applied sciences

MDPI

Review

A Literature Review on the Charging Behaviour of Private Electric Vehicles

Natascia Andrenacci * and Maria Pia Valentini

Laboratory of Systems and Technologies for Sustainable Mobility, ENEA C.R. Casaccia, via Anguillarese 301, 00123 Roma, Italy; mariapia.valentini@enea.it
* Correspondence: natascia.andrenacci@enea.it

Abstract: Electric mobility is one of the ways of containing greenhouse gas and local pollutants emissions in urban areas. Nevertheless, the massive introduction of battery-powered electric vehicles (EVs) is introducing some concerns related to their energy demand. Modelling vehicle usage and charging behavior is essential for charge demand forecasting and energy consumption estimation. Therefore, it is crucial to understand how the charging decisions of EV owners are influenced by different factors, ranging from the charging infrastructure characteristics to the users' profiles. This review examines the approaches used to investigate charging behavior and highlights the trends and differences between the results, remarking on any gaps worthy of further investigation.

Keywords: electric vehicles; charging behavior; private electric mobility

check for updates

Citation: Andrenacci, N.; Valentini, M.P. A Literature Review on the Charging Behaviour of Private Electric Vehicles. *Appl. Sci.* **2023**, *13*, 12877. https://doi.org/10.3390/app132312877

Academic Editor: Muhammad Aziz

Received: 10 October 2023
Revised: 24 November 2023
Accepted: 29 November 2023
Published: 30 November 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The switch to electric mobility is one of the ways of containing emissions of both greenhouse gas and local pollutants in urban areas. Electric vehicles (EVs) come in different types, such as pure or battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs). BEVs are electric vehicles that rely solely on batteries to transmit energy. BEVs need an external source of energy to recharge the batteries. HEVs use both an internal combustion engine (ICE) and an electric powertrain, which can be combined in various ways. PHEVs also have both an ICE and an electric powertrain, but unlike HEVs, electric propulsion is the primary driving force. These vehicles require larger battery capacity than HEVs and can be recharged directly from the grid. FCEVs are powered by fuel cells that use chemical reactions to produce electricity. The electricity generated by the fuel cells drives the wheels through an electric motor, and any excess energy is stored in storage systems like batteries or supercapacitors [1]. The focus of the present study is on the charging behaviors of BEVs and, partially, PHEVs. The widespread adoption of electric vehicles hinges on two key factors: technological advancements and market acceptance. In order to optimize vehicle costs, electric vehicle manufacturers strive to select the best battery technology that ensures both safety and performance, including long-range autonomy and high power [2]. To facilitate the adoption of EVs and make their widespread use feasible, it is necessary to develop an adequate charging network [3,4]; this, in turn, involves the correct planning that satisfies real demand. Elements such as power request, charge duration, and the spatial and temporal distribution of demand influence the planning and subsequent utilization rate of charging infrastructure, the emissions associated with the generation of electricity for charging, and the impact of charging on grid electricity [5,6]. For these reasons, understanding and predicting charging behaviors with sufficient accuracy are essential. It is thus important to elucidate how the charging decisions of EV owners are influenced by external variables related to charging infrastructure and mobility needs, by intrinsic socioeconomic and psychological factors, and by charging network design, which could also maximize utilization rates and user satisfaction.

Electric vehicles can be charged at various locations and speeds, and the costs may differ. EV supply equipment (EVSE) can be composed of one or more charging points (CP), which connect the power grid to the electric vehicles, drawing AC power to charge the EV battery in DC form. The converters can be either onboard or offboard, depending on the type of charging. The chargers can be classified into two categories: 'level' and 'mode'. Charging levels have been defined by the Society of Automotive Engineers (SAE), while the four charging modes are defined by the International Electrotechnical Commission (IEC). 'Level' refers to the power and voltage of the charging system, while 'mode' refers to the electronic communication between the vehicle and the power supply. This communication is critical for ensuring safety and proper charge control. The International Electrotechnical Commission (IEC) has defined four charging modes [7].

Mode 1 refers to home charging directly from a standard power outlet with a simple extension cord. However, this charging method does not provide shock protection against DC current. Moreover, mode 1 is prohibited in many countries. Mode 2 charging involves the use of a special cable, provided with the EV, with integrated shock protection. Mode 3 charging involves a dedicated charging station or a home-mounted wall box for EV charging. Both provide shock protection against AC or DC currents. In Mode 3, the connecting cable is provided with the wall box or charging station. Mode 4 is mainly used for DC fast-charging applications. In this mode, AC is converted to DC in an external charger, which is then used to charge the EV battery. In the first three modes, the EV is directly connected to the AC distribution network, and the conversion to DC takes place in the vehicle. In mode 4, the conversion takes place in the charger.

Level 1 charging corresponds to 120 AC voltage with a power of 2 kW; it is typically used in residential settings and does not require special equipment. It is not allowed in the EU. Level 2 corresponds to the standard European 230/240 V AC plug. It can be used for domestic charge or in public charging poles. The delivered power usually ranges from 3 kW to 20 kW. Level 3 indicates quick-charging stations using high-voltage direct current (DC), typically 400 V DC. The charging power of these stations ranges from 50 kW up to 130 kW. Level 4 chargers use 400–800 V DC voltage, with a power level up to 500 kW, and are mainly intended for long-distance driving and heavy vehicles [8,9].

The need for an in-depth analysis of the real and potential charging demand has led to a significant number of studies on EV energy demand modeling, conducted at different levels of aggregation depending on the purpose of the study. Disaggregated approaches directly consider individual patterns of mobility and EV recharge, whilst aggregated ones often start from the energy demand of the EV supply equipment (EVSE). These approaches are not mutually exclusive, and the data from different sources are often combined to model EV loading.

The characterization of charging behavior is inextricably linked to the diffusion of EVs. Indeed, the individual characteristics of EV users also influence charging behaviors. EV users are often male and middle-aged and typically have higher levels of education, an above-average income, and multiple cars per household [10–12], corresponding to the profile of early EV adopters [13]. With the spread of electric mobility, this audience tends to widen and include different user groups with presumably diverse needs and behaviors. Some research refers to a relatively immature phase of the adoption of electric mobility, and their results must be analyzed considering that the behaviors of EV early adopters may not coincide with those emerging from mass adoption.

In fact, the propensity to adopt EVs depends on many factors, both economic and psychological, investigated in the literature. Economic studies usually compare the alternatives between different types of vehicles described by their characteristics, based on which consumers make decisions by making trade-offs between attributes. Psychological studies focus on motivations by examining the influence of a broad range of individual-specific psychological or social constructs [14]. Financial, technical, and infrastructural factors have a significant impact on the choice of switching to EVs, while psychological variables have a stable effect demonstrated by several studies. The influence of socioeconomic and

demographic variables is still unclear and sensitive to small changes [14]. However, early EV users show some prevalent characteristics, such as a high level of education and a high income, being predominantly young or middle-aged males, living in large families that own more than one car, and living in small to medium-sized cities [10]. Having experienced EV driving and one's awareness of environmental values are factors that dispose one to the purchase of an electric car [15], as well as satisfaction with use, which appears to be high among both experienced and novice EV users [16]. Adding vehicle-to-grid functionality seems to be an option that tends to favor EV adoption, probably because it can represent a possible economic income for owners [15]. The self-perception of belonging to a specific category of people and the perception of the electric car as a status symbol seem to positively influence the decision to purchase [17,18].

Increasing experience with EVs raises awareness of many aspects of electric mobility. For example, battery range was rated less critical for people who have owned EVs longer than neophytes or conventional car owners. On the other hand, charging anxiety seems less present among early adopters, while potential users appear more concerned of not having enough autonomy or sufficient charging infrastructure [19]. Battery life is considered a more critical factor for internal combustion engine vehicle (ICEV) owners than EV owners [15], although it has emerged that range and battery charging are the two main reasons for dissatisfaction among EV users [16]. According to surveys and interviews, traditional car buyers' knowledge and awareness of EV charging infrastructure are currently low [20], possibly because of a scarcity of intentions to buy an EV or continue to use the specific knowledge derived from experience with ICEVs when buyers imagine using EVs. This fact should be considered in analyses, as some surveys infer charging behavior from data that include ICEV owners.

This work collects several studies that focus on the charging habits and choices of private EV owners in urban areas based on technological, environmental, or socio-demographic variables. Some of these studies are explicitly dedicated to the investigation of charging behavior, while others aim to acquire other results, such as the determination of the optimal locations for charging structures, the smart management of charging requests at stations, or the assessment of demand for scenarios of the penetration of electric mobility. Our own aim is to highlight prevalent criteria regarding charging behavior, detect different approaches across studies, and identify gaps in this research field. We also want to illustrate the different data frameworks and related limits. Given the vastness of the subject, establishing a classification based on a single interpretation is practically impossible. We have therefore decided to present the papers based on the approaches used. In particular, we identify the following:

1. Review works;
2. Articles focused on demand-side data (mobility or charging behaviors);
3. Works based on offer-side data (usage of the charging infrastructure).

We further categorize the works based on the subject they investigate within the previous larger macro-categories.

It should be noted that the categorization used is somewhat arbitrary and obviously not definitive, as some studies rely on multiple data sources and produce intricate and multifaceted findings.

Our goal is to identify the shared characteristics of urban charging behavior. Consequently, we will pay particular attention to the aspects related to users' decision-making processes.

In the next section, we will briefly outline the search parameters used for collecting the papers. Afterwards, we will present a roundup of recent review work that has dealt with the EV charging behavior. We then present the results of some studies investigating the charging behavior of private EV users. Lastly, we highlight common factors and differences in the behaviors observed in the different contexts. The conclusions also present some topics worth considering for future research.

2. Literature Review and Method

The analysis of charging behavior is of fundamental importance for the correct planning of infrastructures, the selection of optimal charge management strategies, and the application of policies centered on improving the penetration of electric mobility and demand integration with the electricity distribution network. There are different possible approaches to such an investigation, which may depend on the type of data used, the variables taken into consideration, and the specific purposes of the studies being conducted. Indeed, charge demand analysis can rely on different data and information sources. Some studies reviewed in this work are devoted to behavioral investigation, while others use data to obtain load estimates for further purposes. The studies were generally conducted on limited geographical areas and for well-defined periods. The datasets used to obtain information on charging choices and load curves include charging point (CP) information, historical charging session series, traffic monitors, travel surveys, user questionnaires, and EV information. The relevant data analysis approaches include statistical characterization, stochastic processes, and machine learning.

Aggregated or disaggregated analysis can be used for the assessment of demand. Aggregated analyses generally do not consider the characteristics of a vehicle and/or its user. They rely on data in which the charge requests are evaluated according to various recharge parameters, such as time, location, power, and, when available, the state of charge (SOC) of a battery. Disaggregated analysis, on the contrary, starts from the "mobility profile" of individuals, often correlating these data with socio-economic information. While in principle it is possible to determine disaggregated demand starting from aggregated load curves [21], using disaggregated data allows for more precise analysis and calculation of the aggregate demand [22].

The works included in this review are presented according to the following scheme: first, we will illustrate some recent review papers on EV charging; then, we review the literature based on their approaches to charging behavior analysis, conducted from the point of view of users' preferences or the exploitation of the existing charging infrastructure.

A search was carried out using the keywords 'charging behavior'; 'EV charging'; 'charge infrastructures usage'; 'EV user behavior'; 'EV charge'; and combinations of the previous ones using the main search tools of scientific publications (Google Scholar, Internet Archive Scholar (IAS), and CORE). We limited the search to papers published after 2015, except for some particularly relevant works. In the searches conducted on Google Scholar and CORE, we used the "OR" operator between keywords. For IAS, the string used was "charg* behav*" for the search in the 'Description' field. Google Scholar returned around 24.400 results; 2.374 research outputs were found using CORE. For IAS, we obtained 5.721 results. Out of these, 1.098 were texts. When we filtered for Subject (Subject and number of texts: Computing Research Repository, 26; Mathematical Physics, 18; Chemical Physics, 17; Systems and Control, 10; Computational Physics, 9; Disordered Systems and Neural Networks, 9; Information Theory, 7; Qualitative Research, 2; *CHEMICAL REACTIONS, 2.), only 84 texts were returned.

We selected articles that specifically mentioned the charging behavior of EV users in their titles or abstracts. From this selection, we further refined our search to include only those articles that relied on survey data related to mobility and charging habits, charging infrastructures, or floating car data. We excluded papers that only evaluated aggregated charging behaviors without analyzing individual charging behavior patterns. Additionally, we disregarded studies that solely relied on synthetic models to assess charging behavior and demand. Our research terms were comprehensive enough to cover all types of charging except for those that are still in the early stages of diffusion, such as wireless charging.

