in 5 years (2016-)	Public procurement	
	Ban ICE manufacturing (2019-)	National regulations	
	Ambition of creating 120,000 EV charging stations and 4.8 million EV charging points by 2020	National plan	
	Cheaper and faster vehicle license plates for EVs	Local benefits	
	Free and preferential parking spaces	Local benefits	
	EVs are exempt from traffic restrictions of driving for certain days based on license plate number	Local benefits	
	Gradual adoption of electric taxis within several years	Local plan	
	Ban fossil fuel cars	Local regulations	
Canada	Targets for zero-emissions cars: 10% of new sales by 2025, 30% by 2030 and 100% by 2040 (2019-)	National plan	Till Bunsen et al. (2019)
	ZEV mandate in Quebec	Local regulations	
	Purchase incentive for ZEV available to individuals and businesses (2019-)	Subsidies	
	Incentives to OEMs for providing ZEVs on the Canadian car market (2019-)	Subsidies	
	Incentives to support EVSE deployment (2019-)	Subsidies	
	Target to install 900 new fast chargers (2019-)	National plan	

United States	Zero-emissions vehicles (ZEVs) mandate in ten states (2016-): 22% ZEV credit sales in passenger cars and light-duty trucks by 2025	Local regulations	Till Bunsen et al. (2019)
	Targets of 3.3 million EVs in eight states combined by 2025 (2014-)	Regulations	
	California aims to have 5 million EVs by 2030 (2016-)	Target	
	Incentives to deploy charging infrastructure are provided in more than half of US states (2019-)	Subsidies	
	Support development of battery and electric drive systems (2019-)	Subsidies	

Table B1. Overview of empirical studies on public charging preferences

Author(s) (year)	Research object	Type of charging	Type of travel	Charging power	Willingness to pay	Data	Respondents	Country	Modelling approach
Gutjar and Kowald (2023)	Choices among different public charging options	Not specified	NA	Not mentioned	No	SC	450 users and potential users	Germany	MNL, MMNL
Li et al. (2023)	Charge or not along the route	En-route	NA	Not mentioned	No	SC	308 BEV users	China	BL, RPL, RPLEC
Visaria et al. (2022)	Choices among three public charging options	En-route	Long trip	Fast	Yes	SC	558 BEV users	Denmark	MXL
Zhang et al. (2022)	Travel and charge or not charge, or cancel travel	Not specified	Work, recreation	Not mentioned	No	SC	494 BEV users	China	RSBP
Ge and MacKenzie (2022)	Charge or not at stations along route	En-route	Long-distance trip	Slow, fast	Yes	SC	309 PEV users	US	DDC, LC
Ma et al. (2022)	Charge choices among two options	Destination	Home, workplace, request locations	Slow, fast	Yes	SC	2,637 potential EV users	China	MNL, MXL
Wang et al. (2021)	Charge or not at a destination	Destination	Home, work, shopping	Not mentioned	Yes	SC	300 EV users	Beijing, China	BL, LC
Lee et al. (2020)	Choices among home, workplace, public, and mix use of these locations	Not specified	NA	Slow, fast	No	RP	7,979 PEV users	California, US	MNL
Ten Have et al. (2020)	Choices among destination charging (22kW), fast charging (50 kW),	Not specified	NA	Slow, fast, ultrafast	No	SC	171 EV users	Netherlands	MXL

	ultrafast charging (>350 kW), and no preference									
Pan et al. (2019)	Charge or not at a destination	Destination	Home, shopping mall	Slow	No	SC	160 EV users	Beijing, China	BL, LC	
Wolff and Madlener (2019)	Charging choices among home, work, roadside	Not specified	NA	Slow, fast	Yes	SC	4,101 driving license holders	Germany	CL	
Wolbertus and Van den Hoed (2019)	Choices between standard slow charging stations, charging hub, fast charging stations	Not specified	NA	Slow, fast	No	SC	100 EV users	Netherlands	MXL	
Chakraborty et al. (2019)	Choices among home, work, public, multiple locations, not charge	Not specified	Commute trips	Not mentioned	No	RP	1,769 BEV users, 1,432 PHEV users	California US	ECL	
Sheldon et al. (2019)	Choices among public charging stations at different locations	Not specified	NA	Not mentioned	Yes	SC	1,261 potential PHEV users	California US	MNL, MXL	
Anderson et al. (2018)	Choices among public charging infrastructure	Not specified	NA	Slow, fast	No	SP	843 BEV users	Germany	FA	
Ge et al. (2018)	Charge or not	Not specified	NA	Slow	No	SC	157 PHEV users	US	LC	
Moon et al. (2018)	Choices among public charging infrastructure	Not specified	NA	Slow, fast	No	SC	418 current and potential EV users	South Korea	MXL	
Latinopoulos et al. (2017)	Charge now or later under dynamic charging pricing	Destination	NA	Not mentioned	No	SC	118 current and potential EV users	UK & Ireland	EUT, DEU, PT	
Xu et al. (2017)	Choices between slow home/workplace and fast public charging	Not specified	NA	Slow	No	RP	234 BEV users	Japan	MXL	
Kim et al. (2017)	Public charging choices	Not specified	NA	Not mentioned	No	RP	9,027 EV users	Netherlands	HD	

Sun et al. (2016)	Choices between fast charging stations	En-route	NA	Fast	No	RP	24 BEV users	Japan	MXL
Wen et al. (2016)	Charge or not at the destination in given situation	Destination	NA	Slow, fast	Yes	SC	315 PEV users	US	MXL, LC
Nienhueser and Qiu (2016)	Choices for public charging options	Not specified	NA	Slow, fast	Yes	SC	181 EV users	US	MXL

Notes: Binary logit model (BL); Multinomial logistic regression (MNL); Latent class logit model (LC); mixed logit model (MXL); Discounted expected utility (DEU); Expected utility theory (EUT); Prospect theory (PT); Hybrid choice model (HCM) latent class logit model (BL); Hybrid choice model (HC) latent class logit model (LC); Error component logit model (ECL); Conditional logit model (CL); Frequency analysis (FA); Dynamic discrete choice models (DDC); Random parameter logit model (RPL); Random parameter logit with error components model (RPLEC); Recursive simultaneous bivariate probit model (RSBP); Mixed multinomial logit model (MMXL); Ordered logit model (OL); Ordered probit model (OP); Hazard-based duration model (HD); SC: revealed preference study with an experiment, RP: revealed preference study without an experiment, RP: stated preference study

Appendix B2: Overview of grey literature

Author(s) (year)	Research object	Determinants	Data	Respondents	Country	Modelling approach
Department for Transport (2022b)	Key aspects of public charging	Dependability, proximity, cost and speed, sustainability	SP	1,006 non-EV users	UK	FA
Department for Transport (2022a)	Survey about public charging	Charging behaviour (accessibility, frequency, reliability), charging satisfaction, improvements needed	SP	848 EV users	UK	FA
Hink (2021)	Key aspects of public charging	Payments, pricing transparency, open data, reliability, weatherproofing and lighting, signage, accessibility	SP	1,216 PEV users	UK	FA
Burroughs et al. (2021)	Choices of the factors that can improve the public charging experience	Access (27%), quantity (20%), location (19%), miscellaneous (11%), queue (8%), power (8%), cost (7%)	RP	932 EV users	New Zealand	FA
Dodson and Slater (2019)	Charging choices of empirical charging events	Time of day, Time of week, Time of season	RP	8.3 million charging events	UK	FA
California Air Resources Board (2019)	Regulations for all public level 2 and fast charging infrastructure	Payment methods and security; clear information about all fees; clear pricing models; no compulsory membership; interoperability billing standards; sharing station information.			California, US	-
Bedir et al. (2018)	Predict the number of chargers needed by 2025 for the state's ZEV goals	99,000 to 133,000 destination chargers, including at workplaces and public locations, and 9,000 to 25,000 fast chargers			US	EVI-Pro
Wood et al. (2017)	Predict necessary amount and ideal types of locations for charging stations	Charging locations (corridor fast-charging stations for long-distance travel, urban and rural communities); About 8,000 fast-charging stations would be required to provide a minimum level of coverage nationwide;			US	EVI-Pro

Appendix B3 Overview of willingness to pay estimates in previous literature (in UK pounds)

