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A Literature Review on Charging Behaviour of Private Electric Vehicles

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A Literature Review on Charging Behaviour of Private Electric Vehicles

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Abstract: Electric mobility is one of the ways to contain greenhouse gas and local pollutants emissions in urban areas. Nevertheless, the massive introduction of battery-powered electric vehicles (EVs) brings 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 intends to examine the approaches used to investigate on charging behavior and highlight trends and differences between the results, remarking on any gaps worthy of further investigation.

Keywords: electric vehicles; charging behavior; private electric mobility

1. Introduction

The switch to electric mobility is one of the ways to contain 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 engine 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 correct planning that satisfies real demand. Elements such as power request, charge duration, 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 the grid electricity [5,6]. For these reasons, understanding and predicting charging behaviors with sufficient accuracy is 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, and by intrinsic socioeconomic and psychological factors, as well as by charging network design, that could also maximize utilization rate and user satisfaction.

Electric vehicles can be charged at various locations and speeds, and the costs may differ. An EV supply equipment (EVSE) can be composed by one or more charging points (CP), that connect the power grid to the electric vehicles, drawing AC power to charge the EV battery in DC. The converters

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can be either onboard or offboard, depending on the type of charging. The chargers can be classified into two categories, 'level' and 'mode'. Charging level 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 currents. 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 the mode 4, the conversion takes place in the charger.

Level 1 charging refers to 120 AC voltage with a power of 2 kW, it is typically used in residential settings and requires no special equipment. It is not allowed in EU. Level 2 corresponds to the standard European 230/240V 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 power up to 500 kW, and are mainly intended for long-distance driving and heavy vehicle [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 the EVs energy demand modeling, 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 energy demand at 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, of higher education and middle age, with above-average income and with multiple cars per household [10–12], which corresponds to the profile of EV early adopters [13]. With the spread of electric mobility, this audience tends to widen and include different users' groups with presumably diverse needs and behavior. Some research refers to a relatively immature phase of the adoption of electric mobility, and their results must be analyzed considering that the behavior of the EV early adopters may not coincide with those springing from the mass adoption.

In fact, the propensity to adopt EVs depends on many factors, both economic and psychological, investigated in literature. Economic studies usually compare the alternative 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 awareness of environmental values are factors that dispose to the purchase of an electric car [15], as well as satisfaction for 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 as belonging to a specific category of people, and the perception of the electric car as a status symbol seem to influence positively the purchase choice [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 for longer than for newbies or conventional car owners. On the other hand, charging anxiety seems less present in 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 emerges 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 is currently low [20], possibly because of scarce intentions to buy an EV or continue to use the specific knowledge derived from experience with ICEV when they imagine using EVs. This fact should be considered in the analysis, 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 the charging behavior, while others aim at other results, such as the determination of the optimal location of the charging structures, or the smart management of charging requests in stations, or the assessment of demand for scenarios of penetration of electric mobility. Our own aim is to highlight prevalent criteria in 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 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 process.

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 results for some studies investigating the charging behavior of private EVs. 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 and Method

The analysis of the charging behavior is of fundamental importance for the correct planning of the infrastructures, the choice of optimal charge management strategies, and the application of policies aimed at improving the penetration of electric mobility and the demand integration with the electricity distribution network. There are different possible approaches to the investigation, which may depend on the type of data used, the variables taken into consideration, and the specific purposes of the studies. Indeed, the charges demand analysis can rely on different data and information sources. Some studies reviewed in this work are devoted to behavioral investigation, while others use the data to obtain load estimates for further purposes. The studies are generally conducted on limited geographical areas and for well-defined periods. The datasets used to obtain

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information on charging choices and load curves include charging point (CP) information, historical charging session series, traffic monitors, travel surveys, users' questionnaires, and EV information. Data analysis approaches include statistical characterization, stochastic processes, and machine learning.

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

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

The 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 on the main search tools of scientific publications (Google Scholar, Internet Archive Scholar (IAS), CORE). We limited the search to papers published after 2015, except for some particularly relevant works. The search on Google Scholar and CORE used the "OR" operator between keywords. For IAS, the string used is "charg* behav*" for the search in 'Description' field. Google Scholar returned around 24.400 results; 2.374 research outputs found in CORE; For IAS, we obtained 5,721 results. Out of these, 1098 were text. When we filtered for Subject[1], only 84 texts returned.