2.1. Review Papers

Defining user charging behavior is a complex task for several reasons. First, as already mentioned, charge behavior is influenced by many factors, which can be psychological, sociological, demographic, or geographical or linked to the maturity of the EV market and the

diffusion of charging infrastructures. Secondly, the data from which to extract or infer these behaviors are limited, as in the case of targeted surveys, or suffer from intrinsic limitations, such as mobility data also relating to ICE vehicles or charging data relating only to certain operators or geographical areas. Several review articles have addressed the problem of examining and classifying papers that have dealt with the charging question. Patil et al. [23] examined the approaches and data sources used to model charging behaviors, aiming to address their implementation in the planning of charging infrastructures. Liao et al. [14] presented a review of studies to identify which characteristics of an EV and its system of services, including the infrastructure system and policies for promoting electric mobility, impact consumer choices. Amara-Ouali et al. [24] reviewed open databases relevant to EV charging demand modeling and gave an overview of the forecasting models, with approaches ranging from statistical characterization, stochastic processes, and machine learning. An examination of studies on the impact of charging demand on the energy distribution grid is presented in Deb et al. [5]. Jia & Long [25] provided a collection of data sets on sales volumes, driving, EV charging, and automotive battery performance. Their discussion includes an analysis of some EV models and types of EVSE, the impact of EV charging behavior on the local infrastructure, and some smart-charging optimization approaches. Hardman et al. [26] analyzed studies on user interactions and preferences for charging infrastructure, using data based on questionnaires, GPS data from vehicles, and EVSE data. Although home charging emerged as the preferred option, the authors stressed that further analysis is needed to determine the best strategy for developing the infrastructure needed to support EV rollouts. In addition, Funke et al. [27] reviewed studies investigating the medium-long-term demand for recharging infrastructure, comparing the framework conditions in different countries to highlight the differences. The authors concluded that public charging infrastructure seems necessary as an alternative to home charging only in some densely populated areas. Daramy-Williams et al. [19] reviewed the literature related to user experience, including driving and travel behaviors, vehicle interactions, and subjective aspects of the user experience, including symbolic and social aspects such as environmentalism, futurism, and social status. The current work focuses on the charging behavior of private electric vehicle users, disregarding aspects related to the impact on the network that some previous reviews may have covered. Our primary objective was to provide a comprehensive overview of the different factors that can impact user charging demand. More specifically, our objective was to verify whether it is possible to identify, within the literature, the variables that influence charging behavior beyond contextual differences; in addition, we aimed to verify if and how local characteristics affect individual behaviors. Some recommendations on areas that require further investigations are also given in the conclusions.

2.2. Analysis of Users' Preferences and Needs

User preferences regarding charging can be detected directly, through surveys, or indirectly, by analyzing mobility and travel needs from data collected via traffic acquisition systems or GPS. Surveys usually provide disaggregated data, from which information on users' characteristics can be extracted, while mobility data are usually aggregated, with no or limited information on users.

2.2.1. Survey-Based Papers

Valid tools with which to investigate charging behavior are questionnaires addressed to actual or potential EV users. These questionnaires can explore various aspects related to mobility, such as travel and charging habits, responses to policies, and attitudes toward EVs. At the same time, they are intended to highlight possible influences of different parameters on the results, such as socio-economic, territorial, and infrastructural aspects, which are more difficult to identify or are even undetectable using other approaches based, e.g., on charge events or traffic data.

Travel Surveys

Some questionnaires and surveys collect travel data, from which it is possible to infer charging behavior. In fact, the travel pattern of an EV user is a key factor in simulating and predicting the distribution of charging demand. The validity of household travel surveys in terms of estimating charging load was tested in the Swiss context in [28]. In the cited study, the results of a survey on ICE cars were used, and a complete transition to EVs, both pure battery (BEV) and plug-in hybrids (PHEV), was assumed. The load curves obtained under this hypothesis were compared with measurements made in various field tests for EVs, showing a good agreement. The charging decision scheme modeled depended solely on the SOC. The same charging criterion was adopted by Iqbal et al. [29] to determine the power demand for residential EVSE. Using traffic survey data on ICEs and assuming a transition to EV, they classified daily usage based on different categories of car owners and provided an estimate of SOC based on distances traveled. The importance of travel choices in charging decisions is illustrated in the study by Zhang et al. [11]. They explored the relationship between two models of causal choices: in the first, the charging strategy was determined first and affects the travel chain; in the other, the journey influences the charge decision. The preferences from about 500 questionnaires showed that the model in which the travel choice precedes that of recharging is more suitable for interpreting the experimental charging curves.

Gao et al. [30] used mobility questionnaires explicitly devoted to EV owners to determine the spatial and temporal distribution of stops as a function of destinations. The findings show that the charging demand in residential areas and workplaces is the largest, followed by public parking lots and curbside parking spaces.

A survey on driving and ownership data serving as the basis of charging demand estimation for public infrastructure in urban areas where domestic charging is not broadly available was conducted in [31]. The results reveal that nearly 78% of energy demand can be supplied by private CPs, of which 11% can be provided by chargers installed in shared residential parking lots, reducing the need for public CPs by up to 58%. For commuters without home-charging equipment, workplace charging could lower the need for public charging by 68%. DC fast charging would amount only to 3% of the total charging demand due to the significantly higher cost and greater inconvenience of the dedicated stop. Charge demand at workplace charging facilities is also evaluated in [32]. The survey outcomes show that slow chargers in the workplace can almost completely meet the intra-city travel demand of private EV users, even if the size of the city greatly influences the mobility patterns and the charging demand curves due to the different travel needs.

User Charging Preferences Surveys

Survey results are often combined with data from other sources to obtain even more reliable charging behavior simulations, especially to account for the impact that the variability of trips and charging behaviors has on the estimation of aggregate charging demand [33]. The study reported in [34] crosses the topographic data of various points of interest with the time users spend near them, the average stops for daily activity, and vehicle fleet data. Data from travel surveys are combined with those from the charging of an EV fleet to evaluate the impact of charging on the grid [35,36].

Other survey-based studies explicitly focus on investigating users' charging preferences and which factors affect these decisions. A joint study based on stated mobility and charging choices [37] showed that the instantaneous SOC is the most important factor influencing the decision to charge, while the predicted SOC at the destination affects the route choice. Charging time, proximity to the origin, and consistency with the direction of travel significantly influence the charging station selection process [37]. Users often recharge with SOCs above 50%, especially at home or work, and the availability of slow charging at the destination leads to a failure to consider the choice of fast charging [38].

The results presented in [39] show that Korean consumers prefer charging mainly during the evening at home. However, during peak hours, people favor fast public charging.

Similar results were reported in an Australian survey [40]: in general, charging habits are strongly influenced by costs, and drivers prefer charging their EVs at home or work rather than at a public charging station. However, people with travel commitments involving other family members prefer using a public charging station. Daina et al. [41] investigated home-charging preferences, showing that the energy required for charging has a positive marginal utility in most cases, while the charging time has a more complex influence: most users keep their vehicles in a charging state until they can remain at home and do not to finish charging if this causes delays in departure. The charging cost always has a negative marginal utility.

An extensive analysis of charging behaviors in the USA [42] collected data on the location, time, and power of charge events. In total, 57% of users stated that they only charge their EVs at home, and 40% reported that they charge their EVs at home and away from home, mainly at work. Most users start charging when they plug in their vehicles, but around 20% use a timer to shift their EV load to off-peak hours. In addition, the higher the EV range, the more likely the respondent was to use public charging.

A stated choice survey and willingness-to-pay (WTP) analysis confirmed home charging to be the primary charging method employed, while public infrastructure was deemed insufficient [43]. The determining factors in charging choice are price, the occupancy rate, and the waiting time at the charging facility. An acceptable distance from the destination to the charging infrastructure is a 5–10 min walking distance [43]. Another WTP analysis showed that it increases proportionally to the CP power and the CP's distance from the city center [44]. Dorcec et al. [45] obtained similar conclusions; moreover, the lower the SOC, the more willing EV owners are to pay for charging. Attention to environmental issues emerges when investigating the positive correlation between the WTP and the portion of recharge energy from renewable sources [46]. The willingness to participate in smart-charging projects that can reduce costs and increase the share of renewable energy has also been confirmed [47]. Controlled charging is an efficient method for minimizing peak demand and maximizing the use of renewable sources while reducing costs, although privacy concerns remain [48]. For this reason, user-controlled charging is preferred over network-operator-driven charging [49].

Fast charging represents an interesting technological solution that could positively affect the diffusion of electric mobility. A stated-preferences survey on users' fast-charging choices on long-distance trips revealed that SOC and the possibility of reaching a fast station without deviations from the planned trip are the primary factors influencing charging decisions [50]. A survey of EV usage in Japan analyzed the SOC when fast charging began during road trips. Users' anxiety about charge opportunities strongly affects this value, which varies according to the type of user and their activities [51]. Based on a revealed preferences survey [52], the factors influencing the charging mode choice are battery capacity and SOC, the possibility of charging overnight, and the number of past fast-charge events. In addition, the interval of days between the current charge and the next trip has a positive effect on slow charging at home/workplace. Using a survey of BEV owners, Wen et al. [53] identified three basic types of charging behavior: triggered by price and need; replenish whenever the opportunity arises; and based on a wider range of factors, including charging power, dwell time, and the cost of home charging. It also emerged that the majority of respondents were willing to pay more for fast charging compared to slow charging. The preferences expressed on some social media platforms by consumers highlight that direct current (DC) fast charging is popular with consumers for reducing charging times; that vehicle range is a concern when traveling long distances or using air conditioners; and that private charging is particularly appreciated by consumers but is hampered by the lack of dedicated parking spaces, especially in large cities [54]. From a questionnaire administered in Germany to owners and potential users of electric cars [13], it was found that motorway service stations, shops, and traditional filling stations are optimal candidates for fast-charging stations. A survey conducted by Globisch et al. [55] suggests that it is more important to build a fast charging network than to strengthen a slow one.

Socio-Demographic and Psychological Aspects

Demographic and social attributes impact travel patterns and influence daily EV load profiles [56]. In [57], a charging demand simulation method is proposed that considers people's demographics and social characteristics, e.g., gender, age, and education level, as well as travel-related spatiotemporal variables, which appear to have a considerable effect on the shape of the EV load profile, particularly for working days and workplaces. Males and workers are generally more likely to charge away from home, while owning an ICEV alongside an EV appears to increase the likelihood of only using home charging; age does not appear to have a statistically significant effect on the choice of charging location [58]. Those who claim to have travel flexibility and those who perceive mobility as a necessity tend to charge on the go. Drivers who plan their travels less tend to charge at home instead [58]. Users who choose public charging have a high-income level, tolerate waiting in line, and travel long distances; conversely, consumers who prefer to charge home at night are sensitive to charging prices [59]. Y. Zhang et al. [60] showed that the choice of charging is significantly influenced by socio-demographic variables such as gender and risk aversion as well as by structural factors such as travel chain, the coverage of recharging facilities, travel distance, and perception of SOC. The choice of CP is affected by destination type, parking duration, charge price, next travel distance, travel chain, SOC, and risk aversion [60].

The aspects related to the charging experience are increasingly arousing the interest of researchers. Asensio et al. [61] analyzed user reviews collected online for public and private charging stations. The results show that nearly half of users reported having a negative experience at charging stations. The judgments of other users on EVSE quality of service and their attitudes toward risk influence the choice of infrastructure, especially for younger and higher-income users [62].

An approach combining survey and EV data is presented in [63]. The charging choice is influenced by sociodemographic characteristics, such as the type of home, income, and age but also the availability of domestic charging or free charging in the workplace. Charging network subscriptions have a positive impact on the likelihood of using public infrastructure [64]. Interestingly, commute length is a significant factor only for PHEV owners and not for BEV owners [63].

An interesting notion in the psychology behind charging behavior is the so-called user–battery interaction style (UBIS) introduced by Franke & Krems [65]: users with low UBIS have a lower awareness of the meaning of the energy level of their devices, which leads to recharging based on contextual triggers rather than on battery SOC. The correct assessment of the residual range is linked to range anxiety. The same survey found that some personality traits, such as self-control and low impulsivity, and greater technical competence were positively correlated with decreased autonomy anxiety [66]. A survey on ICE drivers and BEV users with varying levels of experience revealed that stress levels regarding vehicle range are similar between the two groups, even though BEV users demonstrate greater confidence in the vehicle and tank/battery indicators [67]. Conversely, Yuan et al. [68] found that BEV drivers tend to have more range anxiety than ICE vehicle drivers if driving on a long journey. Connected to the previous aspects is the attitude toward risk in the charging choice [69]. The inclusion of the risk attitude, in the form of a latent variable, improved the adaptation to the experimental data of the developed forecasting model [11].

In some studies, the aim was to investigate which actions can improve access to charging and users' perceptions of charging infrastructure as available, reliable, and sufficient for their needs. A pilot experiment on dedicated neighborhood charging [70] showed that potential EV users consider parking-combined and bookable charging options within the city to be of paramount importance, especially as parking is a problem common to both EV users and non-EV users. A survey of stated preferences without a private residential charging option found that the most important aspects of public charging are closely related to personal safety and proximity to one's home, especially if the service is used overnight [71].

With a view to a comparison with conventional mobility, Dixon et al. [72] analyzed travel diaries to quantify the inconvenience deriving from longer recharging times compared to the refueling times of ICE cars. They verified that around 95% of people with access to domestic-charging equipment and medium-sized EV batteries can achieve equal convenience. That is not the case for people who rely only on workplace or public charging, for whom a percentage of trips would become unattainable.