Determinants	Denmark ^[1]	US ^{[2][6][7][8]}	China ^{[3] [4]}	Germany ^[5]
Less charging cost	5.59 min of detour or £1.04 (8.76 DKK) against 1 less DKK/kWh in charging cost;			
Higher charging power	0.28 min of detour or £0.052 (0.44 DKK) for an extra km/min	£1.58/h (\$1.91/h) for level 2 vs. level 1 ^[7] ; £0.041 (\$0.05) for an extra mile from charging ^[6]		
Number of chargers	7.87 mins of detour or £1.46 (12.32 DKK) for an available charger; 0.53 min of detour or £0.099 (0.83 DKK) for an occupied charger			
Amenities	1.23 min of detour or £0.23 (1.93 DKK) for availability of restrooms vs. none ; 9.55 min of detour or £1.78 (14.97 DKK) for availability of restrooms, restaurants, supermarkets vs. none	£17.25 (\$21) for restroom, dining facilities and Wi-Fi vs. none ^[2]		
Increase SOC			£0.083/kWh (0.7 yuan/kWh) for 10% ^[4]	
Increase of excess range			£0.041/kWh (0.346 yuan/kWh) ^[4]	
Shorter charging duration (min)		£0.33 (\$0.4) ^[2]		£0.14/month (€0.16/month)
Shorter waiting time (min)				£0.72/month (€0.82/month)
Shorter access time (min)		£2.05 (\$2.5) ^[2]		

Higher share of renewable energy (%)	[£0.50 (\$0.61) per hour for Level 2 EVSE; £1.49 (\$1.82) per hour for Direct Current Fast Chargers (DCFC);] ^[8]	£0.37/month (€0.42/month)
Inductive charging technology vs. cable charging		£7.40/month (€8.38 /month)
Charging locations	[£2.31 (\$2.81) for grocery; £1.35 (\$1.65) for mall, £1.13 (\$1.38) for quick charge near home; £1.03 (\$1.26) for quick charge near freeway; £0.0082 (\$0.01) for at transit; - £0.78 (-\$0.95) for gym; - £1.01 (- \$1.23) for school] ^[6]	- £40.84/month (-€46.26/month) for en-route charging on the road vs. at home; -£31.46/month (-€35.64/month) for destination charging on the road vs. at home; -£19.70/month (-€22.31/month) for charging at work vs. at home;
Avoid having to deviate from the originally planned route	£200.37 (\$244) ^[2]	
Time of day		[Workday: £0.19 (CNY 1.614) for 10:00–17:00; £0.24 (CNY 2.042) for 17:00–22:00; £0.14 (CNY 1.194) for 22:00–10:00+1 ; weekend: £0.18 (CNY 1.527) for 10:00–17:00; £0.22 (CNY 1.838) for 17:00–22:00; £0.28 (CNY 2.372) for 22:00–10:00+1] ^[3]

Notes: [1] Visaria et al. (2022); [2] Ge and MacKenzie (2022); [3] Ma et al. (Ma et al. 2022); [4] Wang et al. (2021); [5] Wolff and Madlener (2019); [6] Sheldon et al. (2019); [7] Wen et al. (2016); [8] Nienhueser and Qiu (2016)

Table B4. Overview of explanatory factors for public charging choices: temporal attributes

Respondents	Measurement of attributes (+/-)	Levels/supplement information	Reference
BEVs	Midnight (-)	Less likely to occur at midnight between 23:00 to 7:00	Xu et al. (2017)
	Working day (+)	A working day indicator	Xu et al. (2017)
Potential EV users	Time period *	High demand time periods: 6AM-9AM, 9AM-12PM, 6PM-9PM	Moon et al. (2018)
	Time of day	High demand time periods: 17:00-22:00 > 10:00-17:00 > 22:00 -10:00 for workday, 22:00 -10:00 > 17:00-22:00 > 10:00-17:00 for weekend	Ma et al. (Ma et al. 2022)
EV users	Time of day *	Fast charging sessions concentrated around the centre of the day; level 2 charging sessions show a small peak in the morning and a larger peak in the afternoon	Wolbertus and Van den Hoed (2019)
	Length of trip chain (+)		Zhang et al. (2022)
	Complex trip chain (+)		

Notes: '+' indicates a significant positive effect on public charging choices, and '-' represents a significant negative effect, * refers to the results of the descriptive analysis and they are not significant.

Table B5. Overview of explanatory factors for public charging choices: vehicle attributes

Attributes	Respondents	Measurement of attributes (+/-)	Levels	Reference
SOC	EV users	SOC (-)	7%, 10%, 13%, 17%, 20%, 23%, 27%, 30%, 33%, 40%, 50%, 53%, 57%, 60%, 67%, 80%	Pan et al. (2019)
	EV users	SOC (-)	0%; 20%; 40%; 60%; 80%	Wang et al. (2021)
	BEV users	SOC (-)	45 km (23%), 65 km (33%), 85 km (43%), 105 km (53%), 125 km (63%), 155 km (78%)	Zhang et al. (2022)
	PEV users	SOC (-)	State of charge at station t for respondent I (%)	Ge and MacKenzie (2022)
	PEV users	Initial SOC (-)	Revealed study: values are different among respondents	Xu et al. (2017)
Excess range	PEV users	ER remaining in vehicle battery (-)	3-70 mi	Wen et al. (2016)
	EV users	ER (-)	0; 5 km; 20 km; 50 km	Wang et al. (2021)
		ER (-) *	-5 km, 5 km, 10 km, 20 km, 40 km	Pan et al. (2019)
	PEV users	Whether the current range is enough to next charging opportunity (-)	0: if current range < distance to next charging opportunity; 1: if current range $\geq$ distance to next charging opportunity	Wen et al. (2016)
Driving range	BEV users	Battery capacity (+)	Revealed study: values are different among respondents	Xu et al. (2017)
	PHEV users	Electric range (+)	Revealed study: values are different among respondents	Chakraborty et al. (2019)
	BEV users	Initial available range at origin (+)	30, 50, 60, 70 km	Li et al. (2023)
		Available range uncertainty (interval) at destination (-)	2, 10, 20, 30, 40 km	

Notes: '+' means significant positive effect for public charging choices, and '-' represents significant negative effect; '*' means the result is not significant.

Table B6. Explanatory factors for public charging choices: physical infrastructure attributes

Attributes	Respondents	Order of preference	Reference
Charging location	PEV owners	Home only (53%), home & public (16%), home & work (13%), work only (8%), all (4%), public only = work & public (3%)	Lee et al. (2020)
	BEV owners	Home, work, not charge, multi-location, public	Chakraborty et al. (2019)
		Activities during charging (77%) (shopping and leisure (18%), work (16%), chores (5%), house/apartment (3%), education/day care (1%)), stop-to-charge (19%)	Anderson et al. (2018)
		Prefer to use chargers located at gas stations^F	Sun et al. (2016)
	Private owners	BEV Home, public	Xu et al. (2017)
		Prefer to charge at fast stations encountered earlier on working days, then prefer stations encountered later when choosing a station in peak hours^F	Sun et al. (2016)
	EV users	Public car parks (4%), supermarkets (3%), retail stores/malls (2%), petrol stations (1%), street side/roadside (1%), private car parks (1%), other destinations (1%) ^G	(Burroughs et al. 2021)
		Motorway service areas (28%), at other destinations (26%), near home (10%), at workplace/education (9%) ^G	(Department for Transport 2022a)
	PHEV owners	Home, multi-location, work, not charge, public	Chakraborty et al. (2019)
	Potential EV users	At home, at work, on the road: charging as side activity, on the road: charging as main goal	Wolff and Madlener (2019)
		Grocery, at work, mall, quick chargers near home, quick chargers by freeway, gym, school	Sheldon et al. (2019)
		Motorway service stations; workplace, gas stations and shopping facilities; leisure facilities and education institutions	Philipsen et al. (2016)

Attributes	Respondents	Order of preference	Reference
Charging power	BEV owners	Fast (level 3), normal (level 1 & level 2)	Xu et al. (2017)
	EV users	Ultrafast (>350 kW), fast (around 50 kW), standard charging (up to 22 kW)	Ten Have et al. (2020)
	BEV owners	Semi-fast charging power (22 kW AC), slow (3.7 kW AC) = fast (50 kW DC) stations	Anderson et al. (2018)
	PEV owners	DC fast chargers, public L2 chargers, public L1 chargers	Lee et al. (2020)
		50 kW, 6.6 kW, 1.9 kW	Wen et al. (2016)
Amenities	Potential EV users	Fast chargers (+)	Ma et al. (Ma et al. 2022)
	EV users	Slow charging: near shopping area, without facilities	Ten Have et al. (2020)
		Fast charging: without facilities	
		Amenities with restroom, supermarket and restaurants	Visaria et al. (2022)
	PEV users	Amenities with restrooms, dining and WIFI	Ge and MacKenzie (2022)
Number of vacant chargers (+)	EV users	None	Visaria et al. (2022)

Note: Order of preference in bold imply that the results of the study were significant, while the order of preference not in bold represent the descriptive analysis results and they are not significant, and the superscript ^F refers to studies focused on fast charging stations, superscript ^G refers to the grey literature.