We selected articles that specifically mentioned the charging behavior of EV users in their title or abstract. 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 that can be psychological, sociological, demographic, or geographical or linked to the maturity of the EV market and the diffusion of charging infrastructure. Secondly, the data from which to extract or infer these behaviors is limited, as in the case of targeted surveys, or suffers from intrinsic limitations, such as, for example, 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 aimed at their implementation in the planning of charging infrastructures. Liao et al. [14] presented a review of studies to identify which characteristics of the EV and its system of services, including the infrastructure system and policies to promote electric

[1] 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.

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mobility, impact on consumer choices. Amara-Ouali et al. [24] reviewed open databases relevant for EV charging demand modeling and gave an overview of the forecasting models, ranging from statistical characterization, stochastic processes, and machine learning. An examination of the studies on the charging demand impact on the energy distribution grid is presented in Deb et al. [5]. Jia & Long [25] provided a collection of data sets on sales volume, driving, EV charging, and automotive battery performance. The discussion includes the 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 emerges 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 the studies investigating the medium-long-term demand for recharging infrastructure, comparing the framework conditions in different countries to highlight the differences. The authors conclude 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 experiences 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, while disregarding aspects related to the impact on the network that some previous reviews may have covered. The primary objective is to provide a comprehensive overview of the different factors that can impact the users' charging demand. More specifically, our objective is to verify whether it is possible to identify, within the literature, the variables that influence charging behavior beyond context differences; mutually, we aim at verifying 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 by 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 none or limited information on users.

2.2.1. Survey Based Papers

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

2.2.1.1. Travel Survey

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 estimating charging load has been tested in the Swiss context in [28]. The study uses the results of a survey on ICE cars, and assumes a complete transformation into EVs, both pure battery (BEV) and plug-in hybrids (PHEV). The load curves obtained under this hypothesis are compared with the measurements made in various field tests for the EVs, showing a good agreement. The charging decision scheme modeled depends solely on the SOC. The same charging criterion is adopted by Iqbal et al. [29] to determine the power demand for residential EVSE. Using traffic survey data on ICE and assuming a transition to EV, they classify daily usage based on different categories of car owners and provide an estimate of SOC based on distances traveled. The importance of travel choices in the charging decisions is illustrated in Zhang et al. [11]. They explore the relationship between two models of causal choices: in the first, the charging strategy is determined first and affects the travel chain; in the other, the journey influences the charge decision. The preferences from about 500 questionnaires show 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] use mobility questionnaires explicitly devoted to EV owners to construct the spatial and temporal distribution of stops as a function of destinations. Findings show that the charging demand in residential area and workplaces are the largest, followed by public park lots and curbside parking.

A survey on driving and ownership data is the basis of the charging demand estimation for public infrastructure in urban areas where the domestic charging is not broadly available [31]. The results reveal that nearly 78% of energy demand can be supplied by private CPs, of which 11% provided by chargers installed in shared residential parking lots, reducing the need for public CPs by up to 58%. For commuters without home charging, workplaces 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 evaluated also in [32]. The survey outcomes show that slow chargers in the workplace can almost completely meet the intra-city travel demand of private EVs, even if the size of the city greatly influences the mobility patterns, and the charging demand curves due to the different travel needs.

2.2.1.2. Users Charging Preferences Survey

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 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 stop 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 surveys-based studies explicitly focus on investigating users' charging preferences and which factors affect the decision. A joint research based on stated mobility and charging choices [37] shows that the instantaneous SOC is the most important factor in 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 not considering the choice of fast charging [38].

Results 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 are 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] investigate home charging preferences showing that the energy to charge has a positive marginal utility in most cases, while the charging time has a more complex influence: most of the users keep the vehicle under charge until they stay at home and do not to finish charging if this causes delays in departure. The charge cost always has a negative marginal utility.

An extensive analysis of charging behaviors in the USA [42] collected data on location, time, and power of charge events. 57% of users stated that they only charge at home, and 40% at home and away from home, mainly at work. Most users start charging when they plug in their vehicle, 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 is to use public charging.

