

Planning for public charging: Contrasting choices by electric-vehicle and non-electric vehicle users

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ARTICLE INFO

Keywords:

Electric vehicles
Public charging choices
Latent class model
Segmentation
Great Britain

ABSTRACT

Accessible and well-designed public charging points are key elements towards the wider adoption of electric vehicles (EVs), highlighting the need to understand user preferences. This study examines public charging choices of 300 EV users and 288 non-EV users in Great Britain through a stated choice experiment and latent class modelling. Results revealed two distinct segments within each user group. Among EV users, a larger segment prioritised charging price, while a smaller one valued waiting time, charging speed, convenience, available amenities, and high station ratings. By contrast, both non-EV segments remained sensitive to charging price and waiting time, including the larger service-oriented segment. These patterns align with Rogers' Diffusion of Innovation Theory, highlighting behavioural and socio-demographic variations in readiness to engage with public charging infrastructure. The findings provide practical guidance for developing more inclusive and targeted public charging infrastructure that improves user experiences, lowers adoption barriers, and supports the broader shift towards electric mobility.

1. Introduction

Electric vehicles (EVs) are increasingly seen as a key part of the shift towards a low-carbon future. Governments worldwide are promoting the electrification of private mobility as a key strategy for reducing greenhouse gas emissions and improving urban air quality (IEA, 2025). As a result, EV markets have expanded rapidly over the past decade, supported by a combination of regulatory targets, EV mandates, financial and non-financial incentives for EV purchases, and large-scale investment in charging infrastructure (Song & Potoglou, 2020).

Infrastructure plays a central role in enabling and accelerating EV adoption (Anilan & Vij, 2024). A growing body of evidence shows that the availability, accessibility, and reliability of charging infrastructure are among the most important determinants of consumers' willingness to adopt electric vehicles, as they directly shape perceived range anxiety, convenience, and usability (Hardman et al., 2018; Sierczula et al., 2014). Although home charging remains the dominant charging mode in many countries, public charging infrastructure performs a critical complementary function by supporting long-distance travel, enabling access for users without private parking, and reducing both perceived and actual range constraints (Neaimeh et al., 2017). Therefore,

understanding consumers' public charging preferences is central to designing and implementing the infrastructure required to achieve these ambitious goals.

Empirical research has thus far examined factors associated with public charging choices and station utilisation, highlighting the role of temporal conditions (e.g., time of day and charging duration), vehicle attributes (e.g., battery range and state of charge), charging infrastructure characteristics (e.g., speed, price, availability, and reliability), and individual factors (e.g., income and travel behaviour) (Potoglou et al., 2023). In addition, land-use patterns and built-environment characteristics that are central to urban planning, including metro and bus station density (e.g., Cai et al., 2023; Jin et al., 2025), population density (e.g., Cai et al., 2023; Jin et al., 2025), land-use mix (e.g., Cai et al., 2023; He et al., 2022; Liu & He, 2025; Zhao et al., 2024), and road network accessibility (Zhao et al., 2024), have also been shown to affect public charging choices and station utilisation.

These studies provide important insights and are frequently used to inform infrastructure planning and policy decisions. However, in most existing research, planning considerations are largely derived ex post from observed charging behaviour or utilisation patterns, or spatial demand distributions, with charging infrastructure treated primarily as

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<https://doi.org/10.1016/j.cities.2026.107578>

Received 12 September 2025; Received in revised form 25 August 2026; Accepted 7 September 2026

Available online 16 September 2026

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an outcome of behavioural and spatial processes (Potoglou et al., 2023). In contrast, relatively limited research has adopted a planning-led, ex ante perspective that conceptualises public charging stations as designable infrastructure units and systematically examines how their intrinsic characteristics, such as location type, charging speed, capacity, service quality, and on-site amenities, shape consumer charging preferences.

Moreover, most studies have examined EV- and non-EV-users separately (Potoglou et al., 2023). For instance, Ge and MacKenzie (2022) focused on public charging choices of BEV users during long-distance travel, while Ma et al. (2022) investigated how potential EV users choose between charging at home, at work, or other requested locations. Few studies directly compare their public charging choices within a unified analytical framework. Such comparisons are crucial for understanding adoption readiness and for designing an inclusive charging infrastructure from a planning perspective that meets the needs of both current and potential EV users.

This study addresses this gap by comparing public charging choices between EV and non-EV users from a planning perspective, with particular attention to how infrastructure attributes, such as charger location and type, speed, cost, accessibility, and on-site amenities, are linked with their public charging choices. The key objectives are to: (1) identify how EV users and non-EV users make trade-offs across different public-charging features and (2) explore the heterogeneity of preferences between these two groups.

This study contributes to the literature and policy debate in three main ways. Firstly, it advances a planning-led perspective on public charging by conceptualising charging stations as designable infrastructure units and examining how their intrinsic attributes, such as location context, charging speed, pricing, accessibility, and on-site amenities, shape consumer preferences. Secondly, it provides a unified empirical comparison of public charging choices between EV users and non-EV users, offering new evidence on how current and potential adopters differ in their valuation of alternative charging configurations. Thirdly, by translating consumer preference evidence into planning-relevant insights, the study informs the design configuration and service provision of public charging networks to better support EV adoption in the future.

The remainder of this paper is structured as follows: Section 2 provides a targeted literature review on public charging choices. Section 3 outlines the materials and methods used in the study, including the design and implementation of a choice experiment on public charging, and the analytical approach employed to analyse the data. The results of the study are presented in Section 4, followed by an interpretation and discussion of the key insights in Section 5. Finally, Section 6 summarises the main concluding points of this study.

2. Literature review

Understanding public charging choices is critical in promoting EV adoption and developing effective, user-oriented charging infrastructure. Research in this field generally draws upon two types of data paradigms: revealed preference (RP) and stated preference (SP) or stated choice (SC) data.

2.1. Revealed preference evidence on public charging behaviour

Revealed preference data is based on actual/observed behaviours, such as charging events logged by charging networks or vehicle usage patterns captured through GPS and on-board diagnostics. Recent RP studies have increasingly relied on large-scale charging transaction data and mobility datasets to examine real-world public charging behaviour under contemporary infrastructure and market conditions. For example, Liu and He (2025) analysed large-scale GPS trajectory and charging data from electrified taxi fleets and demonstrated that charging behaviour is strongly shaped by built-environment characteristics, temporal

conditions, and service demand, with significant spatial heterogeneity across urban areas. Similarly, Jin et al. (2025) employed multi-source ride-hailing data to identify spatially varying charging demand and showed that accessibility to transit nodes, residential density, and surrounding activity intensity play a key role in determining observed charging patterns. Using detailed charging session data from Montreal, Lamontagne et al. (2025) analysed more than 180,000 charging events across Level 2 and Level 3 stations and found that distance to stations, proximity to home locations, and the number of charging outlets are significant predictors of station usage. While amenities surrounding charging stations exhibited a neutral effect on average, substantial heterogeneity was observed, with some users showing strong preferences for, or aversion to, such locations.

While RP data offer valuable insights into real-world charging patterns, they are constrained by the current market environment and infrastructure (Hensher & Bradley, 1993). For example, they cannot reveal how users would behave if more fast chargers were available in residential areas, if dynamic pricing schemes were introduced, or if new technologies such as wireless charging were implemented.

2.2. Stated choice approaches and multidimensional public charging decisions

To overcome this limitation, a large body of research has employed SP/SC methods, which present individuals with hypothetical choice scenarios to explore preferences under controlled and policy-relevant conditions (Hensher et al., 2015). In the context of public charging, SC data enable the examination of preferences for alternative charging locations (e.g., leisure destinations, workplaces, motorways) (Bhat et al., 2024), different pricing schemes (Visaria et al., 2022), authentication methods (Gutjar & Kowald, 2023), and improvements in charger reliability and service quality (e.g., Letmathe et al., 2025).

Previous SC studies are shaped by an array of factors involving multiple levels of complexity, including temporal patterns, vehicle characteristics, infrastructure attributes, and individual socio-demographics (Potoglou et al., 2023). The multidimensional nature of these factors creates considerable complexity in consumer decision-making, particularly as users must frequently assess trade-offs among competing factors, such as cost versus speed under dynamic conditions (Song & Potoglou, 2024). For example, Ge and MacKenzie (2022) studied charging behaviour during long-distance travel and found that key factors influencing decisions included the vehicle's state of charge (SOC) and whether drivers could access the next charging point without altering their intended route. In contrast, Budnitz et al. (2024) examined local charging preferences in the UK and identified safety, walkability, and affordability as key factors for users without access to home charging.

2.3. Heterogeneity, adoption stages, and latent class studies

More recent studies further highlight a clear heterogeneity in observed public charging behaviour across locations and population groups. Using UK-based evidence, Hopkins et al. (2023) documented substantial spatial and socio-economic disparities in public charging provision and access, highlighting the uneven exposure to charging opportunities across regions. Theoretical insights from innovation diffusion further help to explain heterogeneity in EV-related preferences. According to Rogers' Diffusion of Innovations theory (Rogers, 2003), new technologies are adopted gradually, moving from innovators and early adopters to the early and late majority, and eventually to laggards. These groups differ in their willingness to take risks, their expectations of new technologies, and the conditions needed to support adoption. Building on this framework, Hardman et al. (2024) argued that current EV markets in most countries remained in an early adoption phase, and that progress towards mass adoption depended critically on resolving infrastructure-related barriers, particularly those

associated with availability, reliability, usability, and service quality. From this perspective, public charging infrastructure plays a dual role: for current EV users, it functions as an operational service embedded in everyday mobility, shaping travel routines and parking behaviour (e.g., Adsule & Manoj, 2025; Zhang et al., 2022), while for non-EV users, it represents a critical adoption threshold shaping their perceived feasibility and convenience (e.g., Hardman et al., 2018; Schulz & Rode, 2022). This perspective suggests that charging preferences may vary both between and within EV and non-EV users, and that this heterogeneity may partly reflect differences across stages of EV adoption, as well as the distinct roles that public charging plays for different user groups.