Table B7. Public charging price levels

Attributes	Respondents	Measurement of attributes (+/-)	Attribute levels / supplement information	Reference
Charging price	Potential EV users	Refuelling cost per mile (-)	[\$ per mile, like \$ X gal petrol] ⁴ : e.g. \$0.04, \$0.08	Sheldon et al. (2019)
		Charging cost (-)	[KRW/ kWh] ² : 150, 200, 250, 300	Moon et al. (2018)
		The total price of the charging session (-)	[Booking now: £0.29/kWh–£0.42/kWh; booking later: £0.08/kWh–£0.72/kWh] ²	Latinopoulos et al. (2017)
		Charging cost per month (-)	[€50, €100, €150, €200] ³	Wolff and Madlener (2019)
	EV users	Charging price (-)	[CNY/kWh] ² : 1.5, 2.25, 3	Ma et al. (Ma et al. 2022)
		Charging price (-)	[Yuan/kWh] ² : 0.5, 1.5, 2, 2.5;	Pan et al. (2019)
		Charging price (-)	[€5, €8.49, €11.76, €15.25 for 100 km] ⁴	Ten Have et al. (2020)
		Fast charging price (-)	[€/kWh, €0.20/kWh, €0.40/kWh, €0.60/kWh] ²	Wolbertus and Van den Hoed (2019)
	PEV owners	Charging fee (-)	[1.2 yuan/kWh, 1.6 yuan/kWh, 2 yuan/kWh] ²	Wang et al. (2021)
		Charging price per hour (-)	[0.50, 1.00, 1.50, 2.00, 5.00 \$/h] ¹	Wen et al. (2016)
		Charging price per hour (-)	[\$1/hour, \$1.12/hour, \$1.24/hour, \$1.06/hour, \$1.24/hour for AC level 2 EVSE; \$5.30 /hour, \$5.15 /hour, \$5.60 /hour, \$5.15 /hour, \$5.60 /hour for DC fast charger] ¹	Nienhueser and Qiu (2016)
		Charging price (-)	[Free; \$0.50/kWh; \$1.00/kWh] ²	Ge and MacKenzie (2022)
	BEV users	Working days: free charging (+)	Free/not free	Sun et al. (2016)
	PHEV owners	Charging price (-)	[\$0.50/h, \$1.00/h, \$1.50/h, \$2.00/h, \$5.00/h] ¹	Ge et al. (2018)
		Free workplace charging (-)	Yes/no	Lee et al. (2020)
Parking price	EV users	Parking price while charging and while not charging (-)	Yuan/h: 8 and 8, 8 and 6, 8 and 4, 4 and 0, 0 and 0	Pan et al. (2019)

Attributes	Respondents	Measurement of attributes (+/-)	Attribute levels / supplement information	Reference
Home electricity price	BEV owners	Cost of electricity at home (+)	[cents/kWh] ²	Lee et al. (2020)
	PHEV owners	Electricity cost at home at the end of the travel day (-)	Continuous variable. Max: \$9.93; Min: \$0.18; Mean: \$2.05	Ge et al. (2018)
Workplace charging price		Free workplace charging (-)	Yes/no	Lee et al. (2020)
Petrol price		The cost of petrol that will be used to complete the travel day (-)	Continuous variable. Max: \$1.824; Min: \$0; Mean: \$0.1156	Ge et al. (2018)
Network membership	EV owners	Network membership (+)	Yes/no	Lee et al. (2020), Chakraborty et al. (2019)

Note: '+' indicates a significant positive impact on public charging choices, '-' represents a significant negative impact. The level '['' in square brackets and superscript numbers indicate different payment models, 1 – charging time based, 2 - kWh based payments, 3 – fixed monthly charging fee, 4 – pay for a certain range.

Table B8. Charging and waiting times attributes related to public charging infrastructure

Attributes	Respondents	Measurement of attributes (+/-)	Levels	Reference
Charging time	Potential EV users	Full charge time (-)	30 min, 1 h, 4 h, 8 h	Moon et al. (2018)
		Full charging time (-)	10 min, 30 min, 4 h, 8 h	Wolff and Madlener (2019)
		Refuelling time (-)	Petrol/status quo: 10 min, 15 min; Full charge time: Slow charge: 60 min, 120 min; Medium charge: 30 min, 60 min; Fast charge: 15 min, 30 min;	Sheldon et al. (2019)
	EV drivers	Fast charging time (-)	5 min, 10 min, 15 min, 20 min, based upon a session in which 24 kW needs to be charged	Wolbertus and Van den Hoed (2019)
Waiting time	EV drivers	Full ranging time (-)	50 kW; 100 kW; 150 kW; 300 kW	Ge and MacKenzie (2022)
		Queueing time (-)	0, 15, 30 min	Wang et al. (2021)
		Certainty of charging point availability: ultrafast charging (-), fast and slow public charging (+)	Certain: <5 min waiting time, uncertain: waiting time unknown	Ten Have et al. (2020)
	Potential EV users	Waiting time 30 min (-)	0, 5, 10, 30 min	Wolff and Madlener (2019)
Parking time	EV drivers	Parking time (+)	2 h, 4 h, 8h	Wang et al. (2021)
Dwell time	EV drivers	Dwell time > 30 min (+)	0.25, 0.5, 1, 2, 4, 8 h	Wen et al. (2016)

Note: '+' means significant positive effect on public charging choices, and '-' represents significant negative effect.

Table B9. Accessibility attributes related to public charging infrastructure

Attributes	Respondents	Measurement (+/-)	Levels	Reference
Density of public charging stations	BEVs	BEVs registered and driven in Tokyo and Kanagawa (+)	Tokyo/Kanagawa area (more than 55 stations per 1,000 km ²) compared to other area (less than 30 stations per 1,000 km ²)	Xu et al. (2017)
		Coverage of charging facilities (+)	With or without charging facilities at parking points	Zhang et al. (2022)
Distance to from the charging stations to home/consumers	EV owners	Fast charging distance to home (+) *	150 m, 400 m, 550 m, 700 m	Wolbertus and Van den Hoed (2019)
	Potential EV users	Station accessibility (-)	Average distance a consumer must travel to reach the nearest public charging points: 2 km, 10 km, 20 km	Moon et al. (2018)
	Potential EV users	The distance of public chargers from home/workplace/frequent (-)	Within 1 km, 1–2 km, 2 km away	Ma et al. (Ma et al. 2022)
Detour	EV users	Not having to make a detour for ultrafast charging (-)	Detour (5 min driving or walking), no detour	Ten Have et al. (2020)
	BEV users	Detour (km) (-)	Working days (threshold = 1750 m), non-working days (threshold = 750 m)	Sun et al. (2016)
	EV owners	Detour (minutes) (-)	0/5/10	Visaria et al. (2022)
Access time to the charging station	PEV users	Access time to the charging station (-)	5 min; 15 min; 30 min	Ge and MacKenzie (2022)

Deviation		Deviation from the original plan (-)	Whether to deviate from the original plan if they choose not to charge (yes or no)	
Type of charging stations	BEV users	Accessibility *	Public accessible areas and public street (94%)	Anderson et al. (2018)

Note: '+' means significant positive effect for public charging choices, and '-' represents significant negative effect; '*' means the result is not significant.

Table B10. Convenience attributes related to public charging infrastructure

Attributes	Respondents	Measurement (+/-)	Levels	Reference
Self-service availability	Potential EV users	Availability of self-charging services (+)	Yes , no (employee charging)	Moon et al. (2018)
Authentication Payment methods	Potential EV users		Plug & charge (+) > RFID (+) > app (ref.) Card-based (+) > debit transfer (ref.) > web-based (-)	Gutjar and Kowald (2023)
Whether use inductive charging	Potential EV users	Inductive (+)	Tethered charging (with cable), Inductive charging (without cable)	Wolff and Madlener (2019)

Note: ‘+’ means significant positive effect for public charging choices, and ‘-’ represents significant negative effect.