The effectiveness of policies for influencing charging choices is of great interest to local or national authorities, although the corresponding evaluation is not always simple. For example, the application of a fee is generally effective in inducing users to move their cars at the end of the charging period, but the need for parking can lead to the nullification of the control action [73]. Another strategy for indirect control is to act on the charge price with dynamic pricing. The response to this type of solicitation is heterogeneous among different social groups [74].

In Table 1, we present an overview of the studies presented in this section. We have summarized the information on the survey (SP: stated preferences; RP: revealed preferences; TS: travel survey; Web: social media or web sites) and any other data sources used; the years and countries in which data were collected; and the main topics of the studies, where 'User behavior' is ticked if the study focuses on the charging habits of actual or potential EV users, 'Infrastructures' is ticked if the work also considers aspects related to the planning and management of charging infrastructures (such as optimal location, power, ancillary services, or impact on the grid), and 'Policies' is ticked if interventions for improving or boosting electric mobility, such as the intelligent management of recharging, variable prices, or incentive policies, are explicitly considered.

Table 1. Summary of the investigations based on surveys (SP: stated preferences; RP: revealed preferences; TS: travel survey; Web: social media or web sites).

Source	Survey Source	Sample Size	Year [1]	Country	User Behavior	Infrastructures	Policies	Key Points
Y. Zhang et al. [11]	SP	494 respondents	2021	China	√	√		Relationship between travel chain and charging choices
Philipsen et al. [13]	SP	252 respondents	2015	Germany	√	√		Acceptance of and optimal location for fast charging.
Pareschi et al. [28]	TS	59,090 inhabitants	2015	Switzerland		√		Validation of charge profiles derived from mobility questionnaires
Iqbal et al. [29]	TS	Over 30,000 households	2016	Finland	√	√		Classification of EV daily use and charging behavior based on SOC
Gao et al. [30]	TS	1156 households	2021	China		√		Demand dominated by charging in a residential area and at the workplace
Thingvad et al. [31]	TS	56,328 households	2014–2019	Denmark		√		Evaluation of energy demand at public and private CPs
X. Liu et al. [32]	RP	141 respondents	2021	China	√	√		Use of charging facilities at the workplace in different urban contexts
Crozier et al. [33]	TS + charging data	2 million trips + charging data of 213 Nissan Leaf units	2016	UK	√		√	Impact of the variability of travel and charging behavior on overall demand

Table 1. *Cont.*

Source	Survey Source	Sample Size	Year [1]	Country	User Behavior	Infrastructures	Policies	Key Points
Pagany et al. [34]	TS	Over 5000 households	2012–2013	Germany	√	√		Optimal CP location determined based on EV drivers' route choice and charging preferences
Bollerslev et al. [35]	TS + charging data	160,000 travel surveys + 10,000 Nissan Leaf charging events	2012; 2015–2016	Denmark, Japan		√		Coincidence factor of EV charging given driving and plug-in behaviors
Calearo et al. [36]	TS + charging data	160,000 travel surveys + 7163 Nissan Leaf charging events	2012; 2015–2016	Denmark, USA, Japan		√		Quantification of the load impact of domestic charges on distribution grid feeders
Y. Yang et al. [37]	SP	237 respondents	2014	China	√			Investigation of the mobility and charging choices of EV drivers
Ashkrof et al. [38]	SP	505 respondents	2020	The Netherlands	√			Exploration of BEV drivers' route choices and charging preferences
Moon et al. [39]	SP	418 respondents	2016	Korea	√	√		Estimation of EV expansion scenarios and EVs' electricity demands
Jabeen et al. [40]	SP	54 respondents	2012	Australia	√			Prevalence of home and workplace charging derived from charging habit analysis
Daina et al. [41]	SP	88 respondents	2012	UK	√			Evaluation of the marginal utility of the recharged energy, of time, and of the cost of the recharge
EPRI [42]	TS	4000 PEV owners	2016	USA	√	√	√	Analysis of the private charging and plug-in electric car markets
Anderson et al. [43]	SP	Around 4000 EV users	2020	Germany	√			Analysis of charging behavior and EV preferences
Plenter et al. [44]	SP	435 respondents	2014	Germany	√		√	Analysis of WTP vs power and location of the charging station
Dorcec et al. [45]	SP	101 respondents	2019	Croatia	√			WTP for different charging options
Nienhueser & Qiu [46]	SP	181 respondents	2016	USA	√		√	WTP for charging with renewable energy
Lagomarsino et al. [47]	SP	222 respondents	2020	Switzerland	√		√	EV smart charging preferences and strategies
Bailey & Axsen, [48]	SP	1640 respondents	2015	Canada	√		√	Acceptance of energy supplier-controlled charges.

Table 1. *Cont.*

Source	Survey Source	Sample Size	Year [1]	Country	User Behavior	Infrastructures	Policies	Key Points
Delmonte et al. [49]	SP	60 respondents	2020	UK	√		√	Acceptance of two types of controlled charging: control by user or by network operator
M. Xu et al. [52]	RP	500 respondents	2017	Japan	√			Factors that influence the choice of location and charging method
Wen et al. [53]	SP	315 respondents	2013	USA	√			Identification of three categories of prevalent charging behaviors
Y.-Y. Wang et al. [54]	Web	59,067 pieces of consumer discussion data	2011–2020	China	√		√	Used of natural-language-processing technology to explore consumer preferences for charging infrastructure
Globisch et al. [55]	SP	1030 EV drivers	2018	Germany	√			Factors that influence the attractiveness of public charging infrastructure.
Fischer et al. [56]	TS	40.000 households	2008–2009	Germany		√		EV load impact and management strategies at different parking locations
J. Zhang et al. [57]	TS	Not specified	2009	USA		√		EV charging load simulations considering user demographics
Latinopoulos et al. [58]	SP	118 respondents	2017	UK, Ireland	√			Determination of the factors influencing the demand for EV charging on the go
Y. Chen & Lin [59]	SP	1907 respondents	2019	China	√			Factors influencing consumer satisfaction with charging infrastructure
Y. Zhang, Luo, Wang, et al. [60]	RP+ SP	494 respondents	2021	China	√	√		Relationship between travel chain and charging choices
Asensio et al. [61]	Web	127,257 reviews	2011–2015	USA	√	√		Evaluation of the degree of satisfaction with the charging stations
Y. Wang et al. [62]	SP	300 respondents	2021	China	√			Analysis of the influence of previous users' satisfaction with charging facilities and risk attitude of drivers
Nicholas et al. [63]	RP + EV log data + GPS	About 1400 respondents + GPS and log data of 72 PEV households for a full year	2015–2018	California	√	√		Impact of battery size, range, driving, and charging behavior on PEV energy consumption.
Lee et al., [64]	RP	7979 EV users (completed survey 15%)	2016–2017	California	√			Differences in charging behavior among different types of PEV owners

Table 1. *Cont.*

Source	Survey Source	Sample Size	Year [1]	Country	User Behavior	Infrastructures	Policies	Key Points
Franke & Krems [65,66]	SP+RP	79 EV users	2013	Germany	√			Determination of the psychological dynamics underlying charging behavior
Philipsen et al. [67]	SP	204 respondents	2018	Germany	√			Investigating range stress among ICE and EV users.
Yuan et al. [68]	RP	208 BEV drivers	2018	China	√			Determining range anxiety's effect on drivers' emotions and behaviors
Pan et al. [69]	SP	160 EV drivers	2018	China	√			Design of EV driver charging choice models incorporating risk attitude and different decision strategies
Hardinghaus et al. [70]	RP	377 respondents	2021	Germany	√	√	√	Pilot experiment on dedicated neighborhood charging
Budnitz et al. [71]	SP	2001 respondents	May–June 2020	UK	√			Use of natural-language-processing technology to explore consumer preferences for charging infrastructure
Dixon et al. [72]	TS	39,000 travel diaries	2012–2016	UK	√			Analysis of inconvenience of the duration of EV charging
Wolbertus & Gerzon, 2018 [73]	SP	119 respondents	2018	The Nether-lands	√		√	Effectiveness of a parking fee at the end of the charge
Latinopoulos et al. [74]	SP	118 respondents	2017	UK	√		√	Response of EV drivers to dynamic charging service pricing.
Number of articles for thematic area					39	18	11	

[1] If the survey period was not explicitly reported, we used the year of publication.

2.2.2. Mobility and Charging Behavior Data

Mobility data constitute a valid source for extracting travel and transport habits in each area visited. The quantity and quality of information can vary greatly depending on the methods used to collect and record data. Mobility data can be combined with recordings of the charging events and information from EVs' on-board instrumentation to provide a more comprehensive picture of the charging behaviors [25]. Mobility data can be used to identify the points of greatest attraction and the spatiotemporal distribution of trips. In some cases, they can refer to ICE vehicles and translate to electric mobility data, with the hypothesis that journeys, especially in urban areas, do not change radically with the transition from one type of powertrain to another [75].

EV charging preferences are the subject of various studies based on mobility and EV data. They usually concentrate on initial and final SOC during charges, the frequency of charging with respect to distance travelled, or the number and nature of stops.

Some work referred to the initial phase of EV diffusion. The prevalent use of charging at home and work emerged in two studies [76,77]. Both studies show that the start-of-charging SOC is, on average, above 50%. Using static and dynamic data regarding EVs

and CPs from over 10 European countries, the authors of [78] found four main patterns of behavior, characterized by different temporal distributions of trips and charges, depending on the type of EV and the location of the CP.

Mobile telephone data integrated with census data, a survey on PEV drivers, and measurements made at CPs made it possible to build a high-definition space-time mobility model [79], which detects how charging behaviors follow traffic trends, suggesting the absence of a charging strategy. Furthermore, considering the SOC, the consumption, the charge time, and the distance between successive charges, it emerges that EV users charge more frequently than necessary [80]. This result was confirmed by J. Yang et al. [81]: analyzing driving and recharging behaviors, they found that the distances between consecutive recharges are generally shorter than the average daily distances, indicating a tendency to charge whenever there is a convenient opportunity, regardless of the remaining range. This behavior is comparable with that identified in [82], as well as with the results in [83], highlighting a high daily number of opportunity charges. A risk analysis of the interval times between recharging events showed that both vehicle attributes, such as state of charge, distance traveled, and average driving speed, and individual characteristics (range anxiety, age, and purpose of travel) significantly influence the instantaneous rate of occurrence of charging events [84].

Vehicle usage also influences charging behavior, with commercial EVs needing to be charged after a trip more often than private ones, with a tendency for private BEVs to synchronize charging with the cheapest electricity rates [85]. Regarding fast charging, users generally prefer stations that require shorter detours and are greatly influenced in their choice by the residual SOC [86].

Different approaches have been used to classify private charge behaviors, applying statistical analysis techniques [87,88], clustering [89,90], or data mining [91], substantially confirming the prevalence of slow night charging on weekdays. Using aggregate analysis of charging demand, one can gain insights into the charging behaviors of different types of users [92]. For example, the authors of [93] found that the probability of using public charging in a given area is proportional to the average number of cars per household and inversely proportional to the percentage of private homes in the residential area considered. Powell et al. [94,95] provided a model for estimating the aggregated charging profiles of different driver groups whose charging behaviors were clusters derived from a large data set on workplace, public, and residential charging.

Charging choices are obviously also influenced by charge costs [26,96,97], or the possibility of using free parking [98], which can be used to influence charging preferences [99].

2.3. Analysis of Infrastructure Usage

Charging data directly provide the load curves at charging stations, allowing for a detailed analysis of request distributions. Studies based on these data are often centered on reconstructing or estimating the spatiotemporal distribution of the energy demand for charging rather than characterizing individual recharging behavior, and the granularity of the data reflects in the detail of the result and the speed of the model response. Historical series of customer charges provide relatively faster predictions than those collected at EVSEs; however, they also pose more problems regarding privacy [100]. In general, both datasets generate comparable prediction errors. Although charging and mobility data are commonly used for general analysis, they can also provide insight into specific charging behaviors within the analyzed context. Other studies are explicitly devoted to highlighting charging preferences, and they often rely on multiple-source data. Detailed spatio-temporal patterns of charging infrastructure usage can be extracted from the analysis of EVSE and traffic data, which are more laborious to obtain from a disaggregated analysis. Regarding the temporal distribution of charging events, data from EVs revealed a prevalence of nighttime charging among private EV users [101]. Home charging mainly starts in the evening and lasts until the next morning, and charging at work is concentrated in the morning on weekdays [89,102,103]. Public charging is distributed throughout the day but

is energetically marginal [102], with a prevalence of fast charging during the day and slow charging occurring mainly at night [104,105]. Furthermore, residential charging seems to be less influenced by seasonality, while the use of public charging stations changes at different times of the year, especially in relation to holiday periods [103,106]. Weather also influences the use of public stations [87,107], as do extraordinary events and traffic information [108]. Daytime and weekday public charging occurs mainly at alternating current (AC) charging stations, while direct current (DC) fast-charging stations are more popular on weekends [109]. The temporal distribution of usage also depends on the where the charging stations are located [110]. In general, fast-charging stations show a higher usage rate than public level 2 charging stations [103,111], making higher profits due to better margins [109]. However, the utilization rate of DC stations appears to decrease as one moves toward rural areas [112]. The low utilization rate of AC stations is also due to the stationary times being much higher than the charging times [113–115]. This behavior could indicate that consumers are not yet aware of the time required to recharge their vehicles or do consider parking a primary need, even with respect to recharging [73,116]. Conversely, charging behavior at fast-charging stations is more akin to normal refueling behavior, with short connection times oriented toward the ability to complete the intended journey [73]. Domestic charging has a longer dwell time than other CPs of equal power, while the dwell time is short on commercial premises, probably because these instances are opportunity recharges [116]. The arrival time, permanence, and inactivity at public CPs differ depending on whether the charge takes place near one's home, at work, or in a parking lot [108]. Furthermore, the distribution of recharges on the days of the week appears to differ according to travel habits and travel destinations in different areas in the same country [98]. For example, Chinese research [117] identified the most frequent charging behaviors while commuting: Charging starts when a car is parked, between 8:00 and 10:00, and lasts, on average, 4 h. Evening or nighttime charging behaviors account for 26% and 21% of total charging. The most frequent behavior (30%) was associated with commuting: Charging begins when the car is parked, between 8:00 and 10:00. The average recharge lasts about 4 h. Evening or nighttime charging behaviors account for 26% and 21% of total charging.