Capturing such variation requires approaches that move beyond treating users as a homogeneous group and instead allow for differences in how charging attributes are valued. In this context, a growing number of stated choice studies have adopted latent class models to identify different preference patterns in charging-related decisions (e.g., Hajhashemi et al., 2024; Yao et al., 2026). As synthesised in Table 1, existing latent class studies on public EV charging can broadly be grouped into two strands: those focusing exclusively on EV users, and those based on mixed consumer samples that pool EV and non-EV users.

Latent class studies based on EV-only samples consistently identify two broad types of charging preferences (Pan et al., 2019; Wang et al., 2021; Yao et al., 2026). One group of EV users places strong emphasis on operational efficiency and risk-related considerations, showing high sensitivity to charging cost, state of charge, and charging power. The other group attaches greater importance to the overall charging experience, valuing aspects such as waiting time, parking duration, amenities, perceived range comfort, and user satisfaction. Although different studies adopt varying labels and model specifications, this efficiency-oriented versus service- or experience-oriented distinction emerges consistently across contexts.

By contrast, there are limited studies that examined mixed consumer samples, in which EV and non-EV users are analysed jointly, revealing a broader and more diverse set of charging preference patterns. For example, as shown in Table 1, Hajhashemi et al. (2024) identified five charging styles, including routine-focused frugals, cost-oriented deliberators, range seekers, flexibility seekers, and indifferent late adopters. This suggests that wider consumers' charging preferences are primarily guided by simple decision rules or habits, such as relying on routine,

minimising cost, maintaining sufficient driving range, seeking flexibility, or showing little differentiation across charging options. Similarly, focusing on residential public charging in the UK based on a study of 2001 UK residents without access to private charging, Budnitz et al. (2024) distinguished three user segments, including value seekers, cautious users, and convenience customers, which differ primarily in their prioritisation of cost and parking certainty, safety and walkability, or proximity and continuity with existing parking routines.

While latent class models have deepened the understanding of heterogeneity in EV charging preferences, their use remains uneven across user groups and research perspectives. Firstly, very few studies explicitly examine public charging from a planning perspective, focusing on how the spatial configuration, location types, and surrounding land-use contexts of charging infrastructure influence user preferences. Secondly, and more critically, no existing study systematically compares EV and non-EV users within a unified analytical framework using the same set of planning-relevant public charging attributes. Most studies either focus exclusively on EV users or treat EV and non-EV users as a homogeneous group, despite evidence that these populations may exhibit fundamentally different charging-related decision structures. Without such comparative evidence, it is difficult to evaluate whether public charging infrastructure should be designed primarily to serve existing EV users or to accommodate the needs and expectations of future adopters.

This study addresses both gaps by using stated choice data to compare the public charging location preferences of EV and non-EV users within a unified latent class modelling framework. By focusing on planning-relevant attributes of public charging infrastructure, such as the number of charging points, surrounding amenities, and site accessibility, this research provides evidence to support more effective and inclusive public charging infrastructure planning that responds to the needs of both current EV users and future potential adopters of EVs.

3. Materials and methods

3.1. Study area

In the United Kingdom, the transition towards electric mobility has been underpinned by a comprehensive and evolving policy framework that combines financial incentives for vehicle adoption with large-scale support for charging infrastructure deployment (Song & Potoglou, 2020). While earlier schemes such as the traditional Plug-in Car Grant for private electric cars were phased out in June 2022, the government has subsequently introduced the Electric Car Grant in 2025, offering discounts of up to £3750 on qualifying new EVs. In parallel, a suite of infrastructure funding programmes has supported the expansion of charging capacity across the country through a combination of national schemes and local authority-led initiatives. A summary of the main UK EV policy and funding schemes is provided in Table 2. The EV Charge-point Grant continues to provide subsidies of up to £350 for home and workplace charging installations, while the Workplace Charging Scheme (WCS) offers up to £350 per socket to support businesses and organisations in installing workplace charging infrastructure. In residential neighbourhoods without off-street parking, the On-Street Residential Chargepoint Scheme (ORCS) played a central role in supporting local authorities to procure and install public on-street charge points until its completion in March 2025. Building on this legacy, the Local EV Infrastructure (LEVI) Fund now provides a successor framework in England, enabling local authorities to plan and deliver strategically coordinated charging infrastructure for residents without access to private charging.

Under these policy schemes, the number of battery electric vehicles (BEVs) has grown rapidly, reaching over 1.8 million by December 2025, which was more than four times the level recorded in 2021, when there were 396,945 electric cars representing just 1.2% of all cars on the road. However, by the end of 2025, this figure for BEVs had accounted for approximately 5.3% of all vehicles on UK roads (Zapmap, 2026b). Also,

Table 1
User segments in public EV charging behaviour identified using latent class models.

User group	Broad user types identified	Key distinguished features
EV users	• Efficiency- / cost- / risk-seeking users	Strong sensitivity to SOC (Pan et al., 2019; Wang et al., 2021), charging cost (Pan et al., 2019; Yao et al., 2026), charging power (Yao et al., 2026)
	• Service- / experience- / risk-averse users	Care about SOC (Wang et al., 2021; Yao et al., 2026), dwell or parking time (Wang et al., 2021; Yao et al., 2026), and excess range (Pan et al., 2019), satisfaction (Wang et al., 2021), queueing time (Wang et al., 2021; Yao et al., 2026)
Mixed samples	• Routine-focused frugals; • Cost-oriented deliberators; • Range seekers; • Flexibility seekers; • Indifferent late adopters; • Value seekers; • Cautious users; • Convenience customers;	Guided by simple decision rules or habits, including reliance on routine, cost minimisation, range considerations, flexibility seeking, or generally indifferent preferences (Hajhashemi et al., 2024) Value seekers prioritised low cost and parking certainty; Cautious users prioritised safety and walkability; Convenience customers prioritised proximity and routine continuity (Budnitz et al., 2024)

Table 2
Summary of UK EV-related policies and funding schemes.

Scheme	Aim	Start year/ Duration	Reference
Plug-in Car Grant	Reduce upfront cost of eligible plug-in vehicles to promote early EV adoption.	Started 2011; phased out in June 2022 (ended for private EVs)	Department for Transport (2022)
Electric Car Grant	New generation EV purchase subsidy offering up to £3750 discount on qualifying new EVs to support EV adoption.	Launched July 2025; expected to run to 2028/2029	Department for Transport and Office for Zero Emission Vehicles (2025)
EV Chargepoint Grant	Provide up to £350 subsidy for home/workplace chargepoint installations (part of broader infrastructure deployment support).	Replaced EV Homecharge Scheme from April 2022; available until March 2026	Office for Zero Emission Vehicles (2023b)
Workplace Charging Scheme	Provide up to £350 per socket grant to assist businesses/organisations install workplace chargepoints.	Open from 1 April 2022 to 31 March 2026	Office for Zero Emission Vehicles (2021)
On-Street Residential Chargepoint Scheme	Support local authorities in procuring and installing public on-street charge points for residents without off-street parking.	Started from 2016; Completed/closed in March 2025;	Office for Zero Emission Vehicles (2016)
Local EV Infrastructure (LEVI) Fund	Support local authorities (England) to plan and deliver coordinated charging infrastructure, building on ORCS.	Introduced 2023; ongoing in England	Office for Zero Emission Vehicles (2023a)

according to the EV Outlook 2025 report (IEA, 2025), EVs accounted for around 28% of new car sales in the UK in 2024, and the national EV stock share had reached approximately 6%, indicating that EV adoption in the UK has entered a phase of large-scale market diffusion.

The rapid growth of the EV fleet has been accompanied by a significant expansion of charging infrastructure. More than one million charge points have been installed at homes and workplaces (Zapmap, 2026a), and real-world evidence from London indicates that over 72% of total charging energy is delivered at home (Neaimeh et al., 2017), highlighting the central role of private charging in the UK charging ecosystem. However, public charging infrastructure remains a critical complementary component, particularly for supporting long-distance and inter-urban travel and for users without access to private charging (Neaimeh et al., 2017). In response to rising demand, the public charging network has expanded substantially, from 28,460 charging points in 2021 to 87,796 by December 2025 (Zapmap, 2026a). Of these, 17,935 are Rapid or Ultra-rapid charging devices. Although these high-power chargers account for only around 20% of all public charging devices, they provide approximately 60% of total charging capacity.

Despite this rapid expansion, substantial challenges remain. A major issue is the persistent shortage and uneven spatial distribution of public charging infrastructure relative to the size and geography of the growing EV fleet. As shown in Fig. 1, regional statistics from October 2025 reveal pronounced disparities in charger availability, with London hosting approximately 301 public charging points per 100,000 population, compared with fewer than 80 in regions such as the North West and

Yorkshire and the Humber, and fewer than 40 in Northern Ireland (Office for National Statistics, 2025). This pattern reflects a strong urban concentration, with 84.6% of public chargers in England located in urban areas, leaving many rural communities underserved (Department for Transport, 2025). In addition to issues of availability and accessibility, users also face problems with charger reliability and inconsistent payment systems, which continue to affect consumers' trust and convenience (Hardman et al., 2018).