Table B11. Information attributes related to public charging infrastructure

Attributes	Respondents	Measurement (+/-)	Levels	Reference
Information about source of energy	PEV users	Renewable fraction (+)	0%, 25%, 50%, 75%, 100%	Nienhueser and Qiu (2016)
	Potential EV users	Share of renewables (+) (wind or solar energy in the electricity mix used for charging)	25%, 50%, 75%, 100%	Wolff and Madlener (2019)
		Renewable energy (+)	0%, 50%, 100%	Gutjar and Kowald (2023)
Whether the public charging point is registered in an information system	Potential EV users	Availability of station information (location, charging fee, status of public charging points) (-)	Yes, no	(Moon et al. 2018)

Note: ‘+’ means a significant positive effect for public charging choices, and ‘-’ represents a significant negative effect.

Table B12. Explanatory factors for public charging choices: user (incl. potential) attribute

Respondents		Personal characteristics
EV users	Who prefer public charging	Young (Wang et al. 2021), female (Pan et al. 2019; Lee et al. 2020; Wang et al. 2021), with lower level of education (Pan et al. 2019) and lower level of income (ten Have et al. 2020), purchased EV more than a year (Pan et al. 2019), had rich driving experience (Wang et al. 2021), living in an apartment (Chakraborty et al. 2019) and not having a house (Lee et al. 2020), without home charging point (Zhang et al. 2022), with long and complex trip chains (Zhang et al. 2022), and holding risk-averse attitudes towards EV range (Pan et al. 2019)
	Who prefer slow public charging	Lower level of income (Ten Have et al. 2020)
	Who prefer fast charging	Young (Wang et al. 2021), and rich fast charging experience (Xu et al. 2017), lower level of income (Ten Have et al. 2020), higher current frequency of using fast charging (Ten Have et al. 2020)
	Who prefer ultra-fast charging	Have lower level of income, put higher importance of driving comfort, and have higher level of education (Ten Have et al. 2020)
PHEV users	Who prefer public charging	Less vehicle ownership (Lee et al. 2020), long time of using PHEVs and buy PHEVs not only by financial benefits (Ge et al. 2018)
Potential users	Who prefer public charging	White, believe local air quality is poor, and politically liberal leaning (Sheldon et al. 2019)

Appendix C. Findings from the first-round cognitive interviews on the introductory questions

Five themes were identified in terms of participants' responses towards questions asked in the cognitive interview, including ambiguity, terminology, overlap, general wording issues, and derived new questions.

1 Ambiguity

Bruin (2011) found that participants' responses can be systematically affected by slight variations in question-wording. When the questions are concrete and linguistically simple, participants are more likely to form a determined opinion. Ambiguity occurs when a situation or statement that has more than one possible meaning or interpretation. Lack of appropriate words can result in the respondent misunderstanding the question and giving inappropriate answers or even refusing to answer (Sreejesh et al. 2013).

Table 1: Summary of the frequency of occurrence of ambiguities in questions and options, and examples of evidence

The original question	Ambiguity	Number of participants (out of 20)	Example of evidence
Unclear questions			
“Q14 How do you perceive the current public charging infrastructure/stations/points?”	Different answer directions for the question	20	- Mentioned quantity of public charging infrastructure (#3, #4, #5, #9, #10, #11, #14, #20) - Mentioned quantity and satisfaction with public charging infrastructure (#1, #2, #7, #8, #13, #16) - Mentioned the level of satisfaction with the public charging infrastructure (#12, #15, #17, #18, #19) - Lack of knowledge about public charging infrastructure (#6)
“Q13 What is your understanding of public charging for electric vehicles?”	Did not know what the question meant	6	“I’m not sure what I’ve been asked there, to be honest. What’s my understanding of it? As in how available it is? Or is what do I think public charging is” (#13)
“Q1 What city do you live in currently?”	Question situation was not applicable	5	“I live in Blackpool. It’s a town not a city” (#2)
“Q7 What type of electric car do you drive?”	Did not know what the question meant	2	“Does that mean model of car?” (#15)
Unclear options of the question (14)			
	Different understandings of “Easy to access”	10	- Have enough parking space (#5, #10, #13, #16, #19) - At convenient location (#9, #10, #14, #18)

“Q15. (If you are EV users) What do you think it is important for you to consider when using public charging infrastructure/stations/points? • Location, charging time/speed, amenities • Pricing • Easy to access • Convenient to use • Information provided is clear (location, availability, pricing, energy source) • Safety (personal, vehicle, information security) • Reliability Other [please state]:_____”			• Visible (10, #17, #18) • Have plenty number of charging points (#9, #19) • Have amenities (#13) • Short waiting time (#5) • Higher density (#19) • Reliable (#15)
	Different understandings of “Convenient to use”	7	• Ease of payment (#9, #16, #18) and payment compatibility (#10, #13, #16) • Charging speed (#14) and automatic charging technology (#10, #14) • Have amenities nearby (#19)
	Did not know what “Amenities” meant	3	• Whether they were “toilets nearby” or “shops” (#6) or “something that is added onto the charger itself” (#20)
	Different understandings of “Safety”	2	• Data security (#5) • Personal security (#18)
	Perceived the way to observe the “Reliability” differently	2	• Go to the charging station and see whether it was functioning or not (#9) • View Zap Map (#16)
	Did not know what “Energy source” meant	1	- “...wouldn’t have an idea about that” (#12)

- Different answer directions for the public charging infrastructure perception

Regarding the open-ended question “Q14 How do you perceive the current public charging infrastructure/stations/points?”, participants answered this question from different directions:

- (1) Participant #6 gave an answer more related to the knowledge of public charging as the participant did not have an electric vehicle and therefore the participant did not know which charging stations should be used and which should not be used. This indicates that the participant may not know how to answer the question as a non-EV user who lacks knowledge about EVs and EV charging.
- (2) Six participants (#1, #2, #7, #8, #13, #16) provided their views on both the quantity and satisfaction level of public charging infrastructure in response to the question.
- (3) Conversely, some participants only addressed one aspect. For instance, eight participants only mentioned the quantity of public charging infrastructure (#3, #4, #5, #9, #10, #11, #14, #20), while five participants only shared their level of satisfaction with the infrastructure (#12, #15, #17, #18, #19).

In terms of the adequacy of the number of public charging points, some participants held a negative view, as indicated by responses such as “limited” (#2), “inadequate” (#7), “not enough” (#16), and “not as much as I think would be required” (#20). However, one participant (#13) had a contrasting perspective and perceived the number of public charging points to be sufficient, particularly in supermarket car parks. Participant #10 held a more positive view, characterising the amount of public charging infrastructure as “positive emerging” and “definitely growing.” However, this participant also noted a lack of experience and was unable to provide an assessment of whether the current infrastructure was sufficient.

Regarding the perception of feelings towards public charging, participants expressed both positive and negative sentiments. Positive feelings were expressed through responses such as “good” (#1), while negative feelings were evident through responses such as “quite poor” (#2), “not as good as it should be” (#7), “poor reliability” (#16), and “it is quite bad” (#19) because “long waiting times” that are usually required for an available public charging point (#10), or “the maintenance of the charging points not good as it is should be” (#7). One participant (#18) had a slightly positive view of public charging infrastructure, describing it as “not great, but improving” in their town. Meanwhile, another participant (#15) expressed varied feelings towards the public charging infrastructure in different locations. While fast chargers at service stations on motorways were regarded as “very good,” non-motorway charging networks were

deemed less efficient, except for the Tesla charging network, which was seen as accessible only to Tesla users.

- Unclear question for asking the knowledge of public charging

Regarding the question “Q13 What is your understanding of public charging for electric vehicles?”, six participants (#7, #11, #13, #15, #17, #18) perceived it to be unclear, describing it as “vague” (#17), or “too broad” (#18). Other participants (#7, #11, #13, #15) expressed uncertainty about the meaning of the question at first, and most of them sought clarification by asking, “I don’t understand this question. What exactly is this one” (#11).

- Unclear expression of place of residence

While the first question “Q1 What city do you live in currently?” aimed to capture participants’ location of residence using the term “city”, it resulted in several confused responses as five participants mentioned that they did not live in a city. Two of them specifically identified the town they resided in, such as Blackpool (#2) and a rural area near Etchingham (#7). The remaining three participants mentioned their nearest city, for example, “My nearest city is Exeter” (#6), “I’m in Kent, which is near Maidstone. I would say that’s the major city” (#4), “my closest city to me is Aberdeen” (#15).