A stated choice survey and willingness-to-pay (WTP) analysis confirmed home charging as the primary charging method, while public infrastructure was deemed insufficient [43]. The determining factors in the charging choice are the price, the occupancy rate and the waiting time at the charging infrastructure. An acceptable distance from the destination point to the charging infrastructure is 5-10 minutes walking distance [43]. Other WTP analysis shows that it increases proportionally to the CP power and its distance from the city center [44]. Dorcec et al. [45] obtained similar conclusions; moreover, the lower the SOC, the more EV owners are willing to pay for charging. Attention to environmental issues emerges in 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 to minimize peak demand and maximize 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 to reach the 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 begins during a road trip. 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 the battery capacity and SOC, the possibility to charge 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/company. With a survey of BEV owners, Wen et al. [53] identify three basic types of charging behavior: triggered by price and need; replenish whenever the opportunity arises; based on a wider range of factors, including charging power, dwell time and the cost of home charging. It also emerged that the respondent majority is willing to pay more for fast charging over slow charging. The preferences expressed on some social media by consumers highlights that direct current (DC) fast charging is popular with consumers for reducing charging times; vehicle range is a concern when traveling long distances or using air conditioners; 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 is more important to build a fast charging network than strengthen the slow one.

2.2.1.3. 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 beside 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 the charging price [59]. Y. Zhang et al. [60] show 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, coverage of recharging facilities, travel distance, and perception of SOC. Choice of CPs is affected by destination type, parking duration, charge price, next travel distance, travel chain, SOC, and risk aversion [60].

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The aspects related to the charging experience are increasingly arousing the interest of researchers. Asensio et al. [61] analyze the users' reviews collected online for public and private charging stations. The results show that nearly half of users report a negative experience at charging stations. The judgment of other users on the EVSE quality of service and their attitude to risk influences the choice of the 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 charge or free charging in the workplace. Charging network subscriptions has 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 the 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 the devices, which leads to recharge based on contextual triggers rather than on the 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 and BEV users with varying levels of experience reveals that stress levels for vehicle range are similar in 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 ICEs if driving on a long journey. Connected to the previous aspects is the attitude to risk in the charging choice [69]. The inclusion of the risk attitude, in the form of a latent variable, improves the adaptation to the experimental data of the developed forecasting model [11].

Some studies aim to investigate which actions can improve access to charging and users' perception of the charging infrastructure as available, reliable, and sufficient for their needs. A pilot experiment on dedicated neighborhood charging [70] shows that potential EV users value parking-combined and bookable charging options within the city as of paramount importance, especially as parking is a problem heard among EV users and not. A survey of stated preferences without a private residential charging option finds that the most important aspects of public charging are closely related to personal safety and proximity to home, especially if the service is used overnight [71].

With a view to a comparison with conventional mobility, Dixon et al. [72] analyses travel diaries to quantify the inconvenience deriving from longer recharging times compared to the refueling times of ICE cars. They verify that around 95% of people with access to domestic charge 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 to influence charging choices is of great interest to local or national authorities, although the evaluation is not always simple. For example, the application of a fee is generally effective in inducing users to move the car at the end of the charge, but the need for parking can lead to nullifying 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 the section. We summarize 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 year and country of data collection; the main topic of the study: tick on 'Users behavior' if the study focuses on charging habits of actual or potential EV users; 'Infrastructures' if the work also considers aspects related to the planning and management of charging infrastructures, such as optimal location, power, ancillary services, impact on the grid; 'Policies' if interventions for improving or boost electric mobility are explicitly considered, such as intelligent management of recharging, variable prices, incentive policies.