As a result of these challenges, there is a growing call for a more coordinated, consumer-focused approach to infrastructure planning - one that ensures public charging is affordable, accessible, and aligned with users' everyday needs (HM Government, 2022). This includes delivering the right number of chargers in the right places, supporting local rollout through targeted investment, and ensuring equitable access for all drivers. Achieving this also requires aligning infrastructure deployment with clean energy goals, so that EVs are powered by low-carbon electricity (SMMT, 2022).

3.2. Design of the choice experiment for public charging choices

To investigate public charging user (and anticipated user) preferences in Great Britain and thus address the research objective of this study, a stated preference discrete choice experiment (SPDCE) was designed and implemented. It is a well-established method for presenting individuals with hypothetical scenarios and analysing participants' choices among different alternatives (Guerra & Daziano, 2020).

In the public charging scenario, each participant was presented with five different choice cards with three charging locations: (a) on-street, (b) surface-level car park, and (c) multi-storey car parks (see, an example in Fig. 2). Each location was described by nine (9) attributes, including charging prices, fast charging availability, waiting time, number of charging points, authentication methods, payment methods, energy source, available amenities, and station ratings at different charging locations. Participants were asked to make a choice based on their preference.

The design of the public-charging choice experiment, including its attributes and levels, was guided by literature reviews on the factors associated with public charging choices (Hardman et al., 2018; Potoglou et al., 2023). To refine the preliminary set of attributes and initial experimental design, feedback was gathered through 20 cognitive interviews and thematic analysis within a Great Britain-based convenience sample (see, Song & Potoglou, 2024). The final set of attributes and the choice context of the experiment reflected the most relevant dimensions of public charging infrastructure (e.g., operational, contextual, and user-experience features), along with their respective levels. The selected attributes, along with their respective levels, are shown in Table 3.

The *charging price* attribute in the choice experiment had six levels, ranging from £0.45/kWh to £0.90/kWh. The kWh-based fees were used to measure the cost of charging. This pricing model has been widely used in previous studies on public charging choices, with nearly half of the studies incorporating a charging cost attribute based on this measurement (Potoglou et al., 2023). This indicates that kWh-based fees are easy to accept for potential and existing EV users to make a choice, and this preference was further validated through cognitive interviews. The lower bounds of the charging price for slow and fast charging were derived from official pricing information published by major UK public charging providers (BP Pulse, 2022; Osprey, 2024) (see Table A1 in the Appendix). The intermediate levels were defined on the basis of having equal intervals and thus, ensure sufficient variation when capturing the sensitivity (effect) of respondents on charging prices within the stated choice experiment (Hensher et al., 2015). These points were validated with expert academics in the field. Finally, the charging price range was set from (1) £0.45/kWh, (2) £0.55/kWh, and (3) £0.60/kWh for slow charging, and from (4) £0.75/kWh, (5) £0.85/kWh, and (6) £0.90/kWh for fast charging.

The *waiting time* attribute in the choice experiment refers to the time

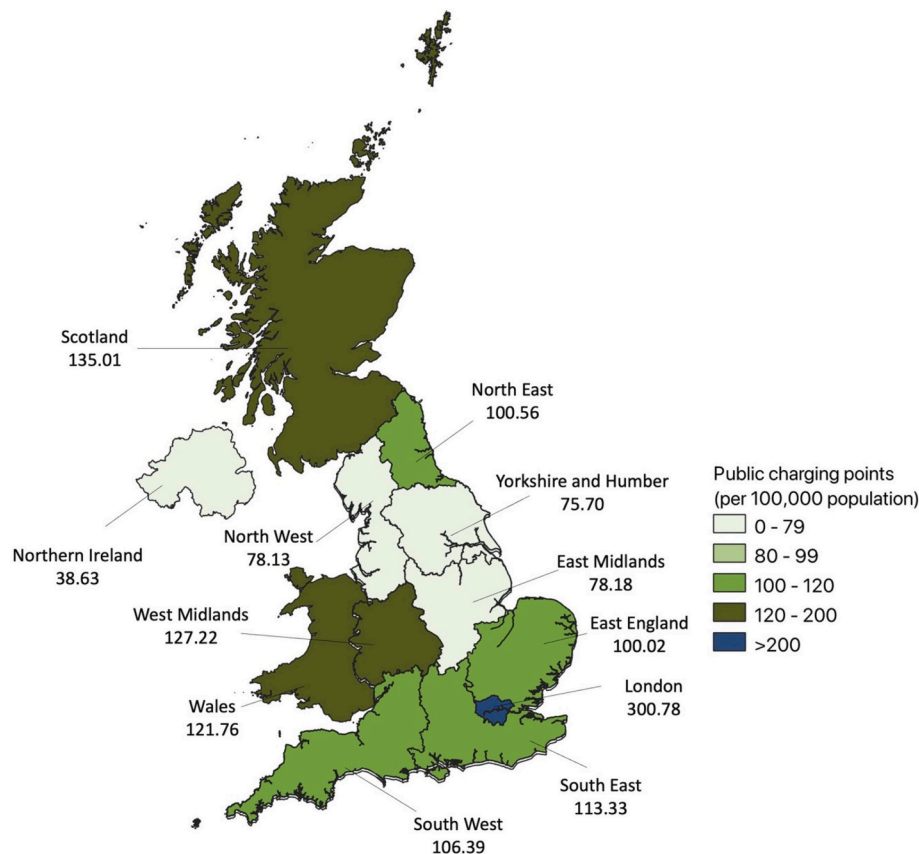


Fig. 1. EV public charging devices at all speeds per 100,000 people, October 2025. (Source: Department for Transport, obtained from Zapmap)

participants would need to wait for an available charging point, measured in minutes. This attribute had four levels: (i) available immediately, (ii) 2 min, (iii) 5 min, and (iv) 10 min. Previous research, for example [Ten Have et al. \(2020\)](#) reported that EV users generally preferred a “certain” waiting time of up to 5 min, over charging stations with uncertain or unpredictable waiting times.

Building on this insight, the choice experiment aimed to further investigate the impact of waiting time uncertainty by introducing another attribute: the number of charging points. This attribute was selected based on feedback from a participant from the cognitive interviews, who highlighted the number of available charging points was significantly associated with EV users' decision-making. As more charging points are added to stations, waiting times are likely to decrease, making the charging process more predictable and appealing to users. Previous studies, such as [Visaria et al. \(2022\)](#), have also highlighted the role of the charging point availability, showing that the number of vacant charging points can significantly affect users' choices to charge or not. Considering these findings, the *number of charging points* attribute was incorporated into the experiment, with four levels: (1) 2 charging points, (2) 4 charging points, (3) 6 charging points, and (4) 8 charging points. This attribute therefore aimed to capture the potential effects of charging station capacity on users' choices, specifically addressing how the number of available charging points can reduce waiting time uncertainty and be linked with their decision-making.

Payment methods for public charging have not been widely studied in previous studies ([Potoglou et al., 2023](#)). However, a report by the [Electric Vehicle Association England \(2021\)](#), based on a sample of 1216 EV users in England, found that 45% of EV drivers considered contactless credit or debit cards to be the most convenient payment method, followed by smartphone apps at 14%. A similar proportion of respondents also found membership using RFID cards to be a convenient

payment option. These payment methods are widely supported by public EV charging operators^{1,2} in the UK ([BP Pulse, 2022](#); [Osprey, 2024](#)). Generally, the operators' apps in the UK allow users to monitor real-time charging activity, review their charging history, download VAT invoices, and access monthly billing linked to credit or debit cards ([Osprey, 2024](#)). However, it's important to note that there is currently no universal app that works across all charging operators in the UK. Given these findings, this study incorporated both real-world and hypothetical payment methods (e.g., an app for all operators) in the choice experiment, including: (1) traditional card or contactless payment, (2) card, contactless, the operator's app, (3) card, contactless, an app for all operators, (4) card, contactless, an operator's card with RFID chip.

EV authentication involves verifying the identity of both the EV and its user, streamlining the charging and payment process to enhance speed and convenience. This attribute was introduced into the choice experiment, inspired by the study by [Gutjar and Kowald \(2023\)](#), which explored the effects of similar methods of EV authentication on public charging choices. The *authentication method* attribute in this study included three levels, each representing a different method of identification via: (1) the operator's app, which requires the user to authenticate their vehicle through a mobile application, (2) an operator's card with RFID chip, which is scanned to authenticate both the vehicle and the

¹ 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 Pawa.

² BP Pulse: contactless bank card, Apple Pay or Google Pay, network access card (RFID card), BP Pulse app.

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:	☐	☐	☐

Fig. 2. An example of a choice card.

Table 3
Attributes and levels used in the stated choice experiment.

Attribute	Levels					
	1	2	3	4	5	6
Fast charging available	V (Yes)	X (No)				
Method of payment	Card, Contactless	Card, Contactless, Operator's app	Card, Contactless, An app for all operators	Card, Contactless, An operator's card with RFID chip		
Waiting time (minutes)	Available right away	2	5	10		
Amenities at the charging station	No amenities	Waiting room	Small shop or café	Shopping centre		
Cost (p/kWh)	Slow charging prices 45	55	60	Fast charging prices 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 stars	4 stars	5 stars			

user, and (3) automatic authentication through the “Plug and Charge” system, where the vehicle automatically communicates with the charging station without the need for any additional user input. These options reflect varying levels of convenience and technology in the charging process.