- Unclear specified options for car ownership

Two participants (#15, #18) raised the issue about the limited options available in response to questions about car ownership. Specifically, the question “Q3 Do you drive an electric car?” only allows for a yes or no answer, which may not accurately reflect the type of car that participants own. Participant #18 suggested that additional options should be added, such as “No, ICE car; Yes, full electric; Yes, plug-in hybrids; ... a hybrid as a fourth option” to allow for more precise responses. Similarly, in response to the question “Q7 What type of electric car do you drive?”, participant #15 asked, “does that mean model of car?”. All of These highlight the need for more specific response options to accurately determine participants’ car ownership.

- Unclear options for factors affecting public charging

14 out of 20 participants in the study reported that certain factors in question “Q15 (If you are EV users) What do you think it is important for you to consider when using public charging

infrastructure/stations/points?” were unclear. This caused difficulty in understanding these factors and raised concerns about potential misunderstandings in the later main questionnaire.

(1) Easy to access

Participants perceived “easy to access” differently. Ten (10) participants (#5, #9, #10, #13, #14, #15, #16, #17, #18, #19) believed it refers places where:

- are at convenience/good locations (#9) associated with amenities (#13), such as “a petrol station” because they were everywhere within a radius of every two or three miles (#14) or at “good road links” that did not require drivers to navigate down back streets to charging points (#18), such as not “somewhere at the end” or “somewhere far away” (#10).
- are no queues (#5); have plenty of chargers (#9, #19).
- have enough space (#5, #19) where it is easy to park and charge (#10, #13), such as having “open” parking spaces (#5), “enough room to manoeuvre around the point” (#16), and not “very narrow layby” which may affect whether someone had a bigger car or was not a confident driver (#10).
- are more visible (#10, #17, #18) that are not “somewhere behind the building” (#10, #17) or car wash (#17), and may need signs (#17, #18) such as “McDonald’s golden arches” (#17).
- are “everywhere” (#19).
- public charging points are working (#15).

In all, as Figure 1 presents, the “easy to access” factor has been associated with parking space (#5, #10, #13, #16, #19), location (#9, #10, #14, #18), visibility (10, #17, #18), number of charging points (#9, #19), amenities (#13), waiting time (#5), density (#19), reliability (#15).

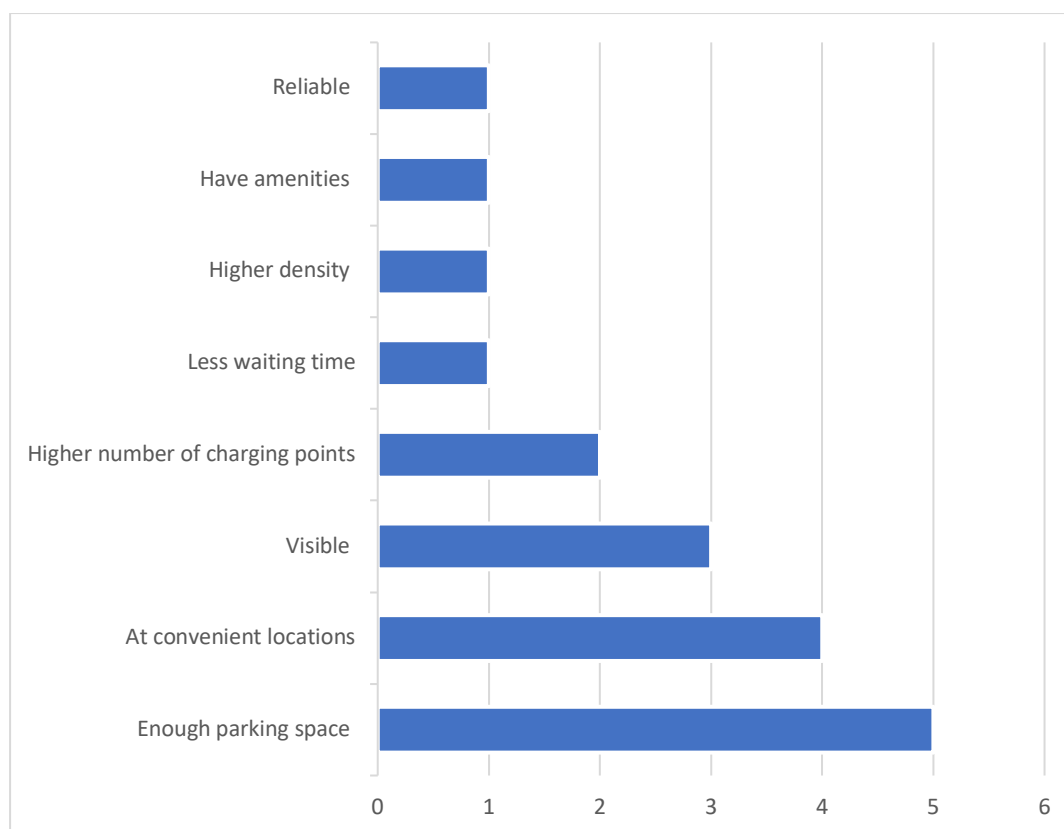


Figure 1: Frequency summary of different understandings of “easy to access”

(2) Convenient to use

Seven (7) participants (#9, #10, #13, #14, #16, #18, #19) had three types of interpretations of the term “convenient to use” in the context of public charging, including ease of payment (#9, #16, #18) and payment compatibility (#10, #13, #16), charging speed (#14) and technological supports (#10, #14), and location amenities (#19), as shown in Figure 2.

The first group of participants associated convenience with ease of payment such as whether a payment card was allowed (#9, #16, #18), without requiring a membership card (#18), or no extra signup process (#9) and more payment options to choose (#9), and also the compatibility of different charging apps (#10, #13, #16) as downloading multiple different apps were not appealing for participants.

The second group of participants linked “convenience to use” with shorter charging times (#14) due to technology development, automatic charging (#10, #14) (e.g., plug-and-play technology without the need of clicking any button) and payment (#10, #14) (e.g., a clear charging scheme that people did not need to look at the car metre).

In contrast, one participant (#19) linked “convenient to use” to amenities around public charging points, for example, whether “near shopping centres” and “not too far away from somewhere you want to be”.

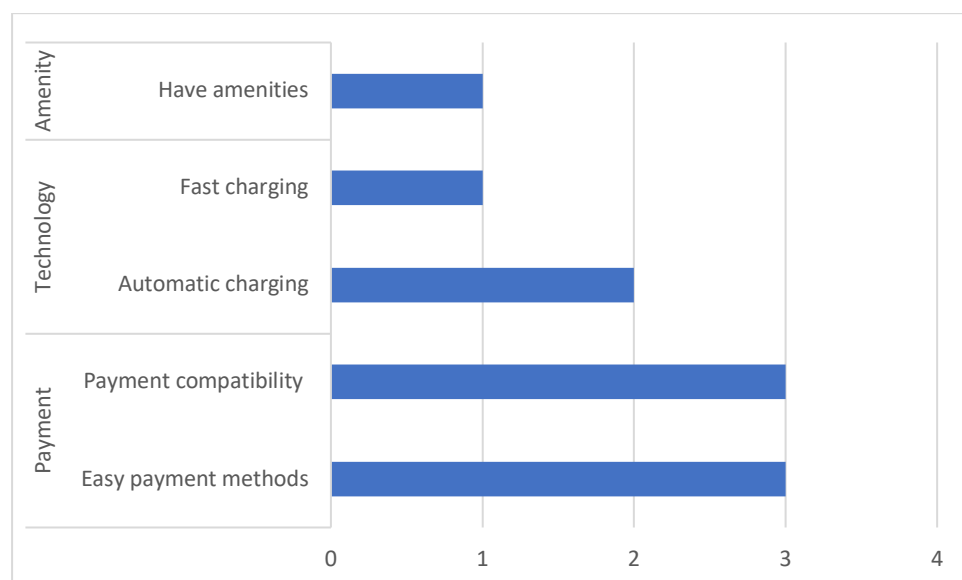


Figure 2: Frequency summary of different understandings of “Convenient to access”

(3) Amenities

In the study, it was reported that three participants (#1, #6, #20) experienced a degree of confusion with regard to the meaning of the term “amenities” in the absence of any accompanying examples to provide context and clarify its definition. For example, participants #6 and #20 expressed that they were unsure about what amenities meant, whether they were “toilets nearby” or “shops” (#6) or “something that is added onto the charger itself” (#20). Meanwhile, participant #1, a non-EV user, reported the importance of all factors except “amenities”, suggesting a possible lack of understanding of its meaning.