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

Source	SurveySource	Sample Size	Year[2]	Country	Users Behavior	Infrastructures	Policies	Keypoints
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 & optimal location of 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	1,156 households	2021	China		◎		Demand dominated by charging in the residential area and workplace
Thingvad et al. [31]	TS	56,328 households	2014-2019	Denmark		◎		Evaluation of energy demand @ public & private CP
X. Liu et al. [32]	RP	141 prespondents	2021	China	◎	◎		Use of charging facilities at the workplace in different urban contexts

Crozier et al. [33]	TS + charging data	2 milions trips + charging data of 213 Nissan Leaf	2016	UK	◎		◎	Impact of the variability of travel and charging behavior on overall demand
Pagany et al. [34]	TS	Over 5000 households	2012-2013	Germany	◎	◎		Optimal CPs location 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 + 7,163 Nissan LEAFs charging events	2012; 2015-2016	Denmark, USAJapan		◎		Quantify the load impact of domestic charges on distribution grid feeders
Y. Yang et al. [37]	SP	237 respondents	2014	China	◎			Investigate the mobility and charging choices of EV drivers
Ashkrof et al. [38]	SP	505 respondents	2020	Netherlands	◎			Explore BEVs drivers route choice and charging preferences
Moon et al. [39]	SP	418 respondents	2016	Korea	◎	◎		Estimate EV expansion scenarios and their electricity demands
Jabeen et al. [40]	SP	54 respondents	2012	Australia	◎			Prevalence of home and workplace charging from charging habit analysis
Daina et al. [41]	SP	88 respondents	2012	UK	◎			Evaluation of the marginal

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								utility of the recharged energy, of the time and of the cost of the recharge
EPRI [42]	TS	4,000 PEV owners	2016	USA	◎	◎	◎	Analysis of the private charging and plug-in electric car market
Anderson et al. [43]	SP	Around 4,000 EV users	2020	Germany	◎			Analysis of charging behavior and EV preferences
Plenter et al. [44]	SP	435 respondents	2014	Germany	◎		◎	WTP vs power and location of the charging station
Dorcec et al. [45]	SP	101 respondents	2019	Croazia	◎			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.
Delmonte et al. [49]	SP	60 respondents	2020	UK	◎		◎	Acceptance of two types of controlled charges: by user or by network operator
M. Xu et al. [52]	RP	500 respondents	2017	Japan	◎			Factors that influence the choice of location and

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								charging method
Wen et al. [53]	SP	315 respondents	20163	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	◎		◎	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	202009	USA		◎		EV charging load simulations considering user demographics
Latinopoulos et al. [58]	SP	118 respondents	2017	UK, Ireland	◎			Understand 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

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							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 of the charging stations
Y. Wang et al. [62]	SP	300 respondents	2021	China	◎◎		Analyze 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 & 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	7,979 EV users (completed survey 15%)	2016-2017	California	◎◎		Differences in charging behavior among different types of PEV owners
Franke & Krems [65,66]	SP+RP	79 EV users	2013	Germany	◎◎		Understanding of the psychological dynamics underlying charging behaviour
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	◎◎			Range anxiety effect on driver's emotions and behaviors
Pan et al. [69]	SP	160 EV drivers	2018	China	◎◎			EV drivers 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 natural language processing technology to explore consumer preferences for charging infrastructure
Dixon et al. [72]	TS	39,000 travel diaries	2012–2016	UK	◎◎			Inconvenience of the duration of the EV charge
Wolbertus & Gerzon, 2018 [73]	SP	119 respondents	2018	Netherlands	◎◎		◎◎	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	

2.2.2. Mobility and Charging Behavior Data

Mobility data is a valid source for extracting travel and transport habits in each area. 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

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from the EV on-board instrumentation to provide a more comprehensive picture of the charging behaviors [25]. Mobility data can identify the points of greatest attraction and the spatiotemporal distribution of travels. In some cases, they can refer to ICE vehicles and are translated to electric mobility 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, frequency of charges with respect to distances travelled, or number and nature of stops.

Some work referred to an initial phase of EV diffusion. The prevalent use of charging at home and work emerges in two studies [76,77]. Both studies show that the start charging SOC is, on average, above 50%. Using static and dynamic data regarding EV and CP in over 10 European countries, [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 CPs.

Mobile telephony data integrated with census data, a survey on PEV drivers, and measurements at the CPs have made it possible to build a high-definition space-time mobility model [79], which detects how the charging behaviors follow the traffic trend, 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 is confirmed by J. Yang et al., [81]: analyzing driving and recharging behaviors, they find that the distances between consecutive recharges are in general shorter than the average daily distances, indicating a tendency to charge whenever there are convenient opportunities, regardless of the remaining range. This behavior is comparable with what obtained in [82], and with the results in [83] that highlights a high daily number of opportunity charges. The risk analysis of the interval times between recharging events shows that both vehicle attributes, such as state of charge, distance traveled, average driving speed, and individual characteristics (range anxiety, age, and purpose of travel) significantly influence the instantaneous rate of occurrence of charging events [84].