The presence of a higher proportion of renewable-sourced energy at public charging points was positively associated with EV users' choices

(Nienhueser & Qiu, 2016; Wolff & Madlener, 2019). Building on these findings, this study introduced an attribute that focused on the percentage of renewable energy (e.g., wind, solar) used to power the charging station. This attribute aimed to further explore how the integration of renewable energy affects the attractiveness of charging stations to users. The *renewable energy* attribute was divided into five levels: (1) 0%, (2) 25%, (3) 50%, (4) 75%, and (5) 100%. These levels

represented different proportions of renewable energy in the charging station's energy mix, allowing the study to assess how users' choices may shift depending on the environmental sustainability of the charging source.

Amenities refer to proximal facilities near public charging locations. Ten Have et al. (2020) explored various amenity configurations, including cafés, small retail outlets, shopping centres, waiting rooms, and locations without any nearby services. Their findings indicated that slow chargers situated near shopping areas were perceived as more appealing. Additionally, in areas lacking supporting amenities, users showed a greater preference for fast and slow chargers over ultrafast ones. The four levels for this attribute in our choice experiment included: (1) none, (2) waiting room, (3) small shop or café, (4) shopping centre.

Finally, the *station rating* attribute was also introduced into the choice experiment to capture EV users' overall satisfaction with the charging service. This attribute reflected the quality of the charging experience as perceived by users. Previous studies, such as Wang et al. (2021), have shown that user satisfaction, often measured using a five-point Likert scale, played a significant role in influencing EV users' charging decisions. For this study, the station rating attribute was divided into three levels: (1) 3 stars, (2) 4 stars, and (3) 5 stars. The decision to exclude 1-star and 2-star ratings was based on the assumption that EV users are unlikely to choose charging stations with low service ratings, as these are typically associated with poor experiences.

As illustrated in Fig. 2, each charging location was characterised by these nine attributes, with levels varied using a D-efficient design based by the multinomial logit model (MNL). To inform parameter estimation, directionally informed priors were applied to attributes, as suggested by Hensher et al. (2015). A very small negative value (e.g., -0.00001) was assigned to attributes like charging price and slow charging speed, reflecting the anticipated negative impact these factors would have on user preference. For attributes with less predictable effects, such as authentication and payment methods, prior parameters were set to zero. The software Ngene 1.3 was used to generate sixty (60) choice tasks, which were divided into five blocks so that each participant was presented with five tasks (ChoiceMetrics, 2021).

3.3. Survey implementation

Prior to the main survey fieldwork, the choice experiment was pre-tested in two rounds of cognitive interviews conducted via the online platform 'Respondents.io', with a total of 25 participants. The first round took place between December 5 and 16, 2022 and included 20 participants: 10 EV users and 10 non-EV users (Song & Potoglou, 2024). Feedback from this round informed revisions to the choice experiment, which were subsequently validated in a second round of cognitive testing with five additional participants (3 non-EV users and 2 EV users).

After conducting internal survey checks, a 'soft launch' pilot involved another 30 respondents in Great Britain, which helped address any data quality issues. During the main survey, response times were monitored and responses completed under five (5) minutes were flagged as potentially insincere or inattentive, given the survey's complexity. These responses were excluded from the dataset and replaced with new valid entries. The mean time for respondents to complete the survey was 10.5 min.

The choice experiment and survey were administered on the Qualtrics survey platform (<https://www.qualtrics.com>) between September and October 2023. A total of 600 participants were targeted using a quota sampling method aiming at achieving an equal split between EV and non-EV users. The non-EV user sample was set to be representative of the 2021 census demographics – namely, age, gender, and region, whereas the EV user sample was relaxed for this restriction due to lack of an appropriate sampling frame for EV users.

3.4. Analytical approach

The analysis was conducted in two stages. Firstly, an exploratory analysis was performed to compare the socio-demographic characteristics of EV and non-EV users. This step was intended to identify potential differences in the profiles of the two groups, including factors such as age, gender, and regional location, which may associate with their choices for public charging infrastructure. Statistical tests were employed to quantify group differences: chi-square tests for categorical variables.

Secondly, Latent Class Logit (LCL) models were specified separately to both the EV user and non-EV user samples. The LCL model can capture the unobserved heterogeneity among individuals. Unlike multinomial logit (MNL) models, which assume independence among responses (in this case, five responses for each respondent) and adhere to the Independence of Irrelevant Alternatives (IIA) axiom, LCL models handle serial correlation within these responses and relax the IIA assumption (Hess, 2014). The LCL model can also identify latent subgroups with homogeneous choices within classes but heterogeneity across classes (Hess, 2014).

As shown in the calculation function below, LCL models categorise respondents into M latent classes, with class membership probabilities s_m derived from socio-demographic variables. Within each class m , a unique set of taste parameters β_m governs utility maximisation. The probability for respondent n choosing i is defined as (Train, 2009):

$$P_{ni} = \sum_{m=1}^M s_m \left(\frac{e^{\beta_m x_{ni}}}{\sum_{j=1}^J e^{\beta_m x_{nj}}} \right)$$

where s_m represents the probability of an individual being in class m , estimated via a logistic function of socio-demographic covariates (e.g., age, income). The nested fraction calculates the class-specific probability of choosing i , conditional on respondents' membership in that class. This dual structure allows the model to classify respondents into different behavioural groups and estimate class-specific choices (Hensher et al., 2015).

The optimal number of latent classes (M) was identified based on model selection criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio tests. Competing models with M classes were estimated, and the solution minimising the BIC (which penalises overfitting more than AIC) was selected. Class-specific parameters were then examined to interpret preferences for different attributes and evaluate how demographic characteristics associated with class membership. These models were estimated using STATA's `llogit2` package (Yoo, 2020).

4. Results

The final sample comprised of 588 responses, including 300 EV users and 288 non-EV users. To ensure data quality and relevance, a multi-step data cleaning process was implemented. Automated checks were used to exclude incomplete surveys, unqualified respondents, and "speeders" – i.e., participants who completed the survey in an unrealistically short time, suggesting insufficient engagement. Additional quality control steps included the exclusion of responses with long completion times and responses from participants who stated lack of understanding of the stated choice tasks. A further check identified non-trading behaviour, defined as consistently selecting the same option across all five choice cards and thus failing to demonstrate engagement with the trade-offs presented (Hensher et al., 2015).

4.1. Exploratory analysis of EV and non-EV user samples

As shown in Table 4, the exploratory analysis of the socio-

Table 4
Characteristics of EV and non-EV users.

	EV users (%)	Non-EV users (%)	Total (%)	Chi-square test
Gender				$\chi^2 (2) = 11.414^{**}$
Males	183 (61.0)	138 (47.9)	321 (54.6)	
Females	116 (38.7)	147 (52.1)	266 (45.2)	
Prefer not to say	1 (0.3)	–	1 (0.2)	
Age group				$\chi^2 (5) = 297.425^{***}$
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+	20 (6.7)	117 (40.6)	137 (23.3)	
Education qualification				$\chi^2 (1) = 72.943^{***}$
University degree or higher	227 (75.7)	118 (41.0)	345 (58.7)	
Below university degree	73 (24.3)	170 (59.0)	243 (41.3)	
Having children				$\chi^2 (2) = 9.167^{***}$
Yes	238 (79.3)	200 (69.4)	438 (74.5)	
No	58 (19.3)	86 (29.9)	144 (24.5)	
Prefer not to say	4 (1.3)	2 (0.7)	6 (1.0)	
Household size				$\chi^2 (2) = 10.391^{***}$
1	56 (18.8)	77 (26.9)	133 (22.8)	
2	156 (52.3)	155 (54.2)	311 (53.2)	
3+	86 (28.9)	54 (18.9)	140 (24.0)	
Rurality				$\chi^2 (2) = 40.725^{***}$
City/urban	156 (52.0)	76 (26.4)	232 (39.4)	
Small town/suburban area	99 (33.0)	139 (48.3)	238 (40.5)	
Rural area	45 (15.0)	73 (25.3)	118 (20.1)	
Type of housing				$\chi^2 (1) = 21.016^{***}$
Detached House	167 (55.7)	106 (36.8)	273 (46.4)	
Not detached house	133 (44.3)	182 (63.2)	315 (53.6)	
Ethnicity				$\chi^2 (2) = 16.752^{***}$
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				$\chi^2 (1) = 45.868^{***}$
London	90 (30.0)	23 (8.0)	113 (19.2)	
Not in London	210 (70.0)	265 (92.0)	475 (80.8)	
Annual household income				$\chi^2 (2) = 136.615^{***}$
< £25,000	23 (7.7)	107 (37.2)	130 (22.1)	
£25,001–£75,000	134 (44.7)	155 (53.8)	289 (49.2)	

Table 4 (continued)

	EV users (%)	Non-EV users (%)	Total (%)	Chi-square test
> £75,000	143 (47.7)	26 (9.0)	169 (28.7)	
No. of cars				$\chi^2 (2) = 46.127^{***}$
0	–	15 (5.2)	15 (2.6)	
1	177 (59.0)	219 (76.0)	396 (67.3)	
2+	123 (41.0)	54 (18.8)	177 (30.1)	
Total	300	288	588	

* $p \leq 0.10$.*** $p \leq 0.01$.** $p \leq 0.05$.

demographics reveals significant differences between EV and non-EV users: EV users were predominantly male (61.0%), younger (65.9% aged 25–44 vs. non-EV users skewed towards 55+), had a university degree or higher (75.7% with university degrees vs. 41.0%), and were ethnically more diverse (18.0% non-white vs. 6.9%). EV users lived in urban settings (52.0%) or London (30.0%), in detached homes (55.7%), earned higher income (47.7% > £75 k), owned multiple cars (41.0%), and had children in smaller sized households (79.3% with kids, 52.3% two-person households). In contrast, non-EV users were older, had lower education qualifications, were predominantly female (52.1%), lived in rural/suburban settings (73.6%), had lower-income (37.2% < £25 k), lived in non-detached housing (63.2%), typically owned one car (76.0%) and lived in larger or single-person households (55.8% single/3+). Ethnicity was more homogenous among non-EV users (92.7% white).