(4) Safety

Two participants (#5 and #18) had uncertainties regarding the meaning of “safety”. Participant #5 connected safety to data security but was unsure about its specific context in the study. On the other hand, participant #18 initially had no understanding of the term, but after clarification from the interviewer regarding the charging process and potential waiting times, they associated safety with “good lighting” for personal security.

(5) Reliability and energy source

Two participants (#9 and #16) responses to “the reliability” of public charging points indicated that they believed there are different approaches to observing the reliability of public charging points. Participant #9 believed there was no need to put this factor within the public charging context as the reliability could be determined simply by observing whether the charging station was functioning or not, which indicates a potential lack of importance the participant placed on reliability. In contrast, participant #16 mentioned that the reliability of public charging points could be observed by using the Zap Map, which provides reviews of charging points. This participant relied on the experiences and opinions of previous users of the public charging point to assess its reliability before trying it out. In addition, participant #12 reported the energy source was not clear enough as no example was provided.

2 Terminology

A terminology issue can be described as the utilisation of specialised vocabulary or technical jargon that impedes comprehension and creates a lack of clarity among the target participants. This can result in a breakdown of effective communication and hinder the intended message from being understood. If key terms in survey questions are not understood consistently, these unclear terms can enlarge systematic error in survey measurement (Fowler 1992).

Regarding the survey question “Q5 Do you drive a conventional car?”, most participants had a clear understanding of the term “conventional car”, and could even specify the type of car, such as petrol or diesel. However, three participants (#2, #4, #10) reported confusion about the meaning of the term “conventional car”. One participant (#2) asked “you just mean like a normal petrol car?”, which indicates that the participant was not very familiar with this term. Meanwhile, this participant also suggested that specifying the fuel type of the car would make the question clearer. Participant #10 wondered if the term “conventional car” refers to a “non-electric vehicle” as the participant perceived this term to be a “normal car”, which also implies that EVs are not normal or unconventional. However, a concern has been pointed out by the participant that electric vehicles are becoming more common and may no longer be considered unconventional nowadays. Another participant (#4) demonstrated a complete misunderstanding of the term “conventional car” by associating it with the travel purpose of the car. This participant stated “... any car that you probably used for leisure”, such as small SUVs are conventional cars, while those used for commercial purposes are not.

3 Overlapping

Overlap issues refer to the presence of multiple questions or question options in the survey materials that cover the same or similar topics or gather redundant information. The presence of overlapping questions can lead to response bias (Biemer 2010) and also increased respondent burden. To ensure high-quality surveys, it is important to identify and minimise overlap issues through careful review and refinement of the survey instrument. This is particularly important for a rating scale question where adjacent points should not overlap to ensure clarity and accurate measurement (Krosnick and Presser 2010).

Table 2: Summary of the frequency of occurrence of overlap issues in questions and options, and examples of evidence

The original question	Overlap issues	Number of participants (out of 20)	Example of evidence
“Q13. What is your understanding of public charging for electric vehicles?” and “Q14. How do you perceive the current public charging infrastructure/stations/points?”	Perceived these two questions the same	8	“It’s not clear to me which of these (public charging points) I could or couldn’t use, and whether I’d have to buy a particular type of car” (#6)
“Q15. (If you are EV users) What do you think it is important for you to consider when using public charging infrastructure/stations/points? Easy to access Convenient to use”	Perceived “easy to access” and “convenient to use” the same	4	“Easy to access and convenient to use sound the same” (#6)
“Q11. Do you have access to public charging? How often you use it?” and “Q12. Do you have access to fast charging? How often you use it?”	Interpreted these two questions the same	2	“I’m not a prolific user of public charging, but my understanding is that it’s all fast charging” (#17)

The overlap can be found among questions. For example:

- Eight participants (#2, #3, #6, #8, #11, #12, #14, #17) interpreted the “understanding of public charging” and “perception of public charging infrastructure” questions the same or mixed up the two questions, by either answering both questions with similar answers (#2, #8, #11, #12), or skipping one of the two questions (#3).
- Two EV users (#16, #17) shared a common perception that there is not much difference between public and fast charging. For example: “I’m not a prolific user of public charging, but my understanding is that it’s all fast charging” (#17).

Meanwhile, an overlap can be found among question options. In terms of the participants’ perception of factors for public charging, four participants (#5, #6, #8, #12) perceived the “easy to access” and “convenient to use” factors to be the same. For example, participant #12 mentioned that it was difficult to park and plug in because of the lack of parking space at public charging points. This indicates that the participant associated “easy to access” and “convenient to use” with the parking space of public charging points.

4 Derived new questions or options

Some extra information from cognitive interviews with the participants can be a valuable source for researchers to derive new survey questions. The following survey questions were derived from participants’ responses towards interview questions.

- A lack of knowledge about “public charging”

Regarding the survey question “Q13. What is your understanding of public charging for electric vehicles”, 11 of the 20 participants (Participants #1, #4, #6, #8, #13, #14, #15, #16, #17, #19, and #20) demonstrated a proficient understanding of the concept of public charging for electric vehicles by accurately interpreting the question and providing relevant responses. These participants identified that public charging points were located in public areas such as supermarkets (#1, #4, #7, #8, #19), shops (#13), restaurants (#8), on-street (#7), shopping centres (#4), cinemas (#4), and motorway service stations or petrol stations (#8, #14). Some of them also recognised that public charging points require payment (#8, #20) and can have different charging speeds (#15, #16) and prices (#20).

However, five participants (#5, #6, #7, #8, #13) displayed limited knowledge and struggled to explain the concept of public charging. For example, some participants did not know how public charging worked (#5, #8), payment requirements (#5), and pricing, including whether

or not it was free (#7, #8). Most participants thought that public charging was charging points in public places according to what was mentioned above. However, there were still some participants who perceived that public charging points were those located at work (#6, #13) or at curbside pavement charging points in newly constructed residential areas (#6), which indicates there was a mix-up between public charging and workplace charging as well as home charging.

Table 3: Summary of the frequency of occurrence of terminology issues in questions, and examples of evidence

The original question	Terminology issues	Number of participants (out of 20)	Example of evidence
“Q13. What is your understanding of public charging for electric vehicles?”	Struggled to explain the concept of “public charging”	3	“I am not sure how it works” and “how do you pay for it?” and “I’m not sure how long these are for you” (#5)
“Q13. What is your understanding of public charging for electric vehicles?”	Mixed up “public charging” with home and workplace charging	2	“New housing areas where they’ve put in curbside pavement side charging points. Where I work ... they’ve put in four. It’s just places that when you’re visiting somewhere, or I guess working somewhere that you can charge up that isn’t your house basically” (#6)

- A need for cities/town classification

Three participants (#1, #2, # 4) mentioned the quantity difference of public charging infrastructure in urban and rural areas or cities and towns. For example, participant #1 expressed the view that they are common around London, but scarce out of London. Participant #2 expressed the public charging infrastructure is “limited” around the participant” because the participant stressed, “[I] can’t comment on other areas”. At the same time, participant #2 mentioned that the town in which the participant lived had poor infrastructure and was a low-income town, which perhaps explains the lack of services, suggesting that there should be a distinction between different settlement sizes in terms of public charging infrastructure, such

as cities and towns, or urban and rural areas. Participant #4 also mentioned charging infrastructure is more in “busy metropolitan areas” such as London, but less in “small towns or villages”. Participant #8 shared that the quantity of public charging infrastructure was “growing” in the participant’s local area, such as “fuel stations” and the participant’s office, which is in the “town centre of Birmingham”, and also a lot of them in “other cities such as London”.

- Reasons for using home, workplace, public slow/fast charging

Some participants mentioned the reasons for using or not using home (#14, #16, #17), workplace, public (#14, #20), and fast charging (#14, #17). Reasons for using home charging are cheap monthly charging cost compared to petrol car (#17), “monthly charging fee (£14) with former used petrol car (£170)”, or cheap overnight tariff (#18, #20). The reasons why respondents did not install home charging mainly because they were not clear about the running cost of charging (#14), or did not have a driveway (#16). In terms of public charging, participant #14 mentioned the density of the infrastructure is sufficient and easy to access as not many people are using this, while participant #20 stated the reason for using it is because the subscription payment model may be cheaper than pay-as-you-go. Participant #17 cautioned against frequent fast charging, as it may have a negative impact on battery life. Meanwhile, this participant expressed a negative attitude towards both public charging stations and fast charging stations, likening them to petrol stations. The participant disliked any form of human interaction at these stations. Therefore, the participant found home charging to be the most comfortable method of charging.