For home charging, the research interest is mainly concentrated on the hourly distribution of recharges since the power levels involved are generally limited. Domestic charges are concentrated in the evening and at night [111,118], with peaks in correspondence with the time slots before and after work [80,119]. The SOC at the start of charge shows a wide range of values, with a tendency to fully charge the battery [120]. The influence of electricity pricing on the temporal distribution of charging is addressed in [121] using machine learning techniques. Data from smart electricity meters are often used to extract EV load curves [122–125]. Users who own cars with higher-capacity batteries seem to favor home charging [116].

As far as workplace charging is concerned, this practice represents a valid charging opportunity, especially when it is perceived as cheaper than charging at home or when home charging is not available. Usage data show regular patterns on working days, with a low rate of exploitation on holidays [126,127].

In [128], the application of a data mining model allowed the authors to study the shape of the typical daily profile, the predictability with respect to weather conditions, and the trend of the EV charging demand.

In Table 2, we present an overview of the papers that explicitly cited the databases used therein. The sources are classified as follows: charging data, registered at the EVSE; mobility data, which represent traffic, GPS, or EV onboard monitor unit log data; and other data if sources different from the above are included in the study. Although cited in the papers, some of the resources are no longer available at present.

Table 2. Sources of charging and mobility data for some of the cited studies.

Authors	Charging Data	Mobility Data	Other Data	Period [1]	Country	Resource
Y. Xu et al. [79]			Mobile phone data	2018	California	http://www.nrel.gov/tsdc (accessed on 30 July 2023) http://nhts.ornl.gov (accessed on 30 July 2023)
Weldon et al. [80]	√			2011–2015	Ireland	http://education.greenemotion-project.eu/ (accessed on 30 July 2023) http://www.greenemotion-project.eu/ (accessed on 30 July 2023)
Märtz et al. [83]	√	√		2019	Germany	https://www.mdpi.com/article/10.3390/en15186575/s (accessed on 30 July 2023) [1]
Daina & Polak [84]		√	User survey	2014	UK	https://innovation.ukpowernetworks.co.uk/projects/low-carbon-london/ (accessed on 30 July 2023)
S. Kim et al., [87]	√	√		2010–2014	The Netherlands	https://elaad.nl/en/ (accessed on 30 July 2023)
Y. Liu et al. [91]	√			2018	UK	https://data.dundeecity.gov.uk (accessed on 30 July 2023)
Singh et al. [89]	√			2020	The Netherlands	https://elaad.nl/en/ (accessed on 30 July 2023)
Schäuble et al. [92]	√	√		2011–2013 2012–2014 2013–2015	Germany	https://crome.forschung.kit.edu/english/index.php [2] https://www.izeus.kit.edu/english/ (accessed on 30 July 2023) https://www.isi.fraunhofer.de/de/competence-center/energietechnologien-energiesysteme/projekte/Get_eReady.html (accessed on 30 July 2023)
Kim et al. [98]	√			2021	Korea	https://www.data.go.kr/data/15076352/openapi.do (accessed on 30 July 2023)
Dodson & Slater [102]	√			2017–2018	UK	https://www.nationalgrideso.com/industry-information/connections/customer-connection-events (accessed on 30 July 2023)
Hecht et al. [109]		√		2019–2021	USA	https://doi.org/10.17632/ddv53zsf9m.1 (accessed on 30 July 2023)
Sadeghianpourhamami et al. [106] Flammini et al. [113]	√		Users survey	2015	The Netherlands	https://elaad.nl/en/ (accessed on 30 July 2023)
Gerossier et al. [118]	√			2015	Texas	https://dataport.cloud/ (accessed on 30 July 2023)
Yi & Scoffield, [121]	√	√		2011–2013	USA	https://avt.inl.gov/content/pubs-az.html#E (accessed on 30 July 2023)
Asensio et al. [126]	√			2020	USA	https://doi.org/10.7910/DVN/QF1PMO (accessed on 30 July 2023) [122]

Table 2. *Cont.*

Authors	Charging Data	Mobility Data	Other Data	Period [1]	Country	Resource
Z. J. Lee et al. [127]	√			2016–2018	California	https://ev.caltech.edu/dataset (accessed on 30 July 2023)
Xydas et al. [128]	√	√		2012–2013	UK	http://www.pluggedinmidlands.co.uk Web site access returned an error (accessed on 30 July 2023)
Mandev et al. [129]		√		2011–2020		https://www.voltstats.net/ (accessed on 30 July 2023)

[1] If the survey period was not explicitly reported, we used the year of publication. [2] The URL is no more accessible.

3. Results

The literature presents a diverse overview of private charging behavior, which can be attributed to various factors [83]. One such factor is the early stages of electric mobility in certain countries, resulting in limited data for analysis. Additionally, charging behavior depends on mobility needs, which are influenced by socioeconomic and geographical factors, as well as the available infrastructure in a region [24,130]. Despite the heterogeneities, some charging behavior patterns are identifiable across several studies [78,79,101], which we will summarize in the following.

3.1. Influence of Mobility Choices

Commuting routines and planned trips have a significant impact on EV-charging choices. According to some studies, charging habits tend to follow traffic patterns, indicating a lack of a well-defined charging strategy. As a result, EVs are often charged immediately upon arrival, leading to spikes in demand [30,79]. A distinction concerns the decision of whether to charge during the journey or at the destination. Charging on the go can influence route choice, as it can involve detours taken to reach a CP, and mainly concerns occasions when EVs cannot complete a journey with their available battery energy. The increase in battery autonomy has made this occurrence uncommon in urban areas [62].

The charging decisions of electric vehicle (EV) owners are influenced by their travel choices, which, in turn, are affected by various factors, such as personal preferences, income, age, gender, and education level [29,130]. The duration of scheduled stops is a significant factor that impacts charging decisions. Longer stops increase the likelihood of EV drivers charging their vehicles [53]. Parking time also impacts charging choices: private chargers are usually used at night, and public charging is generally carried out during the day. Additionally, the selection of a charging station depends on various factors, such as charging duration, proximity to the origin, and consistency with the direction of travel [37].

Regarding driving habits and distances traveled, EVs are often used for urban journeys with limited mileage [58,80,105]. A European study found that 75% of observed cars travelled less than 47 km daily, while rental EVs travelled a daily average of 66.5 km [78]. In urban settings, the authors of [101] found that over 71% of distances traveled were less than 15 km, and about 76% of parking events lasted less than 1 h. An early English trial [131] revealed that the length and average duration of the journey are 9 km and 15 min, respectively. A UK survey showed that only 10% of the respondents drove more than 40 miles a day, and around 30% used EVs for their daily commutes, while around the same percentage used them between 4 and 6 days a week [58]. In the EU, 97% of EV drivers use their vehicles daily or several times a week. Their EVs are mostly new (67%) and privately owned (70%) [12].

Studies also show a difference between the charging habits of owners of PHEVs and BEVs [57,61,64,118]. Both types of EVs rely on home charging as the main source of energy [64,87,116]. The analysis reported in [129] on the recharging behavior of PHEVs in North America highlights the habit of night recharging and the non-intensive use of

additional recharging. Hardman et al. [26] reported that PHEVs are recharged less often than BEVs at public stations or along long-distance corridors. Overall, long-range BEVs are connected more frequently than short-range ones, while the opposite is true for PHEVs [61]. PHEVs are generally recharged at lower SOCs than those for BEVs [116].

3.2. Use of Infrastructure

Analyses of charging behaviors cannot ignore the availability and composition of charging infrastructures and the context of the areas analyzed. This means that the results obtained for specific geographical areas in the literature have limited applicability to other countries. Nonetheless, there are some charging behaviors that are common among most EV users, such as the predominance of home charging, where it is available [26], and the important role of workplace-charging infrastructure for EV commuters [27,64]. Concerning the choice of where to charge, generally, public charging infrastructures are used differently depending on their location in a city [112]. According to a Dutch study on public CPs [106], roadside charging accounted for 62.86% of all sessions, while charging near one's home accounted for 27.84%, and charging sessions near one's workplace amounted to 9.3%.

A general preference for home charging was identified in many studies [26,132], followed by workplace and public charging [26,111,133]. According to the IEA, approximately 89% of charging stations are private, located in places of convenient access, such as at home or in offices [1]. According to a survey conducted by the European Alternative Fuel Observatory (EAFO), 76% of EV users in the EU charge their EVs at home, while around 20% do so regularly at work [132]. These results are in line with those obtained in the UK [58,134] and Germany [13], although there are some variations in the distribution of percentages. In the USA, about 80% of recharging takes place at home [82,135], and about 50% drivers use this mode exclusively [61]. In addition, in British Columbia, most users have access to home charging [20]. The availability of CPs at work represents an important opportunity [77], especially for users without access to home charging [132]. Users who charge exclusively at work usually have unlimited free or paid access to work CPs [61]. However, free or over-subsidized charging can lead to the inefficient use of CPs if there is no incentive to move a vehicle after the charge is over [136], and this type of charging can encourage plugging in even if the remaining range is enough for subsequent trips, creating congestion for chargers [118]. Furthermore, free charges are not financially viable and could discourage future charge investments by employers. Therefore, suitable pricing policies can significantly influence the use of charging in the workplace [127,136].

Public charging infrastructure can be a valuable alternative for areas with limited home-charging options, particularly densely populated urban areas [31]. Personal safety and proximity to one's home are the most crucial factors in the replacement of private charging with public charging, particularly during nighttime usage [71]. Additionally, public charging infrastructures are used differently depending on their location [112]. In [106], the authors state that public charging along the streets accounts for 62.86% of all sessions, while charging near work amounts to 27.84% of the total, and charging sessions near home make up 9.3%. Public and corridor charging stations are the least-used types of infrastructure [26,113]. An overall analysis of charging demand revealed that the likelihood of using public charging in a given area is proportional to the average number of cars per family and inversely proportional to the percentage of private homes in an area [93]. Fast charging is a promising technological solution that can positively impact the spread of electric vehicles. By reducing charging times, it can potentially increase user acceptance of electric mobility. A questionnaire distributed in Germany revealed that motorway service stations, shops, and traditional refueling stations are ideal locations for fast-charging stations. EV users are willing to take a detour to find fast charging stations, but they reject waiting times [13]. Users are also willing to pay more for fast charging compared to slow charging [53,55].

The connection profiles differ between weekdays and weekends, with about 25% of the total energy supplied during the weekend [113]. Another characteristic that emerges

is that the dwell times at the CP are generally much longer than the actual recharge times, with inactivity percentages ranging from about 40 to 75% [78,79,113]. The idle time, i.e., the period in which an EV is parked without charging, lasts on average 4 h, although it depends on the CP's position and its charging power [73]. Slow charging points typically have much longer dwell times than fast ones [111,112], leading to high operational inefficiency [73,112,137,138]. In general, the shortest stays are recorded at road CPs, and the longest are recorded in office and public access car parks [78] and at residential CPs [103]. As a result, the average charging power rates are often significantly lower than the nominal power [109,112].

The temporal distribution of recharges depends on various factors, including geographical and social variables (work start and end times, commuting rates, etc.). However, a peak can usually be observed in the morning when leaving for work and later when arriving at work, as well as in the evening when returning home, especially for slow charging [104,128] and domestic charging [139]. On weekends, domestic charging is more evenly distributed throughout the day [108]. Fast charging is used more during the day [104], with very short idle times of 48 min on average [106,137]. In [81], the authors found a pattern in the temporal charging distribution, with the mean and median being around 14:00 and some groups preferring to charge at night. It emerges from some studies that charging occurs less than once a day and with a periodicity of approximately 24 h [78,79], although Yang et al. [81] reported an average number of charges in days of use of 1.1. At home, about 70% of cars are charged only once a day, and three or more daily recharges are highly unlikely [119,120].