4.2. Public charging choices between EV and non-EV users

The first step in estimating the LCL models was to determine the optimal number of classes. This was done by examining the Bayesian Information Criterion (BIC). After testing various class configurations (2–4 classes), the model with 2 classes for both EV and non-EV users provided the best fit, as indicated by the lowest BIC values. In addition to information criteria, model selection also considered convergence stability, interpretability of class-specific parameters, and the behavioural plausibility of the resulting class profiles. Alternative specifications with three or more classes either resulted in class structures that were difficult to interpret in behavioural terms or did not converge reliably. Therefore, the two-class solution was selected as it offered the best balance between

Table 5
Goodness-of-fit statistics for latent class models with 2 to 4 classes.

No. of classes	Model characteristics	EV users	Non-EV users
2	df	35	35
	Log-likelihood (LL)	–1526.438	–1361.877
	AIC	3122.875	2793.753
	BIC	3347.29	3016.739
3	df	53	53
	Log-likelihood (LL)	–1488.649	–1304.553
	AIC	3083.298	2715.106
	BIC	3423.125	3052.77
4	df	71	Convergence not achieved
	Log-likelihood (LL)	–1473.745	
	AIC	3089.491	
	BIC	3544.731	
No. of cases		4500	4320
No. of observations (N)		1500	1440
No. of individuals		300	288
LL(0)		–1648	–1582

statistical fit and interpretability for both EV and non-EV user groups. Table 5 presents the characteristics and fit measures of the latent class models for different class configurations (2–4 classes) for both EV and non-EV users.

Tables 6 and 7 present the estimated coefficients for the two-class LCL models for both EV- and non-EV users. Table 6 shows the estimated coefficients for the relationships between various attributes (e.g., charging price, waiting time, amenities) and to the probability of selecting among the charging locations offered (on-street, surface-level car park, multi-storey car park). These coefficients reflect how each attribute was associated with the probability of selecting a particular

Table 6
Estimated coefficients of the latent class models for EV and non-EV users.

	EV users		Non-EV users	
	Class 1	Class 2	Class 1	Class 2
Probability of membership	0.674	0.326	0.417	0.583
Charging price (pence/kWh) × income higher than £75,000	−0.705	0.662	−2.962	−1.949*
Charging price (pence/kWh) × income equal and lower than £75,000	−2.652***	−0.836	−7.892***	−1.598**
Fast Charging Available	−0.129	1.145***	0.174	0.736***
Waiting time (minutes)	−0.007	−0.071***	−0.055***	−0.023**
% of renewable sources (e.g. wind, solar)	0.264**	0.198	0.176	0.509***
Number of charging points	0.023	0.043	0.043	0.006
Method of payment				
Card or contactless	Reference			
Card, contactless, or via operator's app	0.101	−0.217	−0.187	−0.052
Card, contactless, or via an app for all operators	0.003	−0.312	−0.145	0.119
Card, contactless, or an operator's card with RFID chip	0.124	−0.368*	−0.510**	0.017
Authentication methods				
Via the operator's app	Reference			
An operator's card with RFID chip	0.310***	−0.308*	0.230	−0.104
Automatic via Plug and Charge	0.132	0.306**	0.164	0.165*
Amenities at the charging station				
No amenities	Reference			
Waiting room	0.178	0.365*	−0.199	0.136
Small shop or café	0.111	0.494**	0.120	0.298**
Shopping centre	−0.003	0.701***	0.012	0.346***
Station rating				
3 Star	Reference			
4 Star	−0.029	0.475***	0.133	0.029
5 Star	−0.108	0.752***	0.328	0.488***
Alternative-specific constants				
Surface car park	0.049	0.222	−1.137***	0.434***
Multi-storey car park	−1.055***	0.394**	−1.300***	−0.165
No. of individuals	294		285	
No. of observations	1470		1425	
No. of cases	4410		4275	
Log-likelihood at convergence	−1472		−1329	

*** $p \leq 0.01$.

** $p \leq 0.05$.

* $p \leq 0.10$.

Table 7

Class membership model estimates.

	EV users	Non-EV users
Classes ±	Class 1	Class 1
Male	0.780**	1.075***
Age group	0.067	0.443***
Education	1.290***	0.264
White	0.494	−0.356
Children	−0.510	0.028
Detached house	0.205	−0.727*
Residence of living (reference: Non-urban area)		
Urban area	0.890**	−0.416
Constant	−1.380*	−2.523***

Note: ± Class 2 is the reference class for the class membership model.

*** $p \leq 0.01$.

** $p \leq 0.05$.

* $p \leq 0.10$.

station. Table 7, on the other hand, provides the coefficients of individual characteristics that explain the probability of a EV or non-EV user being assigned to a particular class, respectively. These coefficients also account for latent (unobserved) heterogeneity, capturing how individuals with different socio-demographic profiles or other unobserved factors may have distinct choices within each group. Table 6 shows notable differences in public charging choices among both EV and non-EV users, reflecting significant heterogeneity in respondents' choices. This heterogeneity, driven by random factors, was captured using LCL models. Two distinct classes were identified, each exhibiting unique preferences for various charging locations, including on-street chargers, surface parking areas, and multi-storey car parks. The details of these findings are discussed in the following subsections.

The specification of the membership model (see, Table 7) was guided by both statistical relevance and diagnostic tests for multicollinearity. While a broad set of socio-demographic variables was initially considered (see Table 4), only a subset was retained in the final model. Several variables, such as private car ownership, were examined in preliminary specifications but were excluded due to high correlations with other explanatory variables (e.g., income), which led to unstable parameter estimates. To a stable model with a limited number of well-justified variables, statistical robustness, and interpretability of class profiles, only variables with acceptable collinearity diagnostics and theoretical relevance were included in the final membership model reported in Table 7.

4.2.1. EV users

As shown in Table 6, the latent class model identified significant heterogeneity in public charging preferences among EV users, dividing them into two distinct groups. There was a higher probability (67.4%) that EV users belonged to Class 1 and a 32.6% probability of being in Class 2. This suggests that EV users were more likely to belong to Class 1 than Class 2.

Class 1 EV users, particularly those with middle and low household incomes ($\leq$ £75,000), exhibited a significant negative response to charging prices (coefficient = -2.652 , $p \leq 0.01$), indicating they are particularly sensitive to costs. In contrast, high-income EV users ($>$ £75,000) in Class 1 showed no significant sensitivity to charging price changes. Beyond charging prices, Class 1 EV users preferred charging stations that utilised higher levels of renewable energy (coefficient = 0.264 , $p \leq 0.05$). When it comes to authentication options, they were more inclined to use the operator's RFID card over the operator's app (coefficient = 0.310 , $p \leq 0.01$). However, Class 1 EV users did not see any difference in having multiple payment options over traditional cards and contactless payments, as all levels of payment methods were statistically insignificant. They also seemed indifferent to the presence of amenities around the charging station, and the station's rating did not significantly impact their choices. All else being equal, Class 1 EV users

were less likely to choose multi-storey car parks (coefficient = -1.055 , $p \leq 0.01$) when compared to on-street charging whereas there was no significant difference between charging at surface-level car parks and on-street locations. Also Table 7 shows that Class 1 EV users were more likely to be males, hold a university degree or higher education, and lived in urban areas.

On the other hand, Class 2 EV users were indifferent to charging prices, regardless of their income levels. They placed a higher value on the availability of fast charging (coefficient = 1.145 , $p \leq 0.01$) and expressed a strong aversion to long waiting times (coefficient = -0.071 , $p \leq 0.01$). They preferred the convenience of authenticating their vehicles automatically via Plug and Charge over using an RFID card (coefficient = 0.306 , $p \leq 0.05$), and they marginally disliked using the operator's RFID card (coefficient = -0.308 , $p \leq 0.10$), compared to authenticating via the operator's app. They also had a clear preference for stations with various amenities, such as waiting rooms (marginally significant, coefficient = 0.365 , $p \leq 0.10$), small shops or cafés (coefficient = 0.494 , $p \leq 0.05$), and shopping centres (coefficient = 0.701 , $p \leq 0.01$), compared to stations with no amenities. Additionally, they showed a strong preference for charging at higher-rated stations (4 and 5 stars), which both significant at 99% level. In terms of charging locations, Class 2 users preferred multi-storey car parks (coefficient = 0.394 , $p \leq 0.05$) over on-street charging, and perceived there is no difference to charge on street or at surface-level car parks, when all other factors were equal. Table 7 shows that Class 2 EV users were more likely to be female, without a university level or higher education and resided in suburban or rural areas.