The vehicle usage also influences the charging behavior, with commercial EVs charging 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 a shorter detour and are greatly influenced in their choice by the residual SOC [86].

Different approaches have tried 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 behavior of different types of users [92]. For example, [93] find 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] provide a model for estimating the aggregated charging profile of different driver groups whose charging behaviors are 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 the free parking [98], which can be used to influence charging preferences [99].

2.3. Analysis of the Infrastructure Usage

Charging data directly provide the load curves at the stations, allowing a detailed analysis of the request distribution. Studies based on this data often aim at 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 posing more problems for 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

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on multiple source data. Detailed spatio-temporal patterns of charging infrastructures usage emerge 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 for private EV [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 prevalence of fast charging during the day and slow charging 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 at weekends [109]. The temporal distribution of usage also depends on the vocation of the area where 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 towards rural areas [112]. The low utilization rate of AC stations is also due to the stationary times 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 consider parking a primary need, even with respect to recharging [73,116]. Conversely, charging behavior at fast-charging stations is more similar to normal refueling behavior, with short connection times aimed at the ability to complete the intended journey [73]. Domestic charging has a longer dwell time than other CPs of equal power, while at commercial premises the dwell time is short, probably because these are opportunity recharges [116]. The arrival time, permanence and inactivity at public CPs differ depending on whether the charge takes place near the home, work or in a parking lot [108]. Furthermore, the distribution of the recharge on the days of the week appears to be different according to travel habits and travel destinations in different areas of the same country [98]. For example, Chinese research [117] identifies the most frequent charging behavior with commuting: charging starts when the car is parked, between 8:00 and 10:00 and lasts on average 4 hours. Evening or nighttime charging behaviors account for 26% and 21% of total charging. The most frequent behavior (30%) is identified with commuting: charging begins when the car is parked, between 8:00 and 10:00. The average recharge lasts about 4 hours. 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 concentrate 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 charge fully 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]. Cars with higher capacity batteries seem to favor home charging [116].

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

In [128], the application of a data mining model allows 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 database used in the work. The sources are classified as: charging data, registered at the EVSE; mobility data, which represent traffic or GPS or EV onboard monitor units log data; 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[2]	Country	Resource
Y. Xu et al. [79]			Mobile phone data	2018	California	http://www.nrel.gov/tsdc[3] http://nhts.ornl.gov [4]
Weldon et al. [80]	◎			2011-2015	Ireland	http://education.greenemotion-project.eu/[5] http://www.greenemotion-project.eu/[6]
Märtz,et al. [83]	◎	◎		2019	Germany	https://www.mdpi.com/article/10.3390/en15186575/s[1]
Daina & Polak [84]		◎	Users survey	2014	UK	https://innovation.ukpowernetworks.co.uk/projects/low-carbon-london/[7]
S. Kim et al., [87]	◎	◎		2010-2014	Netheralnds	https://elaad.nl/en/[8]
Y. Liu et al. [91]	◎			2018	UK	https://data.dundeecity.gov.uk[9]
Singh et al. [89]	◎			2020	Netherlands	https://elaad.nl/en/[10]
Schäuble et al. [92]	◎	◎		2011-2013 2012-2014 2013-2015	Germany	https://crome.forschung.kit.edu/english/index.php[Errore. Il segnalibro non è definito.] https://www.izeus.kit.edu/english/[11] https://www.isi.fraunhofer.de/de/competence-center/energietechnologien-energiesysteme/projekte/Get_eReady.html[12]
Kim et al. [98]	◎			2021	Korea	https://www.data.go.kr/data/15076352/openapi.do[13]
Dodson & Slater [102]	◎			2017 - 2018	UK	https://www.nationalgrideso.com/industry-information/connections/customer-connection-events [14]
Hecht et al. [109]		◎		2019 - 2021	USA	https://doi.org/10.17632/ddv53zsf9m.1[15]
Sadeghianpourhamami	◎		Users survey	2015	Netherlands	https://elaad.nl/en/[16]