Fast DC stations show a utilization rate nearly three times higher than AC CPs [103,109]. Indeed, European EV owners consider charging speed one of the most important characteristics of a public CP. However, the frequency of use of fast chargers is 10% in the EU, which can be compared to 21% for public slow chargers [132]. This result may be attributed to a minor diffusion of fast chargers compared to slow ones. An adequate public charging network seems to favor the adoption of electric mobility [1,55,75,140,141], but there is no unanimity regarding which alternative, slow or fast, is more important for the diffusion of electric mobility [31,55,75].

The usage patterns of electric vehicle charging stations differ depending on whether they are residential or public. Residential charging occurs mainly at night and is spread out evenly across the week. Public charging, on the other hand, happens mostly during the day and is concentrated on weekdays [103]. Public charging usage is also affected by seasonal changes, with holidays having a particularly significant impact. AC charging stations are more frequently used for weekday and daytime charging, while DC fast charging stations are more popular on the weekends [103,105,106]. The temporal distribution of public station usage also depends on where these stations are located [110].

3.3. Sensitivity to Costs

When and where to charge depend on the service cost. The charge price negatively affects the infrastructure choice, while parking opportunity has a positive effect [62,69]. However, some users are more time-sensitive and do not wish to deviate to save money [58]. The possibility to pay via credit card at public charging stations also appears to be an important factor for EU BEV drivers [132]. Drivers often prefer to charge electric vehicles at home or work rather than at a public charging station, as the price is lower [26,40,96,97]. Offering reduced charging prices during certain time slots can have a positive impact on the choices made by infrastructure users, even if the savings are marginal [99]. However, free charging at work can lead to unintended consequences, as it can encourage people to connect even if the residual autonomy is sufficient. This can result in congestion at charging stations, which can inconvenience those who need to charge at work to complete their daily commute [97]. Moreover, providing free charging is not financially sustainable and may discourage employers from investing in charging infrastructure in the future.

3.4. Classification of Charging Behaviors

The identification of groups of users with similar charging behaviors can be helpful in determining charging demand in different scenarios.

Applying clustering techniques to a set of charging sessions revealed four prevalent charging behaviors. The first is the morning behavior, with an average connection duration of 8.5 h, which is primarily associated with charging at work. The second is the daytime behavior, with an average duration of 1.5 h. The third and fourth behaviors are afternoon and evening charging, with average durations of 4.5 and 15 h, respectively. These charging behaviors are mainly associated with home charging [89]. An analysis of approximately 5 million charging transactions at public charging points identified 13 main behaviors. The most prevalent of these are night-time charging at home and charging at work. For quick charges, there are a variety of behaviors linked to different types of users and purposes [90]. According to a survey of electric vehicle (EV) owners in the United States, there are three main types of charging behavior. The first type is charging an EV based on price and need, while the second type is recharging a vehicle whenever there is an opportunity. The third type concerns a wider range of factors, such as charging power, dwell time, and the cost of home charging [53]. Another study by Y. Liu et al. [91] classified EV charging behavior during weekdays, weekends, and holidays for a month in 2018. The findings showed that the largest group of users recharged their EVs primarily during weekdays after dawn, with slow recharges and small amounts of energy. Meanwhile, on weekends, most users started charging mainly after sunrise, with short charges but with a high amount of energy.

In a study conducted by Siddique et al. [116] on 821 charging stations in Illinois, correlations between charger/vehicle characteristics and charging behavior were analyzed. The results indicate that home charging corresponds to a longer dwell time than other charging points at the same charging level, while at commercial destinations, the dwell time is short, which may indicate that customers use these charging points for opportunistic charging. The same study also found that charging sessions are generally shorter on weekdays and in the morning than in the afternoon. Cars with higher-capacity batteries exhibit longer dwell times and are more likely to be recharged at home. At DC charging stations, the dwell times are the lowest, and the initial state of charge (SOC) is more than 20% lower than that of other charging stations, which may indicate that fast charging is used only when needed.

Although home charging is preferred in general, studies show fast public charging is preferred during peak hours or activities beyond one's daily routine [39,40].

3.5. Autonomy and Charging Anxiety

The perception of SOC is closely linked to the evaluation of EV residual autonomy and varies from person to person based on their choice of charging. Accurate assessment of residual autonomy is associated with the concept of recharging anxiety [66] and risk attitude [11].

Overall, the reviewed studies place emphasis on battery SOC, charging time, and prices. Battery SOC is considered to be among the most influential factors when modeling charging choices [28,30,38,45,84,142,143], although its distribution at the beginning of the charging period seems to depend on the type of charging infrastructure used: the higher the power, the lower the initial SOC [143]. From the data collected in pilot studies, surveys, or recharging data, we can see a tendency to recharge when the SOC is quite high, around 50%, even if the range is sufficient to complete subsequent trips [58,76,78], which means that users tend not to use the full capacity of a battery but connect their vehicle as soon as they have the opportunity. This tendency is particularly true for home or private charging, especially regarding overnight charging [101]. Morning charging near multi-family homes occurs with a lower initial SOC than charging near single-family homes [116], and public charging, especially fast forms, has the lowest initial SOC values [105,116,128]. Users tend to overestimate the importance of battery SOC in the charging decision, particularly for

short trips [47], and tend to charge their batteries at a high SOC [81,92,101,104,112,116]. These findings may suggest that people tend to charge based on the availability of charging opportunities rather than necessity. Additionally, one may overestimate the need for charging by focusing on the state of charge (SOC) instead of the available range, especially for shorter trips and larger batteries.

Risk attitude is another important element in charging behavior characterization: risk aversion leads to focusing mainly on the remaining range, while risk-tolerant users tend to balance the cost of recharging with the remaining battery autonomy [69]. The degree of recharging anxiety depends on many factors, such as infrastructure availability, travel plans, and understanding of a battery [58]. Technological knowledge, driving experience, and risk aversion play positive roles in alleviating this stress [62,67,68]. However, range stress also depends on other factors, such as the driver's gender and age. Two studies have produced conflicting results on the relationship between gender and risk perception. While one study conducted by Y. Wang et al. [62] found that women tend to exhibit more cautious behavior than men, it is difficult to establish a correlation between anxiety about autonomy and other socioeconomic variables. On the other hand, another study by Daina & Polak [84] found no significant correlation between gender and perceived risk level, while highlighting a correlation with age.

Distances between consecutive recharges tend to be shorter than the average daily distances, which suggests that EV drivers prefer to recharge whenever they have the opportunity, irrespective of the remaining range [81,82]. Most private EV users charge their batteries almost completely, indicating a preference for maximizing the amount of electricity obtained from each charging event [101,112].

3.6. Socioeconomic, Cultural, Environmental, and Experiential Factors

Conducting questionnaire surveys with users is a useful tool for analyzing the various factors that affect their private charging behaviors. However, due to the complexity of the topic and the challenges involved in isolating the influence of different variables on behavior, it can be challenging to provide conclusive results.

A study conducted by Xu et al. [52] explored the factors influencing the choice of charging mode and location among around 500 BEV users in Japan. This study found that a battery's capacity and state of charge, the possibility of overnight charging, and the number of previous fast charging events were the key factors influencing the users' choice of charging mode and location. Additionally, the interval between the current charge and the next trip positively impacts the choice of slow charging at home or work. Another survey conducted by Anderson et al. [43] involving approximately 4000 EV users identified the price, occupancy rate, waiting time, and distance of the charging infrastructure from the point of interest as key determining factors in the choice of charging. In another study [41], a random utility model was proposed based on stated choices for home charging preferences. The results of this study indicated that the amount of energy to be recharged had a positive marginal utility in most cases, while the actual charging time had a more complex influence. Most users preferred to keep their vehicles charged as long as they were home and avoided ending charging if it caused delays in their departure. The charging cost, on the other hand, always had a negative marginal utility.

A recent survey conducted in California analyzed the charging behavior, mobility, and car diagnostic data of EV owners and lessees [63]. The survey revealed that individuals charging their EVs only at home were typically high-income individuals, seniors, and owners of single-family homes. They owned BEVs with a greater electric range and did not have access to workplace chargers. Renters with higher education were more likely to use workplace charging as a top up. On the other hand, EV users who only charged their vehicles at work were more likely to have unlimited free or paid charging at work. The group of users who relied solely on public grid charging typically consisted of low-income renters (compared to other BEV owners) who owned a Tesla and had multiple drivers in

their household. Lastly, young BEV owners with access to free chargers at work were more likely to use all types of charging facilities.

According to the concept of User–Battery Interaction (UBIS) analyzed by Franke and Krems [65], the psychological approaches adopted by charging users are different for those with low and high UBIS. Users with low UBIS have lower awareness of the battery levels of their devices. Thus, they tend to recharge based on contextual triggers rather than the battery charge level, with the latter being the case for users with high UBIS. Moreover, the survey revealed that personality traits such as self-control, low impulsivity, and greater competence with respect to the system were positively correlated with reduced autonomy anxiety.

Latinopoulos et al. [58] found that men are more likely to charge their electric vehicles away from home compared to women. However, age did not appear to have a significant impact on the choice of charging location. Working individuals were more likely to recharge outside of their homes, most likely due to the availability of charging opportunities at their workplaces. Those who have a conventional ICE vehicle are more likely to use home charging exclusively. In contrast, EV owners tend to charge only at home, while those who rent EVs are more likely to charge in different locations. This study also found that free charging outside of one's home reduces the use of home charging and is positively correlated with trip planning. People who consider travel a necessity or have flexibility in their travel plans tend to charge outside their homes, while those who typically do not plan their travel choices mostly tend to charge their vehicles at home.

Recently, the service experience at charging stations has been recognized as being influential in the charging decision process [45,62,98]. Analyzing the impact of the service level of charging stations on user choice, it has emerged that high satisfaction scores of previous users and short queuing times attract more EV drivers [62]. The cited study identified two types of decision-making models among the participants: (1) those who prioritize service quality, which represents the majority of the interviewees and includes younger drivers with more driving experience and higher incomes, and (2) those who consider multiple factors, such as range, parking time, and charging fees, known as pragmatic drivers. A recent study [59] revealed that individuals with higher income levels who travel longer distances tend to opt for public charging infrastructure. On the other hand, those who prefer charging their electric vehicles at night and are more sensitive to charging prices are likely to be more satisfied with private charging infrastructure.

Furthermore, the choice of charging at public charging stations is directly influenced by weather conditions [98], environmental conditions, comfort, or any faults at the EVSE [45], meaning that the comfort of charging stations is not a trivial factor. These studies emphasize that the service level and users' satisfaction are relevant in the EVSE choice.

Controlled charging is a useful way of reducing peak demand and making the most of renewable energy sources. While people generally accept overnight charging controlled by energy suppliers, some have concerns about privacy. The cost incentives offered by controlled charging are well-received by users, but the goal of maximizing renewable energy use has been less successful [48]. A recent study by Delmonte et al. [49] found that participants were willing to accept controlled charging only if it led to significant reductions in charging costs. Moreover, the participants preferred a user-led strategy over a network manager-led one because it was perceived to have a lower risk of not fully charging a vehicle at the required time.

Effective policies capable of influencing charging choices are of great interest to local or national authorities. Applying a tax is generally effective in inducing users to move their cars when they run out of charge. However, this behavior is not unique, and three categories stand out: subjects sensitive to the application of the tariff, users who move their cars regardless of the tariff, and those who do not move their cars, regardless of the established fee level [73]. The last group may be more sensitive to the scarcity of other parking opportunities and mostly consists of drivers who rely on charging using public infrastructure. Indeed, a pilot experiment on dedicated neighborhood charging showed

that potential users of electric vehicles value charging options combined with parking and spaces bookable within the city, especially because parking is a problem experienced by users of both electric and non-electric vehicles [70].

Another strategy for indirectly controlling charging is to act on its price. The authors of [74] examined user response to dynamic charging pricing. Respondents could choose whether to book immediately with a guaranteed price or wait for a better rate but take on the risk of an increase in costs, with a known probability. Most of the survey participants, particularly those who were older or had a fixed job, preferred a certain price to an uncertain one. Parents, people with a higher education level, and those who have been driving EVs for longer are more likely to exhibit strategic behavior.

4. Discussion

Transport contributes largely to noxious emissions, both greenhouse gases and local pollutants. The electrification of vehicles is leading to a significant reduction in these impacts. A reliable and available charging infrastructure is essential to facilitate the diffusion of electric vehicles. Consumers are becoming more environmentally conscious and are seeking sustainable transportation options. To ensure a smooth transition, it is important to understand the commuting and travel needs of users and how well these needs can be met by electric vehicles. To this end, many studies have been dedicated to analyzing the recharging of EVs, for public, commercial, or private vehicles. Examining what influences private charging behavior is possible through user surveys and the analysis of mobility and charge data. Due to the vastness of this topic and the difficulty of isolating the impacts of various variables on behavior, it is challenging to provide definitive results. Several factors influence charging decisions, including gender, risk aversion, type of travel, availability of charging stations, travel distance, and SOC perception. Destination, parking duration, charging time, price, subsequent travel distance, and travel chain type all impact EV charging [11,26,60,97].