4.2.2. Non-EV users

The analysis also revealed two classes of non-EV users with different choices regarding public charging location characteristics, as shown in Table 6. The probability of a non-EV user belonging to Class 1 was 41.7%, and Table 7 indicates that Class 1 non-EV users were more likely to be older males, not living in detached houses. Non-EV users in this class with high incomes ($> £75,000$) showed no significant sensitivity to charging price changes. However, for those with middle or low incomes ($\leq £75,000$), there was a strong aversion to higher charging prices (coefficient = -7.892 , $p \leq 0.01$) and long waiting times (coefficient = -0.055 , $p \leq 0.01$). Furthermore, Class 1 non-EV users disliked adding an additional payment method - an operator's RFID card, compared to traditional cards or contactless payments (coefficient = -0.510 , $p \leq 0.05$). This group showed little interest in the availability of fast charging, the percentage of renewable energy used, the number of charging points, or the various authentication methods. They were also indifferent to amenities and station ratings. Regarding charging locations, when all else being equal, they strongly disliked charging at both surface car parks (coefficient = -1.137 , $p \leq 0.01$) or multi-storey car parks (coefficient = -1.300 , $p \leq 0.01$) compared to street charging.

On the other hand, there was a higher chance (58.3%) of non-EV users belonged to Class 2. This class of non-EV users tended to be younger females, living in a detached house. Like Class 1, Class 2 non-EV users also disliked higher charging prices, regardless of their income levels, as well as long waiting times (coefficient = -0.023 , $p \leq 0.05$). However, Class 2 non-EV users showed a preference for public charging stations that offered fast charging (coefficient = 0.736 , $p \leq 0.01$) and were powered by a higher proportion of renewable energy (coefficient = 0.509 , $p \leq 0.01$). Additionally, they valued the convenience of automatic authentication via Plug and Charge over using the operator's app (marginally significant, coefficient = 0.165 , $p \leq 0.10$). Like Class 2 EV users, Class 2 non-EV users preferred stations with amenities such as small shops and cafés (coefficient = 0.298 , $p \leq 0.05$), or shopping centres (coefficient = 0.346 , $p \leq 0.01$), and those with five-star ratings (coefficient = 0.488 , $p \leq 0.01$) compared to three-star-rated stations. They were indifferent to the number of charging points available at public charging stations and the type of payment methods offered. In terms of location choices, Class 2 non-EV users preferred charging at

surface car parks (coefficient = 0.434 , $p \leq 0.01$) over street charging when all other factors were equal.

5. Discussion

The findings reveal significant heterogeneity in the choices of both EV and non-EV users regarding different features of public charging stations. Using latent class modelling, this study identified distinct preference segments within both user groups, demonstrating that public charging infrastructure needs to be designed with a wide array of user priorities in mind. These findings provide valuable insights into how charging infrastructure might be tailored to better accommodate the diverse needs of EV- and non-EV users alike.

5.1. Preference heterogeneity among EV users

Among EV users, public charging is not evaluated in a uniform manner. Two distinct segments emerge, reflecting different ways of balancing charging cost, time, and service attributes. The identification of a larger cost-oriented segment alongside a smaller service-oriented segment is consistent with previous latent class studies (Pan et al., 2019; Yao et al., 2026).

The service-oriented segment placed greater importance on fast charging availability, shorter waiting times, higher station ratings, and amenity-rich locations such as multi-storey car parks and commercial areas. These findings are in line with earlier work highlighting the importance of service satisfaction (Wang et al., 2021), convenience (Wang et al., 2021; Yao et al., 2026), and amenities in shaping charging choices for EV users (ten Have et al., 2020; Visaria et al., 2022). The preference for locations integrated with shops or cafés suggests that charging is increasingly combined with everyday activities rather than treated as an isolated technical task. This extends previous research by showing that location context itself, not only service features, shapes how charging is evaluated, as charging is increasingly integrated into everyday activity patterns (He et al., 2022; Liao et al., 2023).

In contrast, the larger cost-oriented segment prioritises affordability, particularly among lower- and middle-income households. Amenities, higher station ratings, and advanced service features play a limited role in shaping choices. This preference echoes earlier findings showing that the absence of nearby facilities can be significant in choices of both slow and fast charging stations (ten Have et al., 2020). Such preferences may reflect efforts to be practical and minimise charging costs, reduce uncertainty and improve efficiency in routine use, particularly where public charging is used frequently.

These patterns in the EV user class can be interpreted through innovation diffusion theory (Hardman et al., 2024; Rogers, 2003). The service-oriented segment resembles early adopters, who are typically more open to new service configurations and place greater value on convenience and experience while exhibiting less sensitivity to price. By contrast, the cost-sensitive segment is closer to the early majority, for whom affordability, ease of use, and sustainability become increasingly important.

5.2. Public charging as a feasibility assessment for non-EV users

Non-EV users also formed two classes, but these did not reproduce the segmentation pattern observed among EV users. Class 1 was primarily cost- and time-sensitive, showing strong negative responses to higher prices and longer waiting times but limited interest in some service features. Class 2 placed greater value on fast charging, renewable energy, amenities, station ratings, and surface-car-park locations, yet remained significantly sensitive to both price and waiting time. This is an important contrast with the service-oriented EV class, for which charging price was not statistically significant.

The cost- and time-sensitive non-EV class showed strong negative responses to higher charging prices and longer waiting times. Individual

preferences for on-street charging over both surface and multi-storey car parks, together with limited interest in advanced service features, suggests that the acceptability of public charging depends primarily on whether it can provide an affordable and easily accessible alternative. This interpretation is consistent with prior evidence suggesting that potential adopters place substantial weight on the perceived financial and time-related risks associated with public charging (Globisch et al., 2019; Hajhashemi et al., 2024). These factors may therefore constitute key barriers to EV adoption.

By contrast, the larger service-oriented non-EV segment responds more positively to fast charging availability, higher station ratings, renewable energy use, and amenity-rich environments. However, unlike the service-oriented EV class, it remains significantly sensitive to charging price for all income groups. This suggests that service improvements do not remove concerns about the recurring cost of public charging. Because non-EV users have not yet established charging routines, they may view charging price as part of the anticipated cost of EV ownership and therefore as an indication of whether adoption would be financially feasible. Fast charging, higher-rated stations, and amenities may instead reduce uncertainty about the practical experience of charging by making it appear more convenient and compatible with everyday routines. This interpretation is consistent with evidence that charging convenience and perceived service quality influence adoption intentions, particularly among people without established charging experience (Budnitz et al., 2024).

From a diffusion perspective (Rogers, 2003), these patterns reflect later-stage adoption dynamics, where decisions depend strongly on perceived practicality. The service-oriented non-EV segment may resemble early- or late-majority adopters who are open to adoption once infrastructure becomes affordable, convenient and routine-compatible. In contrast, the cost- and time-sensitive segment reflects characteristics closer to laggards, who require stronger evidence of affordability and ease of use before adoption.

5.3. Implications for planning and user-centred public charging provision

These findings suggest that public charging infrastructure should not be treated as a uniform technical provision, but as a planning challenge shaped by heterogeneous user needs (Hajhashemi et al., 2024; Wang et al., 2021; Yao et al., 2026) and adoption stages (Hardman et al., 2024; Rogers, 2003). While charging infrastructure functions as an operational service for current EV users, it may also play a critical role in shaping EV adoption-related evaluations among non-EV users.

An important implication concerns the spatial and land-use context of charging provision. Preferences for stations located near commercial amenities, such as shopping areas or cafés, suggest that charging is increasingly integrated into everyday activity patterns rather than undertaken as an isolated technical task (ten Have et al., 2020; Visaria et al., 2022). This supports planning approaches that co-locate charging infrastructure with activity hubs, enabling users to combine charging with routine activities and enhancing perceived convenience and time efficiency (Jin et al., 2025; Lamontagne et al., 2025). Specifically, rapid chargers with seamless authentication and nearby amenities could be prioritised for time- and service-oriented EV users at multi-storey car parks and activity centres. For the larger service-seeking non-EV segment, provision at surface car parks and activity hubs could combine fast charging with a higher share of renewable energy.

At the same time, strong cost sensitivity across several segments indicates that affordability remains critical for equitable access. Planning strategies that focus exclusively on high-service, amenity-rich charging environments may improve user experience but risk reinforcing inequalities if affordable options remain limited (Hopkins et al., 2023). More specifically, an inclusive deployment strategy should prioritise cost-accessible on-street or neighbourhood charging to accommodate the cost-sensitive EV segments and cost- and time-constrained non-EV

users, particularly in areas with limited off-street parking. Transparent pricing rates (p/kWh) and dynamic information provision would further address the affordability and waiting-time concerns identified within these groups (Hopkins et al., 2023).

Socio-demographic differences further reinforce the need for targeted deployment strategies (Hajhashemi et al., 2024; Song et al., 2025; Yao et al., 2026). Variations associated with income, gender, housing type, and urban context suggest that charging provision should respond to diverse lifestyles and residential conditions rather than assume a single “average” user. Segment-informed planning can help local authorities prioritise infrastructure types and locations that match local demand structures.

While this study provides valuable insights into user choices, several limitations must be acknowledged. Firstly, the study relies on cross-sectional data, which limits the ability to draw conclusions about changes in choices over time. Longitudinal studies could provide deeper insights into how user choices evolve as the EV market matures. Additionally, the study's focus on the Great Britain context limits its generalisability to other regions with different socio-economic and cultural contexts.

6. Conclusion

This study contributes to the existing body of knowledge on EV adoption literature by directly comparing the public charging preferences of EV users and non-EV users, an area that has been relatively underexplored in earlier research. Through a latent class modelling approach, this study revealed two different segments within each group. EV users showed a relatively clear distinction between a dominant cost-oriented class and a smaller time- and service-oriented class, whereas both non-EV classes remained sensitive to price and waiting time, including the class with a higher proportion of participants that also valued service and convenience. These findings demonstrate why public charging should be planned differently as an operational service for current EV users and as part of the feasibility assessment undertaken by prospective adopters.