- Specify the charging frequency

Five questions on the accessibility and frequency of use of charging facilities (Q9-Q12) (home, work, public, fast charging) were asked for EV users. Since these questions were open-ended, the different responses to the frequency of use of different charging facilities were the inspiration for generating options for these questions in later versions of the survey. For private home charging, the frequency of usage was generally mentioned as “every other night” (#15), “every day” (#19), and “daily” (#18), which indicates habitual charging behaviour on a daily basis. When it comes to public charging, participants used the words “on multiple occasions” (#15), “once a month” and “every two weeks” (#19) to describe the frequency of usage.

- Range anxiety attitude

When talking about the fast charging usage frequency question, some participants (#14, #17) seemed to be range anxious. Participant #14 stated that the reason for owning a hybrid car was because the participant “does not want to be stuck with this charging point” with a concern of not knowing where to charge if it is a long-distance journey. This response suggests the need to focus on the range of anxiety attitudes of participants in the main survey.

5 Language issues

The general language issues in survey questions refer to problems or challenges related to the wording, phrasing, or clarity of the questions. They can lead to misinterpretation or confusion among respondents (Peytcheva 2020). Therefore, addressing language issues in survey questions is crucial for ensuring the quality and validity of the collected data (Gabel 2020). Table 8 shows the general language issues in questions and options.

- Grammar issue

Seven (7) participants (#1, #2, #3, #5, #6, #9, #10) expressed confusion about the grammar mistake of “if you were an EV user”, for example, participant #1 showed hesitation, not knowing whether to continue to answer the question as this participant is not an actual EV user. Similarly, participants #2 and #3 also mentioned this issue respectively, “If I am a user? I am not a user at the moment” (#2), and “I am not sure if I can answer the third question” because “I do not have an electric car” (#3).

- Repetition

Participant #6 suggested only use “public charging point” instead of “public charging infrastructure/stations/points” for Q14, if the researcher is interested in the public charging point and deleting other descriptions as this participant perceived all these descriptions, to have the same meaning.

- Language codability

Language codability refers to the degree of ease with which a concept can be effectively conveyed in a given language (Whitney 1998). It is observed that concepts that are more frequently encountered and commonly used tend to possess higher codability. These concepts are typically associated with words that are shorter in length, simple to write, and easy to

pronounce. For example, participant #13 mentioned fast charging is usually called “rapid charging” in everyday life for charging points with more than 50 kWh of charging power.

Table 4: Summary of the frequency of occurrence of general language issues in questions and options, and examples of evidence

The original question	General language issues	Number of participants (out of 20)	Example of evidence
“Q15. (If you are EV users) What do you think it is important for you to consider when using public charging infrastructure/stations/points? ”	Grammar mistake	7	“If I am a user? I am not a user at the moment” (#2)
“Q14. How do you perceive the current public charging infrastructure/stations/points?”	Repetitive information for “charging infrastructure/stations/points”	1	“All these seem to have the same meaning” (#6)
“Q12. Do you have access to fast charging? How often you use it?”	Language codability of “fast charging”	1	“Fast charging is usually called as rapid charging in everyday life for charging points with more than 50 kWh of charging power” (#13)

Appendix D. Official survey questionnaire for data collection

Public Charging Preferences of Potential and Existing Electric Vehicle Users in Great Britain

Start of Block: Introductory questions

Welcome text



Public Charging Preferences of Potential and Existing Electric Vehicle Users in Great Britain

Thank you for your interest in participating in this research!

We advise that you use a laptop or desktop computer to answer these questions instead of a mobile phone. Please, read the information below to learn more about what is involved.

Purpose of the research

The aim of the survey is to better understand which factors could influence preferences for electric vehicle public charging.

What taking part involves

You must be a resident in Great Britain and 18 years of age or older to participate in this study. If you have any questions or concerns about this research, please feel free to contact any of the researchers involved in the project, using the contact details below.

This research will involve completing an online survey, which will take roughly 15 minutes. During this time, you will be asked a series of questions about your car use and public charging for electric vehicles.

No special knowledge is required to complete this survey. Your participation is completely voluntary, you do not have to answer all the questions if you do not wish to, and you may withdraw from the study at any point.

Your data

The information provided by you in the survey will be held anonymously, so it will be impossible to trace this information back to you individually. The anonymous data itself will be held indefinitely and may be used to produce reports, presentations, and academic publications. The anonymous data may be deposited at a recognised and secure repository (UK Data Service).

GDPR statement

The information provided will be held in compliance with UK General Data Protection Regulation. Cardiff University is the data controller and the Data Protection Policy can be found at: <https://www.cardiff.ac.uk/public-information/policies-and-procedures/data-protection>. This study has received ethical approval from the Research Ethics Committee (SREC) in the School of Geography and Planning, Cardiff University. Any complaints or queries should be sent to: GandPEthics@cardiff.ac.uk. The lawful basis for the processing of the data you provide is consent. The data collected in this research is part of a PhD project, only the researchers involved in this project will have access to this data. The lawful basis for processing this information is public interest.

Investigator contact details:

Rongqiu Song, email: Songr3@cardiff.ac.uk

Dr. Dimitris Potoglou, email: PotoglouD@cardiff.ac.uk

Page Break

Q0 If you have read and understood the information on the previous page and are willing to participate in this study, please tick the box below and click "Next" to continue:

☐ I consent to participate in this study (1)

Q1 We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you provide thoughtful answers to each question in this survey.

Do you commit to providing thoughtful answers to the questions in the survey?

- ☐ I can't promise either way (1)
- ☐ Yes, I will (2)
- ☐ No, I will not (3)

Skip To: End of Block If Q1 != 2

Q2 Do you have a full driving license?

- ☐ Yes (1)
- ☐ No (2)

Skip To: End of Block If Q2 = 2

Q3 What is your age group?

- ☐ Under 18 (1)
- ☐ 18-24 (2)
- ☐ 25-34 (3)
- ☐ 35-44 (4)
- ☐ 45-54 (5)
- ☐ 55-64 (6)
- ☐ 65-74 (7)
- ☐ 75+ (8)

Skip To: End of Block If Q3 = 1

Q4 Do you drive a car and what type of car do you drive most often?

- ☐ Yes, an internal combustion engine (ICE) car (e.g., petrol or diesel) (1)
- ☐ Yes, a hybrid car (2)
- ☐ Yes, a plug-in hybrid car (3)
- ☐ Yes, a full battery electric car (4)
- ☐ No, I do not drive a car currently (5)

Skip To: Q6 If Q4 = 5

Carry Forward Selected Choices from "Q4"

Q5 How long have you been driving the car you mentioned?

	Less than 1 year (1)	1-5 years (2)	Over 5 years (3)
Yes, an internal combustion engine (ICE) car (e.g., petrol or diesel) (Q4_x1)	☐	☐	☐
Yes, a hybrid car (Q4_x2)	☐	☐	☐
Yes, a plug-in hybrid car (Q4_x4)	☐	☐	☐
Yes, a full battery electric car (Q5_x5)	☐	☐	☐
No, I do not drive a car currently (Q5_x6)	☐	☐	☐

Q6 What is your understanding of public charging for electric vehicles?

- ☐ I am very familiar with all aspects of public charging including locations, speeds, prices, payment methods as well as concepts of different technologies involved (e.g. smart charging, V2G). (1)
- ☐ I am familiar with some aspects of public charging; for example, locations, speeds, prices, and payment methods. (2)
- ☐ I only know a single aspect of public charging; for example, only locations, speed, price, or payment methods. (3)
- ☐ I do not know anything about public charging. (4)

Q7 Would you agree or disagree that the number of public charging points available in your area is sufficient.

- ☐ Strongly agree (1)
- ☐ Agree (2)
- ☐ Neutral (3)
- ☐ Disagree (4)
- ☐ Strongly disagree (5)
- ☐ Not sure (6)

Display This Question:

If Q4 = 3

Or Q4 = 4

Q8 How often do you use electric vehicle charging according to the following options?

	Dail y (1)	5-6 times/wee k (2)	3-4 times/wee k (3)	1-2 times/wee k (4)	1-2 times/mont h (5)	Less frequentl y (6)	Neve r (7)
Home charging (Q7_1)	☐	☐	☐	☐	☐	☐	☐
Workplac e charging (Q7_2)	☐	☐	☐	☐	☐	☐	☐
Public slow charging (Q7_3)	☐	☐	☐	☐	☐	☐	☐
Public fast charging (Q7_4)	☐	☐	☐	☐	☐	☐	☐

Display This Question:

If Q4 = 3

Or Q4 = 4

Q9 How satisfied are you with the current public charging service in your area?