The study of private users' charging behavior is far from being exhaustive, which can be ascribed to various reasons, among which are the following:

1. At present, most studies investigating charging habits include only few social and demographic groups, excluding many potential users who may have different charging needs and attitudes. Further exploration is needed on the issue of different charging preferences based on gender [71,144]. Despite charging infrastructure manufacturers' efforts to make their systems compliant with the needs of disabled individuals, there has been no research (that the current authors are aware of) conducted on the charging needs and preferences of impaired people. This is a critical gap that needs to be addressed. Additionally, academic research often overlooks EV users in rural areas [145], whose charging habits may have a greater impact on the grid than their urban counterparts [146].
2. Charging behaviors also depend on social and cultural frameworks and the topographical structure of the urban environment. According to research, personal safety, sociodemographic characteristics, and environment are relevant factors influencing the selection of charging infrastructure and the willingness to pay and walk [13,53,67,71]. The topology of urban areas can influence charging preferences. In urban areas with limited access to home charging, parking availability can positively impact infrastructure choice despite charging costs [54,62,69,70,73,98]. Therefore, it is critical to understand these factors and create effective strategies tailored to the specific needs of each community.

As for the evaluation of the energy and power demand for EVs in future scenarios, the following aspects should be considered in the investigation:

3. Inferences regarding EVs obtained from ICE behavior should be treated carefully, as there may be a lack of understanding and familiarity with electric mobility. Conclusions should be carefully weighed against knowledge of EV owners' behavior.

4. Charge behaviors also depend on the available infrastructure. Changes in the deployment, number, and technologies available for EVSE could significantly change charging behavior. An example is wireless charging, a technology that can simplify charge operations [147,148].

These topics can be further explored with the new and more comprehensive data available and via combining different information sources, such as mobile apps for charging management and reservation. A promising line of study concerns employing users' reviews to obtain information on charging preferences and user needs, as well as to determine the optimal design of charging infrastructures and services [54,61]. Using these data can help researchers examine the possible obstacles and desires regarding the usage of infrastructures, especially public ones, by various users, with special attention paid to the most fragile categories. It is also interesting to inspect the relationship between charging behavior and infrastructure technology to comprehend the different uses of the same type of structure that have emerged from some studies. These further investigations will allow decision-makers to plan a more efficient public charging structure, implement actions to encourage developing private charging infrastructure, and design mobility plans that favor sustainable mobility solutions.

Author Contributions: Conceptualization, N.A. and M.P.V.; methodology, N.A.; investigation, N.A. and M.P.V.; resources, N.A.; writing—original draft preparation, N.A.; writing—review and editing, N.A. and M.P.V.; supervision, N.A.; project administration, N.A. and M.P.V.; funding acquisition, N.A. and M.P.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Environment and Energy Security under the three-year plan for electrical system research, Project 1.7 WP3. Technologies for sustainable mobility.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Un-Noor, F.; Padmanaban, S.; Mihet-Popa, L.; Mollah, M.N.; Hossain, E. A Comprehensive Study of Key Electric Vehicle (EV) Components, Technologies, Challenges, Impacts, and Future Direction of Development. *Energies* **2017**, *10*, 1217. [CrossRef]
2. Loganathan, M.K.; Tan, C.M.; Mishra, B.; Msagati, T.A.M.; Snyman, L.W. Review and selection of advanced battery technologies for post 2020 era electric vehicles. In Proceedings of the 2019 IEEE Transportation Electrification Conference (ITEC-India), Bengaluru, India, 17–19 December 2019; pp. 1–5. [CrossRef]
3. International Energy Agency. Global EV Outlook 2023: Catching up with Climate Ambitions. Available online: www.iea.org (accessed on 14 July 2023).
4. White, L.V.; Carrel, A.L.; Shi, W.; Sintov, N.D. Why are charging stations associated with electric vehicle adoption? Untangling effects in three United States metropolitan areas. *Energy Res. Soc. Sci.* **2022**, *89*, 102663. [CrossRef]
5. Deb, S.; Kalita, K.; Mahanta, P. Review of impact of electric vehicle charging station on the power grid. In Proceedings of the 2017 International Conference on Technological Advancements in Power and Energy (TAP Energy), Kollam, India, 21–23 December 2017; pp. 1–6. [CrossRef]
6. Tavakoli, A.; Saha, S.; Arif, M.T.; Haque, E.; Mendis, N.; Oo, A.M. Impacts of grid integration of solar PV and electric vehicle on grid stability, power quality and energy economics: A review. *IET Energy Syst. Integr.* **2020**, *2*, 243–260. [CrossRef]
7. *IEC 61851-1:2017*; Electric Vehicle Conductive Charging System—Part 1: General Requirements. TC 69; International Electrotechnical Commission: Geneva, Switzerland, 2017. Available online: https://webstore.iec.ch/publication/33644 (accessed on 30 July 2023).
8. Mateen, S.; Amir, M.; Haque, A.; Bakhsh, F.I. Ultra-fast charging of electric vehicles: A review of power electronics converter, grid stability and optimal battery consideration in multi-energy systems. *Sustain. Energy Grids Netw.* **2023**, *35*, 101112. [CrossRef]
9. Savari, G.F.; Sathik, M.J.; Raman, L.A.; El-Shahat, A.; Hasanien, H.M.; Almakhles, D.; Aleem, S.H.A.; Omar, A.I. Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review. *Ain Shams Eng. J.* **2023**, *14*, 101938. [CrossRef]
10. Hossain, M.S.; Kumar, L.; Islam, M.M.; Selvaraj, J. A Comprehensive Review on the Integration of Electric Vehicles for Sustainable Development. *J. Adv. Transp.* **2022**, *2022*, 3868388. [CrossRef]

11. Zhang, Y.; Luo, X.; Qiu, Y.; Fu, Y. Understanding the generation mechanism of BEV drivers' charging demand: An exploration of the relationship between charging choice and complexity of trip chaining patterns. *Transp. Res. Part A Policy Pract.* **2022**, *158*, 110–126. [CrossRef]
12. Vanhaverbeke, L.; Verbist, D.; Barrera, G.; VUB-MOBI Electromobility Research Centre; Csukas, M.; FIER. Consumer Monitor 2022. Available online: https://alternative-fuels-observatory.ec.europa.eu/system/files/documents/2023-06/2022%20EAFO_CountryReport_EU.pdf (accessed on 14 July 2023).
13. Philipsen, R.; Schmidt, T.; van Heek, J.; Ziefle, M. Fast-charging station here, please! User criteria for electric vehicle fast-charging locations. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *40*, 119–129. [CrossRef]
14. Liao, F.; Molin, E.; van Wee, B. Consumer preferences for electric vehicles: A literature review. *Transp. Rev.* **2017**, *37*, 252–275. [CrossRef]
15. Chen, C.-F.; de Rubens, G.Z.; Noel, L.; Kester, J.; Sovacool, B.K. Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. *Renew. Sustain. Energy Rev.* **2020**, *121*, 109692. [CrossRef]
16. Chu, W.; Im, M.; Song, M.R.; Park, J. Psychological and behavioral factors affecting electric vehicle adoption and satisfaction: A comparative study of early adopters in China and Korea. *Transp. Res. Part D Transp. Environ.* **2019**, *76*, 1–18. [CrossRef]
17. Febransyah, A. Predicting Purchase Intention towards Battery Electric Vehicles: A Case of Indonesian Market. *World Electr. Veh. J.* **2021**, *12*, 240. [CrossRef]
18. Li, L.; Wang, Z.; Gong, Y.; Liu, S. Self-image motives for electric vehicle adoption: Evidence from China. *Transp. Res. Part D Transp. Environ.* **2022**, *109*, 103383. [CrossRef]
19. Daramy-Williams, E.; Anable, J.; Grant-Muller, S. A systematic review of the evidence on plug-in electric vehicle user experience. *Transp. Res. Part D Transp. Environ.* **2019**, *71*, 22–36. [CrossRef]
20. Axsen, J.; Goldberg, S.; Bailey, J. How might potential future plug-in electric vehicle buyers differ from current "Pioneer" owners? *Transp. Res. Part D Transp. Environ.* **2016**, *47*, 357–370. [CrossRef]
21. Nunes, M.L.; Fernandes, J.F.P.; Oliveira, J.; Branco, P.J.C. Power factor signature analysis for disaggregation of EV charging loads from aggregated power. In Proceedings of the CIRED Porto Workshop 2022: E-Mobility and Power Distribution Systems, Hybrid Conference, Porto, Portugal, 2–3 June 2022; pp. 23–27. [CrossRef]
22. Taha FAl Vincent, T.; Bitar, E. An Efficient Method for Quantifying the Aggregate Flexibility of Plug-in Electric Vehicle Populations. *arXiv* **2022**, arXiv:2207.07067.
23. Patil, P.; Kazemzadeh, K.; Bansal, P. Integration of charging behavior into infrastructure planning and management of electric vehicles: A systematic review and framework. *SSRN Electron. J.* **2022**. [CrossRef]
24. Amara-Ouali, Y.; Goude, Y.; Massart, P.; Poggi, J.-M.; Yan, H. A Review of Electric Vehicle Load Open Data and Models. *Energies* **2021**, *14*, 2233. [CrossRef]
25. Jia, Q.-S.; Long, T. A review on charging behavior of electric vehicles: Data, model, and control. *Control Theory Technol.* **2020**, *18*, 217–230. [CrossRef]
26. Hardman, S.; Jenn, A.; Tal, G.; Axsen, J.; Beard, G.; Daina, N.; Figenbaum, E.; Jakobsson, N.; Jochem, P.; Kinnear, N.; et al. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 508–523. [CrossRef]
27. Funke, S.Á.; Sprei, F.; Gnann, T.; Plötz, P. How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. *Transp. Res. Part D Transp. Environ.* **2019**, *77*, 224–242. [CrossRef]
28. Pareschi, G.; Küng, L.; Georges, G.; Boulouchos, K. Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. *Appl. Energy* **2020**, *275*, 115318. [CrossRef]
29. Iqbal, M.N.; Kütt, L.; Lehtonen, M.; Millar, R.J.; Püvi, V.; Rassõlkin, A.; Demidova, G.L. Travel Activity Based Stochastic Modelling of Load and Charging State of Electric Vehicles. *Sustainability* **2021**, *13*, 1550. [CrossRef]
30. Gao, H.; Yang, L.; Zhang, A.; Sheng, M. Analysis of Urban Electric Vehicle Trip Rule Statistics and Ownership Prediction. *Symmetry* **2021**, *13*, 2052. [CrossRef]
31. Thingvad, A.; Andersen, P.B.; Unterluggauer, T.; Træholt, C.; Marinelli, M. Electrification of personal vehicle travels in cities—Quantifying the public charging demand. *eTransportation* **2021**, *9*, 100125. [CrossRef]
32. Liu, X.; Fu, Z.; Qiu, S.; Li, S.; Zhang, T.; Liu, X.; Jiang, Y. Building-centric investigation into electric vehicle behavior: A survey-based simulation method for charging system design. *Energy* **2023**, *271*, 127010. [CrossRef]
33. Crozier, C.; Morstyn, T.; McCulloch, M. Capturing diversity in electric vehicle charging behaviour for network capacity estimation. *Transp. Res. Part D Transp. Environ.* **2021**, *93*, 102762. [CrossRef]
34. Pagany, R.; Marquardt, A.; Zink, R. Electric Charging Demand Location Model—A User- and Destination-Based Locating Approach for Electric Vehicle Charging Stations. *Sustainability* **2019**, *11*, 2301. [CrossRef]
35. Bollerslev, J.; Andersen, P.B.; Jensen, T.V.; Marinelli, M.; Thingvad, A.; Calearo, L.; Weckesser, T. Coincidence Factors for Domestic EV Charging From Driving and Plug-In Behavior. *IEEE Trans. Transp. Electrif.* **2021**, *8*, 808–819. [CrossRef]
36. Calearo, L.; Thingvad, A.; Suzuki, K.; Marinelli, M. Grid Loading Due to EV Charging Profiles Based on Pseudo-Real Driving Pattern and User Behavior. *IEEE Trans. Transp. Electrif.* **2019**, *5*, 683–694. [CrossRef]
37. Yang, Y.; Yao, E.; Yang, Z.; Zhang, R. Modeling the charging and route choice behavior of BEV drivers. *Transp. Res. Part C Emerg. Technol.* **2015**, *65*, 190–204. [CrossRef]