From a planning and policy perspective, the findings support targeted and inclusive ex-ante provision rather than uniform infrastructure rollout. Affordability remained important for several segments, particularly lower-income EV users and non-EV users, underlining the importance of equitable access to public charging (Hopkins et al., 2023). This priority can be supported through the Local Electric Vehicle Infrastructure (LEVI) Fund, which provides capital and capability funding for local authorities in England to plan and deliver local charging infrastructure, particularly for residents without off-street parking (Office for Zero Emission Vehicles, 2023a). Preferences for fast charging, shorter waiting times, and accessible authentication also underline the importance of a reliable and user-friendly network, aligning with the Public Charge Point Regulations 2023 requirements for pricing transparency, contactless payment, open availability data, and rapid-network reliability (Office for Zero Emission Vehicles & Department for Transport, 2023). However, differences in preferences for amenities, renewable energy, and charging locations suggest that these common standards should be delivered through different local infrastructure configurations (e.g., Axsen et al., 2018; Haustein et al., 2021; Wang et al., 2021). Local strategies could therefore combine affordable neighbourhood charging in areas with limited off-street parking with higher-service rapid-charging hubs at commercial and other activity centres. This also calls for local demand-informed ex-ante planning (Geospatial Commission, 2023), which advocates using data on existing provision, parking, travel demand, site suitability, and grid capacity to determine the number, type, and location of charge points.

Beyond near-term deployment targets, our findings also have implications for long-term infrastructure governance. Attributes valued by both EV users and potential adopters, such as fast charging availability, shorter waiting times, high service quality, and seamless authentication,

are closely linked to system-wide operational requirements. Delivering these features at scale is unlikely to be achieved through charger additions alone, but instead requires coordinated planning between public charging provision and the electricity system, including grid-capacity upgrades and smart charging strategies, such as load shifting and vehicle-to-grid (V2G) integration, to manage peak demand and system reliability (GOV.UK, 2022; IEA, 2025). Looking ahead, the growing diffusion of connected mobility services and the potential emergence of autonomous EV operations may further intensify charging demand concentration, reinforcing the need for integrated charging-grid planning and future-proof infrastructure standards (nationalgrid, 2023; Official Journal of European Union, 2025).

By framing public charging as both a technical and behavioural challenge, this study emphasises the need for consumer-centred infrastructure planning. It also supports broader adoption goals by identifying what public charging features are likely to attract future EV users, which is an essential insight for overcoming barriers such as range anxiety and perceived inconvenience (Pamidimukkala et al., 2024). Future research could build on this by testing behavioural responses to new infrastructure types in real-world pilot projects or examining public

charging preference shifts over time as the EV market matures.

CRedit authorship contribution statement

Rongqiu Song: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dimitris Potoglou:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization, Funding acquisition.

Funding

This study was supported by the UKRI's Engineering and Physical Sciences Research Council (EPSRC) [EP/S032053/1 and EP/Y026233/1]. The first author also acknowledges the financial support of the China Scholarship Council.

Declaration of competing interest

No potential conflict of interest was reported by the author(s).

Appendix A

Table A1

An overview of charging prices from different public charging providers – as of 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 (7 kW) – 31p/kWh		
ubitrinity	Type 2 (5 kW) – 24p/kWh		
Source London	PAYG – 7.4 kW and 22 kW – 59p/kWh	Overnight cape of £14.16 (20:00–07:00)	
Pod point	Rapid charger – 28p/kWh	The cost per kWh for most rapid public chargers is 44p (e.g., the total cost for 30-minute charging is £11)	

Note: 'PAYG' refers to pay as you go.

Table A2

Significant different public charging choices among EV and non-EV users (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			

(continued on next page)

Table A2 (continued)

Parameter	Value	Rob. Std err	Rob. t-test
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		

*** Significant at 99% confidence level.

* Significant at 90% confidence level.

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.

Fig. A1. Introductory text for the choice experiment.

Data availability

The authors do not have permission to share data.

References

- Adsule, P., & Manoj, M. (2025). A stated choice study to assess charging and travel decisions of electric car users considering car attributes and trip chaining complexity – Case New Delhi, India. *Transportation Research Part A: Policy and Practice*, 192 (December 2024), Article 104366. <https://doi.org/10.1016/j.tra.2024.104366>