- ☐ Very satisfied (1)
- ☐ Satisfied (2)
- ☐ Neither satisfied nor satisfied (3)
- ☐ Dissatisfied (4)
- ☐ Very dissatisfied (5)

Q10 How important are the following characteristics of public charging, even if you do not currently drive an electric vehicle?

	Very Important (1)	Important (2)	Neither (3)	Not Important (4)	Not at all Important (5)
Charging speed (Q9_1)	☐	☐	☐	☐	☐
Amenities (e.g., toilets, shops) (Q9_2)	☐	☐	☐	☐	☐
Pricing (Q9_3)	☐	☐	☐	☐	☐
Easy access (e.g., high density and visibility, enough parking space and quantity of chargers) (Q9_4)	☐	☐	☐	☐	☐

Q10 How important are the following characteristics of public charging, even if you do not currently drive an electric vehicle?

	Very Important (1)	Important (2)	Neither (3)	Not Important (4)	Not at all Important (5)
Convenient to pay (e.g., easy to pay, multiple payment methods, app for all operators) (Q9_5)	☐	☐	☐	☐	☐
Clear information (e.g., about location, availability, pricing, use clean energy) (Q9_6)	☐	☐	☐	☐	☐
Safety (e.g., personal, vehicle, personal information privacy) (Q9_7)	☐	☐	☐	☐	☐
Reliability (e.g., whether chargers are working or not) (Q9_8)	☐	☐	☐	☐	☐

Attributes Description

Next, we will present you with five choice cards, like the one below, and we will ask you to make a choice across: on street, surface-level car park, and multi-storey car park. The "Description" column shows different characteristics of public charging for electric vehicles at these locations. The following is a detailed description of these characteristics:

- **Fast charging available** - Indicates whether the public charging location offers fast charging (V) or slow charging (X).
- **Waiting time (minutes)** - This is the time you may need to wait for a charging location to become available.
- **Amenities** - The amenities likely to be available at the charging location can include: a waiting room, small shop or café, or nearby shopping centre.
- **Cost (p/kWh)** - This is the electricity rate in pence per kilowatt hour charged at the location.
- **Percentage of renewable sources (e.g. wind, solar)** - The proportion of clean energy sources utilised to generate the energy provided at the public charging location.
- **Authentication** - Electric vehicle users may be required to provide identification or credentials to start charging. These credentials may include a membership card (RFID card), smartphone app, or users may just simply to plug in the charger to automatically authenticate and start charging.
- **Payment methods** - The methods used by the customer to pay for public charging.
- **Number of charging points** - This is the total number of charging points available at the location.
- **Station rating** - The station rating by previous users.

End of Block: Introductory questions

Start of Block: Block 1



SC2 Card 1 of 5

Given the options below, which location would you choose to charge your electric vehicle?

- ☐ On street (1)
- ☐ Surface level car park (2)
- ☐ Multi-storey car park (3)

SC11 Card 2 of 5

Under these options, which location would you choose to charge your electric vehicle?

- ☐ On street (1)
- ☐ Surface level car park (2)
- ☐ Multi-storey car park (3)

SC28 Card 3 of 5

Now, which location would you choose?

- ☐ On street (1)
- ☐ Surface level car park (2)
- ☐ Multi-storey car park (3)



SC35 Card 4 of 5

Which location would you choose now?

- ☐ On street (1)
- ☐ Surface level car park (2)
- ☐ Multi-storey car park (3)

SC39 Card 5 of 5

Finally, which location would you choose to charge your electric vehicle?

- ☐ On street (1)
- ☐ Surface level car park (2)
- ☐ Multi-storey car park (3)

Q11 Did you understand the choices we presented in the previous five cards?

- ☐ Yes (1)
- ☐ Most parts (2)
- ☐ Only a few (3)
- ☐ No (4)

Display This Question:

If Q11 != 1

Q12 Which, if any, aspects of the choice cards did you find difficult to understand?

Display This Question:If Q11 != 1

Q13 Which of the following attribute was unclear to you, if any? (allow multiple choices)

- ☐ Fast charging availability (1)
- ☐ Method of Payment (2)
- ☐ Waiting time (3)
- ☐ Amenities at the charging station (4)
- ☐ Cost (p/kWh) (5)
- ☐ % of renewable sources (6)
- ☐ Authentication (7)
- ☐ Number of charging points (8)
- ☐ Station rating (9)
- ☐ All attributes were clear (10)

Now, we will ask you some questions regarding your personal attitudes and demographic characteristics.

Q14 To what extent do you agree with the following statements?

	Strongly agree (1)	Somewhat agree (2)	Neither (3)	Somewhat disagree (4)	Strongly disagree (5)
There are natural limits to growth that our industrialised world has reached long ago (Q13_1)	☐	☐	☐	☐	☐
For the environmental benefit, we should all be willing to restrict our current standard of living (Q13_2)	☐	☐	☐	☐	☐
We need more economic growth, even if it pollutes the environment (Q13_3)	☐	☐	☐	☐	☐
More environmental protection also means more quality of life and health for all (Q13_4)	☐	☐	☐	☐	☐

Q15 To what extent do you agree with the following statements, even if you do not currently drive a car?

	Strongly agree (1)	Somewhat agree (2)	Neither (3)	Somewhat disagree (4)	Strongly disagree (5)
When I leave the car in the parking spot, I keep valuables secured out of sight (Q14_1)	☐	☐	☐	☐	☐
When I leave the car in the parking spot, I lock the doors (Q14_2)	☐	☐	☐	☐	☐
I avoid any situation that may cause danger (Q14_3)	☐	☐	☐	☐	☐
I do not care to leave the car in risky neighbourhood (Q14_4)	☐	☐	☐	☐	☐
I usually leave the car on high traffic roads (Q14_5)	☐	☐	☐	☐	☐

Q16 To what extent do you agree with the following statements?

	Strongly agree (1)	Somewhat agree (2)	Neither (3)	Somewhat disagree (4)	Strongly disagree (5)
I am very interested in the latest technology developments (Q15_1)	☐	☐	☐	☐	☐
It doesn't take me long to learn to like new technology developments (Q15_2)	☐	☐	☐	☐	☐
I am always keen to use the latest technological devices (Q15_3)	☐	☐	☐	☐	☐

Q17 How do you self-identify?

☐ Male (1)

☐ Female (2)

☐ Prefer not to say (3)

☐ Please specify (4) _____

Q18 Do you have a university degree or higher?

☐ Yes (1)

☐ No (2)

Q19 What is your approximate household income (before tax) per year?

- ☐ £15,000 or less (1)
- ☐ £15,001-£25,000 (2)
- ☐ £25,001-£35,000 (3)
- ☐ £35,001-£45,000 (4)
- ☐ £45,001-£55,000 (5)
- ☐ £55,001-£65,000 (6)
- ☐ £65,001-£75,000 (7)
- ☐ £75,001-£85,000 (8)
- ☐ £85,001-£95,000 (9)
- ☐ £95,001-£105,000 (10)
- ☐ £105,001 or more (11)

Page Break



Q20 Including yourself, how many individuals over the age of 18 live in your household?

Q21 Do you have children?

☐ Yes (1)

☐ No (2)

☐ Prefer not to say (3)

Display This Question:

If Q21 = 1



Q22 How many children under the age of 18 do you have?

Q23 How many cars do you have?



Q24 What is your ethnic background?

- ☐ Asian or Asian British (1)
- ☐ Black, African, Black British or Caribbean (2)
- ☐ Mixed or multiple ethnic groups (3)
- ☐ White (4)
- ☐ Another ethnic group (5)
- ☐ Prefer not to say (6)

Q25 Where do you currently live?

- ☐ London (1)
 - ☐ North East (2)
 - ☐ North West (3)
 - ☐ Yorkshire and The Humber (4)
 - ☐ East Midlands (5)
 - ☐ West Midlands (6)
 - ☐ East of England (7)
 - ☐ South East (8)
 - ☐ South West (9)
 - ☐ Scotland (10)
 - ☐ Wales (11)
-

Q26 Please select the setting of your place of residence.

- ☐ City/urban (1)
- ☐ Small town/suburban area (2)
- ☐ Village/fringe of town (3)
- ☐ Isolated rural area (4)

Q27 In what type of house are you living?

- ☐ Detached House (1)
- ☐ Attached House (e.g. townhouse, duplex, etc.) (2)
- ☐ Apartment (3)
- ☐ Mobile Home (4)