38. Ashkrof, P.; Correia, G.H.d.A.; van Arem, B. Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands. *Transp. Res. Part D Transp. Environ.* **2019**, *78*, 102206. [CrossRef]
39. Moon, H.; Park, S.Y.; Jeong, C.; Lee, J. Forecasting electricity demand of electric vehicles by analyzing consumers' charging patterns. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 64–79. [CrossRef]
40. Jabeen, F.; Olaru, D.; Smith, B.; Braunl, T.; Speidel, S. Electric vehicle battery charging behaviour: Findings from a driver survey. In Proceedings of the Australasian Transport Research Forum 2013, Brisbane, Australia, 2–4 October 2013.
41. Daina, N.; Sivakumar, A.; Polak, J.W. Modelling electric vehicles use: A survey on the methods. *Renew. Sustain. Energy Rev.* **2017**, *68*, 447–460. [CrossRef]
42. Dunckley, J.; Tal, G. *Plug-in Electric Vehicle Multi-State Market and Charging Survey*; EPRI: Palo Alto, CA, USA, 2016; p. 3002007495.
43. Anderson, J.E.; Bergfeld, M.; Nguyen, D.M.; Steck, F. Real-world charging behavior and preferences of electric vehicles users in Germany. *Int. J. Sustain. Transp.* **2022**, *17*, 1032–1046. [CrossRef]
44. Plenter, F.; von Hoffen, M.; Chasin, F.; Benhaus, S.; Matzner, M.; Paukstadt, U.; Becker, J. Quantifying Consumers' Willingness to Pay for Electric Vehicle Charging. In Proceedings of the 2018 IEEE 20th Conference on Business Informatics (CBI), Vienna, Austria, 11–14 July 2018; pp. 196–203. [CrossRef]
45. Dorcec, L.; Pevec, D.; Vdovic, H.; Babic, J.; Podobnik, V. How do people value electric vehicle charging service? A gamified survey approach. *J. Clean. Prod.* **2019**, *210*, 887–897. [CrossRef]
46. Nienhueser, I.A.; Qiu, Y. Economic and environmental impacts of providing renewable energy for electric vehicle charging—A choice experiment study. *Appl. Energy* **2016**, *180*, 256–268. [CrossRef]
47. Lagomarsino, M.; van der Kam, M.; Parra, D.; Hahnel, U.J. Do I need to charge right now? Tailored choice architecture design can increase preferences for electric vehicle smart charging. *Energy Policy* **2022**, *162*, 112818. [CrossRef]
48. Bailey, J.; Axsen, J. Anticipating PEV buyers' acceptance of utility controlled charging. *Transp. Res. Part A Policy Pract.* **2015**, *82*, 29–46. [CrossRef]
49. Delmonte, E.; Kinnear, N.; Jenkins, B.; Skippon, S. What do consumers think of smart charging? Perceptions among actual and potential plug-in electric vehicle adopters in the United Kingdom. *Energy Res. Soc. Sci.* **2020**, *60*, 101318. [CrossRef]
50. Ge, Y.; MacKenzie, D. Charging behavior modeling of battery electric vehicle drivers on long-distance trips. *Transp. Res. Part D Transp. Environ.* **2022**, *113*, 103490. [CrossRef]
51. Sun, X.; Yamamoto, T.; Morikawa, T. The Timing of Mid-trip Electric Vehicle Charging. In Proceedings of the Transportation Research Board 93rd Annual Meeting, Washington, DC, USA, 12–14 January 2014. Compendium of Papers.
52. Xu, M.; Meng, Q.; Liu, K.; Yamamoto, T. Joint charging mode and location choice model for battery electric vehicle users. *Transp. Res. Part B Methodol.* **2017**, *103*, 68–86. [CrossRef]
53. Wen, Y.; MacKenzie, D.; Keith, D.R. Modeling the Charging Choices of Battery Electric Vehicle Drivers by Using Stated Preference Data. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2572*, 47–55. [CrossRef]
54. Wang, Y.-Y.; Chi, Y.-Y.; Xu, J.-H.; Li, J.-L. Consumer Preferences for Electric Vehicle Charging Infrastructure Based on the Text Mining Method. *Energies* **2021**, *14*, 4598. [CrossRef]
55. Globisch, J.; Plötz, P.; Dütschke, E.; Wietschel, M. Consumer preferences for public charging infrastructure for electric vehicles. *Transp. Policy* **2019**, *81*, 54–63. [CrossRef]
56. Fischer, D.; Harbrecht, A.; Surmann, A.; McKenna, R. Electric vehicles' impacts on residential electric local profiles—A stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Appl. Energy* **2019**, *233–234*, 644–658. [CrossRef]
57. Zhang, J.; Yan, J.; Liu, Y.; Zhang, H.; Lv, G. Daily electric vehicle charging load profiles considering demographics of vehicle users. *Appl. Energy* **2020**, *274*, 115063. [CrossRef]
58. Latinopoulos, C.; Sivakumar, A.; Polak, J. Modeling electric vehicle charging behaviour: What is the relationship between charging location, driving and range anxiety? In Proceedings of the Transportation Research Board 96th Annual Meeting, Washington, DC, USA, 8–12 January 2017. 17p.
59. Chen, Y.; Lin, B. Are consumers in China's major cities happy with charging infrastructure for electric vehicles? *Appl. Energy* **2022**, *327*, 120082. [CrossRef]
60. Zhang, Y.; Luo, X.; Wang, Z.; Mai, Q.; Deng, R. Estimating charging demand from the perspective of choice behavior: A framework combining rule-based algorithm and hybrid choice model. *J. Clean. Prod.* **2022**, *376*, 134262. [CrossRef]
61. Asensio, O.I.; Alvarez, K.; Dror, A.; Wenzel, E.; Hollauer, C.; Ha, S. Real-time data from mobile platforms to evaluate sustainable transportation infrastructure. *Nat. Sustain.* **2020**, *3*, 463–471. [CrossRef]
62. Wang, Y.; Yao, E.; Pan, L. Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. *J. Clean. Prod.* **2021**, *286*, 124982. [CrossRef]
63. Nicholas, M.; Tal, G.; Turrentine, T.S. *Advanced Plug-in Electric Vehicle Travel and Charging Behavior Interim Report*; The Regents of the University of California: California, CA, USA, 2017.
64. Lee, J.H.; Chakraborty, D.; Hardman, S.J.; Tal, G. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. *Transp. Res. Part D Transp. Environ.* **2020**, *79*, 102249. [CrossRef]
65. Franke, T.; Krems, J.F. Understanding charging behaviour of electric vehicle users. *Transp. Res. Part F Traffic Psychol. Behav.* **2013**, *21*, 75–89. [CrossRef]
66. Franke, T.; Krems, J.F. Interacting with limited mobility resources: Psychological range levels in electric vehicle use. *Transp. Res. Part A Policy Pract.* **2013**, *48*, 109–122. [CrossRef]

67. Philipsen, R.; Brell, T.; Biermann, H.; Ziefle, M. Under Pressure—Users' Perception of Range Stress in the Context of Charging and Traditional Refueling. *World Electr. Veh. J.* **2019**, *10*, 50. [CrossRef]
68. Yuan, Q.; Hao, W.; Su, H.; Bing, G.; Gui, X.; Safikhani, A. Investigation on Range Anxiety and Safety Buffer of Battery Electric Vehicle Drivers. *J. Adv. Transp.* **2018**, *2018*, 8301209. [CrossRef]
69. Pan, L.; Yao, E.; MacKenzie, D. Modeling EV charging choice considering risk attitudes and attribute non-attendance. *Transp. Res. Part C Emerg. Technol.* **2019**, *102*, 60–72. [CrossRef]
70. Hardinghaus, M.; Anderson, J.E.; Nobis, C.; Stark, K.; Vladova, G. Booking Public Charging: User Preferences and Behavior towards Public Charging Infrastructure with a Reservation Option. *Electronics* **2022**, *11*, 2476. [CrossRef]
71. Budnitz, H.; Meelen, T.; Schwanen, T. Residential Neighbourhood Charging of Electric Vehicles: An exploration of user preferences. *SocArXiv* **2022**. [CrossRef]
72. Dixon, J.; Andersen, P.B.; Bell, K.; Træholt, C. On the ease of being green: An investigation of the inconvenience of electric vehicle charging. *Appl. Energy* **2020**, *258*, 114090. [CrossRef]
73. Wolbertus, R.; Gerzon, B. Improving Electric Vehicle Charging Station Efficiency through Pricing. *J. Adv. Transp.* **2018**, *2018*, 4831951. [CrossRef]
74. Latinopoulos, C.; Sivakumar, A.; Polak, J. Response of electric vehicle drivers to dynamic pricing of parking and charging services: Risky choice in early reservations. *Transp. Res. Part C Emerg. Technol.* **2017**, *80*, 175–189. [CrossRef]
75. Gnann, T.; Plötz, P.; Wietschel, M. Can public slow charging accelerate plug-in electric vehicle sales? A simulation of charging infrastructure usage and its impact on plug-in electric vehicle sales for Germany. *Int. J. Sustain. Transp.* **2019**, *13*, 528–542. [CrossRef]
76. Neaimeh, M.; Wardle, R.; Jenkins, A.M.; Yi, J.; Hill, G.; Lyons, P.F.; Hübner, Y.; Blythe, P.T.; Taylor, P.C. A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts. *Appl. Energy* **2015**, *157*, 688–698. [CrossRef]
77. Speidel, S.; Bräunl, T. Driving and charging patterns of electric vehicles for energy usage. *Renew. Sustain. Energy Rev.* **2014**, *40*, 97–110. [CrossRef]
78. Corchero, C.; Gonzalez-Villafranca, S.; Sanmarti, M. European electric vehicle fleet: Driving and charging data analysis. In Proceedings of the 2014 IEEE International Electric Vehicle Conference (IEVC), Florence, Italy, 17–19 December 2014; pp. 1–6. [CrossRef]
79. Xu, Y.; Çolak, S.; Kara, E.C.; Moura, S.J.; González, M.C. Planning for electric vehicle needs by coupling charging profiles with urban mobility. *Nat. Energy* **2018**, *3*, 484–493. [CrossRef]
80. Weldon, P.; Morrissey, P.; Brady, J.; O'mahony, M. An investigation into usage patterns of electric vehicles in Ireland. *Transp. Res. Part D Transp. Environ.* **2016**, *43*, 207–225. [CrossRef]
81. Yang, J.; Dong, J.; Zhang, Q.; Liu, Z.; Wang, W. An Investigation of Battery Electric Vehicle Driving and Charging Behaviors Using Vehicle Usage Data Collected in Shanghai, China. *Transp. Res. Rec. J. Transp. Res. Board* **2018**, *2672*, 20–30. [CrossRef]
82. INL. Nissan Leaf Vehicle Summary Report. 2014. Available online: https://avt.inl.gov/sites/default/files/pdf/EVProj/EVProjectNissanLeafQ42013.pdf (accessed on 14 July 2023).
83. Märtz, A.; Langenmayr, U.; Ried, S.; Seddig, K.; Jochem, P. Charging Behavior of Electric Vehicles: Temporal Clustering Based on Real-World Data. *Energies* **2022**, *15*, 6575. [CrossRef]
84. Daina, N.; Polak, J.W. Hazard based modelling of electric vehicles charging patterns. In Proceedings of the 2016 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific), Busan, Republic of Korea, 1–4 June 2016; pp. 479–484. [CrossRef]
85. Sun, X.-H.; Yamamoto, T.; Morikawa, T. Charge timing choice behavior of battery electric vehicle users. *Transp. Res. Part D Transp. Environ.* **2015**, *37*, 97–107. [CrossRef]
86. Sun, X.-H.; Yamamoto, T.; Morikawa, T. Fast-charging station choice behavior among battery electric vehicle users. *Transp. Res. Part D Transp. Environ.* **2016**, *46*, 26–39. [CrossRef]
87. Kim, S.; Yang, D.; Rasouli, S.; Timmermans, H. Heterogeneous hazard model of PEV users charging intervals: Analysis of four year charging transactions data. *Transp. Res. Part C Emerg. Technol.* **2017**, *82*, 248–260. [CrossRef]
88. Helmus, J.; Hoed, R.V.D. Unraveling User Type Characteristics: Towards a Taxonomy for Charging Infrastructure. *World Electr. Veh. J.* **2015**, *7*, 589–604. [CrossRef]
89. Singh, S.; Vaidya, B.; Mouftah, H.T. Smart EV Charging Strategies Based on Charging Behavior. *Front. Energy Res.* **2022**, *10*, 773440. [CrossRef]
90. Helmus, J.R.; Lees, M.H.; Hoed, R.v.D. A data driven typology of electric vehicle user types and charging sessions. *Transp. Res. Part C Emerg. Technol.* **2020**, *115*, 102637. [CrossRef]
91. Liu, Y.; Hong, Y.; Hu, C. Research on Big Data Mining Technology of Electric Vehicle Charging Behaviour. *Elektron. Ir Elektrotechnika* **2019**, *25*, 55–61. [CrossRef]
92. Schäuble, J.; Kaschub, T.; Ensslen, A.; Jochem, P.; Fichtner, W. Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany. *J. Clean. Prod.* **2017**, *150*, 253–266. [CrossRef]
93. Steenbrink, M.; Jochemsen, T.; Piersma, N.; van der Mei, R.; Dugunji, E. A Prediction Model for the Demand of Charging Stations for Electric Vehicles in the Municipality of Amsterdam. 2016. Available online: https://research.hva.nl/en/publications/a-prediction-model-for-the-demand-of-charging-stations-for-electr (accessed on 28 November 2023).