- Anilan, V., & Vij, A. (2024). Taking the wheel: Systematic review of reviews of policies driving BEV adoption. *Transportation Research Part D: Transport and Environment*, 136 (August), Article 104424. <https://doi.org/10.1016/j.trd.2024.104424>
- Aksen, J., Cairns, J., Dusyk, N., & Goldberg, S. (2018). What drives the pioneers? Applying lifestyle theory to early electric vehicle buyers in Canada. *Energy Research & Social Science*, 44(March), 17–30. <https://doi.org/10.1016/j.erss.2018.04.015>
- Bhat, F. A., Tiwari, G. Y., & Verma, A. (2024). Preferences for public electric vehicle charging infrastructure locations: A discrete choice analysis. *Transport Policy*, 149 (April 2023), 177–197. <https://doi.org/10.1016/j.tranpol.2024.02.004>
- BP Pulse. (2022). bp pulse. <https://www.bppulse.co.uk/charging-on-the-go>
- Budnitz, H., Meelen, T., & Schwanen, T. (2024). Public residential charging of electric vehicles: An exploration of UK user preferences. *European Transport Studies*, 1 (August), Article 100004. <https://doi.org/10.1016/j.ets.2024.100004>
- Cai, H., Wu, F., Cheng, Z., Li, B., & Wang, J. (2023). A large-scale empirical study on impacting factors of taxi charging station utilization. *Transportation Research Part D*, 118, Article 103687. <https://doi.org/10.1016/j.trd.2023.103687>
- ChoiceMetrics. (2021). Ngene 1.3 user manual & reference guide. <https://www.choice-metrics.com/NgeneManual130.pdf>
- Department for Transport. (2022). Plug-in grant for cars to end as focus moves to improving electric vehicle charging. <https://www.gov.uk/government/news/plug-in-grant-for-cars-to-end-as-focus-moves-to-improving-electric-vehicle-charging>
- Department for Transport. (2025). Electric vehicle public charging infrastructure statistics: January 2025. <https://www.gov.uk/government/statistics/electric-vehicle-public-charging-infrastructure-statistics-january-2025>
- Department for Transport, & Office for Zero Emission Vehicles. (2025). *How to apply for vehicle eligibility for the Electric Car Grant*.
- Electric Vehicle Association England. (2021). Improving drivers' confidence in public EV charging. <https://www.evaengland.org.uk/wp-content/uploads/2021/04/EVA-England-Consumer-Charging-Survey-Report.pdf>
- Ge, Y., & MacKenzie, D. (2022). Charging behavior modeling of battery electric vehicle drivers on long-distance trips. *Transportation Research Part D: Transport and Environment*, 113, Article 103490. <https://doi.org/10.1016/j.trd.2022.103490>
- Geospatial Commission. (2023). Charging ahead: Using location data to boost local EV chargepoint rollout. https://assets.publishing.service.gov.uk/media/64ec5d46635870000dc147ce/Charging_Ahead_.pdf
- Globisch, J., Plötz, P., Dütschke, E., & Wietschel, M. (2019). Consumer preferences for public charging infrastructure for electric vehicles. *Transport Policy*, 81, 54–63. <https://doi.org/10.1016/j.tranpol.2019.05.017>
- GOV.UK. (2022). Regulations: Electric vehicle smart charge points. <https://www.gov.uk/guidance/regulations-electric-vehicle-smart-charge-points>
- Guerra, E., & Daziano, R. A. (2020). Electric vehicles and residential parking in an urban environment: Results from a stated preference experiment. *Transportation Research Part D: Transport and Environment*, 79(January), Article 102222. <https://doi.org/10.1016/j.trd.2020.102222>
- Gutjar, M., & Kowald, M. (2023). The configuration of charging stations: What do potential users want? *Travel Behaviour and Society*, 32, Article 100579. <https://doi.org/10.1016/j.tbs.2023.100579>
- Hajhashemi, E., Sauri Lavieri, P., & Nassir, N. (2024). Identifying electric vehicle charging styles among consumers: A latent class cluster analysis. *Transportation Research Interdisciplinary Perspectives*, 27(August), Article 101198. <https://doi.org/10.1016/j.trip.2024.101198>
- Hardman, S., Jenn, A., Tal, G., Aksen, J., Beard, G., Daina, N., ... Witkamp, B. (2018). A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, 62, 508–523. <https://doi.org/10.1016/j.trd.2018.04.002>
- Hardman, S., Shafaeen, M., & Tal, G. (2024). Identifying mass market adoption in the transition to electric vehicles. *Environmental Research Letters*, 19, Article 111005. <https://doi.org/10.1088/1748-9326/ad7bd1>
- Haustein, S., Jensen, A. F., & Cherchi, E. (2021). Battery electric vehicle adoption in Denmark and Sweden: Recent changes, related factors and policy implications. *Energy Policy*, 149(November 2020), Article 112096. <https://doi.org/10.1016/j.enpol.2020.112096>
- He, S. Y., Kuo, Y. H., & Sun, K. K. (2022). The spatial planning of public electric vehicle charging infrastructure in a high-density city using a contextualised location-allocation model. *Transportation Research Part A: Policy and Practice*, 160(April), 21–44. <https://doi.org/10.1016/j.tra.2022.02.012>
- Hensher, D. A., & Bradley, M. (1993). Using stated response choice data to enrich revealed preference discrete choice models. *Marketing Letters*. <https://doi.org/10.1007/BF00994072>
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). Applied choice analysis. In *Applied Choice Analysis*. <https://doi.org/10.1007/9781316136232>
- Hess, S. (2014). Latent class structures: Taste heterogeneity and beyond. In *Handbook of choice modelling*. <https://doi.org/10.4337/9781781003152.00021>
- HM Government. (2022). Taking charge: The electric vehicle infrastructure strategy. <https://www.gov.uk/government/publications/uk-electric-vehicle-infrastructure-strategy>
- Hopkins, E., Potoglou, D., Orford, S., & Cipcigan, L. (2023). Can the equitable roll out of electric vehicle charging infrastructure be achieved? *Renewable and Sustainable Energy Reviews*, 182, Article 113398. <https://doi.org/10.1016/j.rser.2023.113398>
- IEA. (2025). Global EV outlook 2025 expanding sales in diverse markets. <https://www.iea.org/reports/global-ev-outlook-2025>
- Jin, Z., Sun, X., Xu, Z., & Tu, H. (2025). A data-driven approach to uncovering the charging demand of electrified ride-hailing services. *Transportation Research Part D*, 139, Article 104599. <https://doi.org/10.1016/j.trd.2025.104599>
- Lamontagne, S., Carvalho, M., & Frejinger, E. (2025). What makes a good public EV charging station? A revealed preference study. *Transportation Research Part D, Transport and Environment*, 149, Article 105066. <https://doi.org/10.1016/j.trd.2025.105066>
- Letmathe, P., Sperling, D., & Woeste, R. (2025). Consumer preferences for public EV charging tariffs and infrastructure reliability: A choice experiment. *Transport Policy*, 170(April), 147–162. <https://doi.org/10.1016/j.tranpol.2025.05.010>
- Liao, Y., Tozluoglu, Ç., Sprei, F., Yeh, S., & Dhamal, S. (2023). Impacts of charging behavior on BEV charging infrastructure needs and energy use. *Transportation Research Part D*, 116, Article 103645.
- Liu, M., & He, S. Y. (2025). E-taxi drivers' charging behavior: Effects of the built environment, temporal factors, and ridership. *Journal of Transport Geography*, 123, Article 104118. <https://doi.org/10.1016/j.jtrangeo.2025.104118>
- Ma, S. C., Yi, B. W., & Fan, Y. (2022). Research on the valley-filling pricing for EV charging considering renewable power generation. *Energy Economics*, 106, Article 105781. <https://doi.org/10.1016/j.eneco.2021.105781>
- nationalgrid. (2023). Distribution Future Energy Scenarios 2023 Results and assumptions report. <https://commercial.nationalgrid.co.uk/downloads-view-reciteme/654884>
- Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Sco, D. R., & Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108, 474–486. <https://doi.org/10.1016/j.enpol.2017.06.033>
- Nienhueser, I. A., & Qiu, Y. (2016). Economic and environmental impacts of providing renewable energy for electric vehicle charging – A choice experiment study. *Applied Energy*, 180, 256–268. <https://doi.org/10.1016/j.apenergy.2016.07.121>
- Office for National Statistics. (2025). Electric vehicle public charging devices. <https://www.ons.gov.uk/explore-local-statistics/indicators/electric-vehicle-public-charging-devices>
- Office for Zero Emission Vehicles. (2016). On-street residential chargepoint scheme guidance for local authorities. <https://www.gov.uk/government/publications/grant-s-for-local-authorities-to-provide-residential-on-street-chargepoints>
- Office for Zero Emission Vehicles. (2021). *Workplace charging scheme: guidance for installers*.
- Office for Zero Emission Vehicles. (2023a). *Apply for local electric vehicle infrastructure (LEVI) funding*.
- Office for Zero Emission Vehicles. (2023b). *Electric vehicle chargepoint and infrastructure grant guidance for installers*.
- Office for Zero Emission Vehicles, & Department for Transport. (2023). Public charge point regulations 2023 guidance. <https://www.gov.uk/government/publications/the-public-charge-point-regulations-2023-guidance/public-charge-point-regulations-2023-guidance>
- Official Journal of European Union. (2025). Commission delegated regulation (EU) 2025/656: Amending Regulation (EU) 2023/1804 of the European Parliament and of the Council as regards standards for wireless recharging, electric road system, vehicle-to-grid communication and hydrogen supply for road. <https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=OJ%3A%202500656#tit.1>
- Osprey. (2024). Osprey EV charging network. https://www.ospreycharging.co.uk/easy-enjoyable-charging?utm_source=google&utm_medium=cpc&utm_campaign=AlwaysOn&utm_id=AlwaysOn&gad_source=1&gclid=CjwKCAiAPuuBhBsEiwAS7fsNaLyGIV8rKKVWpmAVDew3zBHUprrpF5XQgk7G8_vqHh7KXGJ18xTFBoCdwMQAvD_BwE
- Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., & Hladik, G. (2024). Barriers and motivators to the adoption of electric vehicles: A global review. *Green Energy and Intelligent Transportation*, 3(2), Article 100153. <https://doi.org/10.1016/j.geits.2024.100153>
- Pan, L., Yao, E., & MacKenzie, D. (2019). Modeling EV charging choice considering risk attitudes and attribute non-attendance. *Transportation Research Part C: Emerging Technologies*, 102(3), 60–72. <https://doi.org/10.1016/j.trc.2019.03.007>
- Potoglou, D., Song, R., & Santos, G. (2023). Public charging choices of electric vehicle users: A review and conceptual framework. *Transportation Research Part D: Transport and Environment*, 121, Article 103824. <https://doi.org/10.1016/j.trd.2023.103824>
- Rogers, E. M. (2003). Diffusion of innovations. In *Social networks* (5th ed.). Free Press.
- Schulz, F., & Rode, J. (2022). Public charging infrastructure and electric vehicles in Norway. *Energy Policy*, 160(March 2021), Article 112660. <https://doi.org/10.1016/j.enpol.2021.112660>
- Sierczula, W., Bakker, S., Maat, K., & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68, 183–194. <https://doi.org/10.1016/j.enpol.2014.01.043>
- SMMT. (2022). Delivering consumer-centric charging infrastructure for zero emission mobility. <https://www.smm.co.uk/reports/electric-vehicle-infrastructure-position-paper/>
- Song, R., & Potoglou, D. (2020). Are existing battery electric vehicles adoption studies able to inform policy? A review for policymakers. *Sustainability*, 12(16), Article 6494. <https://doi.org/10.3390/su12166494>
- Song, R., & Potoglou, D. (2024). Electric vehicle public charging choices: A qualitative investigation. *Transportation Planning and Technology*, 1–23. <https://doi.org/10.1080/03081060.2024.2367754>
- Song, R., Haggag, P., Xenias, D., & Potoglou, D. (2025). Exploring the role of Technophilia on electric vehicle use: a structure equation modelling approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, 115, 103328. <https://doi.org/10.1016/j.trf.2025.103328>
- ten Have, S. Y., Gkiotsalitis, K., & Geurs, K. T. (2020). Investigating the future of ultrafast charging: A choice experiment in the Netherlands. *World Electric Vehicle Journal*, 11 (4), 1–22. <https://doi.org/10.3390/wevj11040070>
- Train, K. E. (2009). *Discrete choice methods with simulation*.

- Visaria, A. A., Jensen, A. F., Thorhauge, M., & Mabit, S. E. (2022). User preferences for EV charging, pricing schemes, and charging infrastructure. *Transportation Research Part A: Policy and Practice*, 165, 120–143. <https://doi.org/10.1016/j.tra.2022.08.013>
- Wang, Y., Yao, E., & Pan, L. (2021). Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. *Journal of Cleaner Production*, 286, Article 124982. <https://doi.org/10.1016/j.jclepro.2020.124982>
- Wolff, S., & Madlener, R. (2019). Charged up? Preferences for electric vehicle charging and implications for charging infrastructure planning. *SSRN Electronic Journal*, 3. <https://doi.org/10.2139/ssrn.3491629>
- Yao, M., Lu, X., & Cao, S. (2026). Modeling EV charging behavior: The impact of service experience and user heterogeneity. *Travel Behaviour and Society*, 43, Article 101216. <https://doi.org/10.1016/j.tbs.2025.101216>
- Yoo, H. I. (2020). Iclgit2: An enhanced command to fit latent class conditional logit models. *Stata Journal*, 20(2). <https://doi.org/10.1177/1536867X20931003>
- Zapmap. (2026a). EV charging statistics 2025. <https://www.zapmap.com/ev-stats/how-many-charging-points>.
- Zapmap. (2026b). EV market stats 2025. <https://www.zapmap.com/ev-stats/ev-market>.
- Zhang, Y., Luo, X., Qiu, Y., & Fu, Y. (2022). Understanding the generation mechanism of BEV drivers' charging demand: An exploration of the relationship between charging choice and complexity of trip chaining patterns. *Transportation Research Part A: Policy and Practice*, 158(August 2021), 110–126. <https://doi.org/10.1016/j.tra.2022.02.007>
- Zhao, M., Wang, D., Li, W., & Liu, J. (2024). Unraveling influencing factors of public charging station utilization. *Transportation Research Part D: Transport and Environment*, 137(November 2024), Article 104506. <https://doi.org/10.1016/j.trd.2024.104506>