94. Powell, S.; Cezar, G.V.; Rajagopal, R. Scalable probabilistic estimates of electric vehicle charging given observed driver behavior. *Appl. Energy* **2022**, *309*, 118382. [CrossRef]
95. Powell, S.; Cezar, G.V.; Min, L.; Azevedo, I.M.L.; Rajagopal, R. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. *Nat. Energy* **2022**, *7*, 932–945. [CrossRef]
96. Azadfar, E.; Sreeram, V.; Harries, D. The investigation of the major factors influencing plug-in electric vehicle driving patterns and charging behaviour. *Renew. Sustain. Energy Rev.* **2015**, *42*, 1065–1076. [CrossRef]
97. Chakraborty, D.; Bunch, D.S.; Lee, J.; Tal, G. *What Factors Drive Commuters' Demand for Electric Vehicle Charging Infrastructure?* UC Office of the President, University of California Institute of Transportation Studies, University of California: Berkeley, CA, USA, 2020. [CrossRef]
98. Kim, D.; Kwon, D.; Han, J.; Lee, S.M.; Elkosantini, S.; Suh, W. Data-Driven Model for Identifying Factors Influencing Electric Vehicle Charging Demand: A Comparative Analysis of Early- and Maturity-Phases of Electric Vehicle Programs in Korea. *Appl. Sci.* **2023**, *13*, 3760. [CrossRef]
99. Kacperski, C.; Ulloa, R.; Klingert, S.; Kirpes, B.; Kutzner, F. Impact of incentives for greener battery electric vehicle charging—A field experiment. *Energy Policy* **2022**, *161*, 112752. [CrossRef]
100. Majidpour, M.; Qiu, C.; Chu, P.; Pota, H.R.; Gadh, R. Forecasting the EV charging load based on customer profile or station measurement? *Appl. Energy* **2016**, *163*, 134–141. [CrossRef]
101. Sun, M.; Shao, C.; Zhuge, C.; Wang, P.; Yang, X.; Wang, S. Uncovering travel and charging patterns of private electric vehicles with trajectory data: Evidence and policy implications. *Transportation* **2022**, *49*, 1409–1439. [CrossRef]
102. Dodson, T.; Slater, S. Electric Vehicle Charging Behaviour Study. 2019. Available online: https://www.element-energy.co.uk/publications/ (accessed on 14 July 2023).
103. Jonas, T.; Daniels, N.; Macht, G. Electric Vehicle User Behavior: An Analysis of Charging Station Utilization in Canada. *Energies* **2023**, *16*, 1592. [CrossRef]
104. Wang, R.; Xing, Q.; Chen, Z.; Zhang, Z.; Liu, B. Modeling and Analysis of Electric Vehicle User Behavior Based on Full Data Chain Driven. *Sustainability* **2022**, *14*, 8600. [CrossRef]
105. Hu, L.; Dong, J.; Lin, Z.H. Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. *Transp. Res. Part C Emerg. Technol.* **2019**, *102*, 474–489. [CrossRef]
106. Sadeghianpourhamami, N.; Refa, N.; Strobbe, M.; Develder, C. Quantitive analysis of electric vehicle flexibility: A data-driven approach. *Int. J. Electr. Power Energy Syst.* **2018**, *95*, 451–462. [CrossRef]
107. ElaadNL. 2023. Available online: https://elaad.nl/en/ (accessed on 14 July 2023).
108. Shahriar, S.; Al-Ali, A.R.; Osman, A.H.; Dhou, S.; Nijim, M. Prediction of EV Charging Behavior Using Machine Learning. *IEEE Access* **2021**, *9*, 111576–111586. [CrossRef]
109. Hecht, C.; Figgener, J.; Sauer, D.U. Analysis of electric vehicle charging station usage and profitability in Germany based on empirical data. *iScience* **2022**, *25*, 105634. [CrossRef]
110. Chen, C.; Song, Y.; Hu, X.; Guardiola, I.G. Analysis of Electric Vehicle Charging Behavior Patterns with Function Principal Component Analysis Approach. *J. Adv. Transp.* **2020**, *2020*, 8850654. [CrossRef]
111. Morrissey, P.; Weldon, P.; O'mahony, M. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. *Energy Policy* **2016**, *89*, 257–270. [CrossRef]
112. Lim, K.L.; Speidel, S.; Bräunl, T. A comparative study of AC and DC public electric vehicle charging station usage in Western Australia. *Renew. Sustain. Energy Transit.* **2022**, *2*, 100021. [CrossRef]
113. Flammini, M.G.; Prettico, G.; Julea, A.; Fulli, G.; Mazza, A.; Chicco, G. Statistical characterisation of the real transaction data gathered from electric vehicle charging stations. *Electr. Power Syst. Res.* **2019**, *166*, 136–150. [CrossRef]
114. Kara, E.C.; Macdonald, J.S.; Black, D.; Bérges, M.; Hug, G.; Kiliccote, S. Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach. *Appl. Energy* **2015**, *155*, 515–525. [CrossRef]
115. van der Kam, M.; van Sark, W.; Alkemade, F. Multiple roads ahead: How charging behavior can guide charging infrastructure roll-out policy. *Transp. Res. Part D Transp. Environ.* **2020**, *85*, 102452. [CrossRef]
116. Siddique, C.; Afifah, F.; Guo, Z.; Zhou, Y. Data mining of plug-in electric vehicles charging behavior using supply-side data. *Energy Policy* **2022**, *161*, 112710. [CrossRef]
117. Li, X.; Zhang, Q.; Chibane, H.; Cavallucci, D.; Tang, X.; Zuo, J.; Song, H. Data-Driven Temporal Charging Patterns of Electric Vehicles in China. *Energy Technol.* **2021**, *9*, 2100421. [CrossRef]
118. Gerossier, A.; Girard, R.; Kariniotakis, G. Modeling and Forecasting Electric Vehicle Consumption Profiles. *Energies* **2019**, *12*, 1341. [CrossRef]
119. Quiros-Tortos, J.; Ochoa, L.F.; Lees, B. A statistical analysis of EV charging behavior in the UK. In Proceedings of the 2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM), Montevideo, Uruguay, 5–7 October 2015; pp. 445–449. [CrossRef]
120. Quiros-Tortos, J.; Espinosa, A.N.; Ochoa, L.F.; Butler, T. Statistical Representation of EV Charging: Real Data Analysis and Applications. In Proceedings of the 2018 Power Systems Computation Conference (PSCC), Dublin, Ireland, 11–15 June 2018; pp. 1–7. [CrossRef]

121. Yi, Z.; Scoffield, D. A Data-Driven Framework for Residential Electric Vehicle Charging Load Profile Generation. In Proceedings of the 2018 IEEE Transportation Electrification Conference and Expo (ITEC), Long Beach, CA, USA, 13–15 June 2018; pp. 519–524. [CrossRef]
122. Kim, J.D. Insights into residential EV charging behavior using energy meter data. *Energy Policy* **2019**, *129*, 610–618. [CrossRef]
123. Munshi, A.A.; Mohamed, Y.A.-R.I. Extracting and Defining Flexibility of Residential Electrical Vehicle Charging Loads. *IEEE Trans. Ind. Inform.* **2018**, *14*, 448–461. [CrossRef]
124. Zhao, H.; Yan, X.; Ren, H. Quantifying flexibility of residential electric vehicle charging loads using non-intrusive load extracting algorithm in demand response. *Sustain. Cities Soc.* **2019**, *50*, 101664. [CrossRef]
125. Muratori, M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nat. Energy* **2018**, *3*, 193–201. [CrossRef]
126. Asensio, O.I.; Lawson, M.C.; Apablaza, C.Z. Electric vehicle charging stations in the workplace with high-resolution data from casual and habitual users. *Sci. Data* **2021**, *8*, 168. [CrossRef]
127. Lee, Z.J.; Li, T.; Low, S.H. ACN-Data: Analysis and Applications of an Open EV Charging Dataset. In Proceedings of the Tenth ACM International Conference on Future Energy Systems, Phoenix, AZ, USA, 25–28 June 2019; pp. 139–149. [CrossRef]
128. Xydas, E.; Marmaras, C.; Cipcigan, L.M.; Jenkins, N.; Carroll, S.; Barker, M. A data-driven approach for characterising the charging demand of electric vehicles: A UK case study. *Appl. Energy* **2016**, *162*, 763–771. [CrossRef]
129. Mandev, A.; Plötz, P.; Sprei, F.; Tal, G. Empirical charging behavior of plug-in hybrid electric vehicles. *Appl. Energy* **2022**, *321*, 119293. [CrossRef]
130. Cheng, L.; Chen, X.; Yang, S.; Wu, J.; Yang, M. Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. *Transp. Lett.* **2019**, *11*, 341–349. [CrossRef]
131. Blythe Prof, P.; Hill, D.G.; Huebner, D.Y.; Suresh, V.; Austin, J.; Gray, L.; Wardle, J. The North East England Electric Vehicle and Infrastructure Trials. *World Electr. Veh. J.* **2012**, *5*, 856–865. [CrossRef]
132. LaMonaca, S.; Ryan, L. The state of play in electric vehicle charging services – A review of infrastructure provision, players, and policies. *Renew. Sustain. Energy Rev.* **2022**, *154*, 111733. [CrossRef]
133. Ge, Y.; Simeone, C.; Duvall, A.; Wood, E. *There's No Place Like Home: Residential Parking, Electrical Access, and Implications for the Future of Electric Vehicle Charging Infrastructure*; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2021. [CrossRef]
134. Chen, T.; Zhang, X.-P.; Wang, J.; Li, J.; Wu, C.; Hu, M.; Bian, H. A Review on Electric Vehicle Charging Infrastructure Development in the UK. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 193–205. [CrossRef]
135. Blonsky, M.; Munankarmi, P.; Balamurugan, S.P. Incorporating Residential Smart Electric Vehicle Charging in Home Energy Management Systems. In Proceedings of the 2021 IEEE Green Technologies Conference (GreenTech), Denver, CO, USA, 7–9 April 2021; pp. 187–194. [CrossRef]
136. Winn, R. Electric Vehicle Charging at Work. 2019. Available online: https://innovation.luskin.ucla.edu/wp-content/uploads/2019/03/EV_Charging_at_Work.pdf (accessed on 14 July 2023).
137. Desai, R.R.; Chen, R.B.; Armington, W. A Pattern Analysis of Daily Electric Vehicle Charging Profiles: Operational Efficiency and Environmental Impacts. *J. Adv. Transp.* **2018**, *2018*, 6930932. [CrossRef]
138. Günther, M.; Fallahnejad, M. Strategic_Planning_of_Public_Charging_In. UBH Discussion Papers, Reihe: IT & Engineering. 2021. Available online: https://www.iubh-university.de/forschung/publikationen/ (accessed on 14 July 2023).
139. Develder, C.; Sadeghianpourhamami, N.; Strobbe, M.; Refa, N. Quantifying flexibility in EV charging as DR potential: Analysis of two real-world data sets. In Proceedings of the 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), Sydney, NSW, Australia, 6–9 November 2016; pp. 600–605. [CrossRef]
140. Greene, D.L.; Kontou, E.; Borlaug, B.; Brooker, A.; Muratori, M. Public charging infrastructure for plug-in electric vehicles: What is it worth? *Transp. Res. Part D Transp. Environ.* **2020**, *78*, 102182. [CrossRef]
141. Maness, M.; Lin, Z. Free Charging: Exploratory Study of Its Impact on Electric Vehicle Sales and Energy. *Transp. Res. Rec. J. Transp. Res. Board* **2019**, *2673*, 590–601. [CrossRef]
142. Daina, N.; Sivakumar, A.; Polak, J.W. Electric vehicle charging choices: Modelling and implications for smart charging services. *Transp. Res. Part C Emerg. Technol.* **2017**, *81*, 36–56. [CrossRef]
143. Schaden, B.; Jatschka, T.; Limmer, S.; Raidl, G.R. Smart Charging of Electric Vehicles Considering SOC-Dependent Maximum Charging Powers. *Energies* **2021**, *14*, 7755. [CrossRef]
144. Csillak, K.; Kamenz, S. Electric charging infrastructure and gender equality: An overview for USER-CHI (H2020 project). *Open Res. Eur.* **2023**, *3*, 47. [CrossRef]
145. McKinney, T.R.; Ballantyne EE, F.; Stone, D.A. Rural EV charging: The effects of charging behaviour and electricity tariffs. *Energy Rep.* **2023**, *9*, 2321–2334. [CrossRef]
146. Gupta, R.; Pena-Bello, A.; Streicher, K.N.; Roduner, C.; Farhat, Y.; Thöni, D.; Patel, M.K.; Parra, D. Spatial analysis of distribution grid capacity and costs to enable massive deployment of PV, electric mobility and electric heating. *Appl. Energy* **2021**, *287*, 116504. [CrossRef]

147. Gadgil, S.; Ekambaram, K.; Davies, H.; Jones, A.; Birrell, S. Determining the Social, Economic, Political and Technical Factors Significant to the Success of Dynamic Wireless Charging Systems through a Process of Stakeholder Engagement. *Energies* **2022**, *15*, 930. [CrossRef]
148. Sylvia, H.; Omar, H.; Thierry, C.; Joeri, V.M. Social acceptance of wireless battery charging systems: Belgium case study. In Proceedings of the 2014 IEEE International Electric Vehicle Conference (IEVC), Florence, Italy, 17–19 December 2014; pp. 1–6. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.