[2] If the survey period is not explicitly reported, we use the year of publication.
[3] Access on 30 July 2023
[4] Access on 30 July 2023
[5] Access on 30 July 2023
[6] Access on 30 July 2023
[7] Access on 30 July 2023
[8] Access on 30 July 2023
[9] Access on 30 July 2023
[10] Access on 30 July 2023
[11] Access on 30 July 2023
[12] Access on 30 July 2023
[13] Access on 30 July 2023
[14] Access on 30 July 2023
[15] Access on 30 July 2023
[16] Access on 30 July 2023

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et al. [106] Flammini et al. [113]						
Gerossier et al. [118]	◎			2015	Texas	https://dataport.cloud/[17]
Yi & Scoffield, [121]	◎	◎		2011 - 2013	USA	https://avt.inl.gov/content/pubs-az.html#E [18]
Asensio et al. [126]	◎			2020	USA	https://doi.org/10.7910/DVN/QF1PMO [19] [122]
Z. J. Lee et al. [127]	◎			2016–2018	California	https://ev.caltech.edu/dataset [20]
Xydas et al. [128]	◎	◎		2012-2013	UK	http://www.pluggedinmidlands.co.uk[21]
Mandev et al. [132]		◎		2011 - 2020		https://www.voltstats.net/[22]

3. Results

The literature presents a diverse view 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 available infrastructure in the region [24,129]. Despite the heterogeneities, some charging behavior patterns are identifiable across several studies [78,79,101], that 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 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 charging during the journey or at the destination. Charging on the go can influence route choice, as it can involve detours to reach a CP, and mainly concerns occasions when EVs cannot complete the journey with the available battery energy. The increase in battery autonomy made this occurrence usually uncommon in urban areas [62].

The charging decisions for 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 [29,129]. The duration of scheduled stops is a significant factor that impact the charging decision. Longer stops increase the likelihood of EV drivers charging their vehicles [53]. Parking time also impacts on charging choices: private chargers are usually used at night, and public charging is generally done 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].

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[17] Access on 30 July 2023

[18] Access on 30 July 2023

[19] Access on 30 July 2023

[20] Access on 30 July 2023

[21] Web site access returned an error (30 July 2023).

[22] Access on 30 July 2023

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 travel less than 47 km daily, while rental EVs travel a daily average of 66.5 km [78]. In urban settings, [101] find that over 71% of distances traveled were less than 15 km, and about 76% of parking events lasted less than 1 hour. An early English trial [141] finds that the length and average duration of the journey are 9 km and 15 minutes, respectively. A UK survey shows that only 10% of respondents drive more than 40 miles a day, around 30% use EV for their daily commute, while around the same percentage use it between 4 and 6 days a week [58]. In EU, 97% of EV drivers use their vehicles daily or several times a week. Their EV are mostly new (67%) and privately owned (70%) [12].

Studies also show a difference between the charging habits of PHEVs and BEVs [57,61,64,118]. Both types of EVs use home charging as the main source of energy supply [64,87,116]. The analysis reported in [142] 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] reports that PHEVs recharge less often than BEVs at public stations or along long-distance corridors. Overall, long-range BEVs connect more frequently than short-range ones, while the opposite is true for PHEVs [61]. PHEVs generally recharge at lower SOCs than BEVs [116].

3.2. Use of Infrastructure

Charging behaviors cannot ignore the availability and composition of charging infrastructures and the context of the area 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 the city [112]. According to a Dutch study on public CPs [106], roadside charging accounts for 62.86% of all sessions, while charging near home is 27.84%, and charging sessions near work cover 9.3%.

The general preference for **home charging** emerges 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 by the European Alternative Fuel Observatory (EAFO), 76% of EV users in the EU charge at home, while around 20% do so regularly at work [132]. This results is in line with what obtain in the UK [58,134], and in Germany [13], although with some variations in the percentages distribution. In the USA, about 80% of recharging takes place at home [82,135], and about 50% drivers use it 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 inefficient use of the CPs if there is no incentive to move a vehicle after the charge is over [136], and it 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 in densely populated urban areas [31]. Personal safety and proximity to the home are the most crucial factors in public charging replacing private charging, particularly during nighttime usage [71]. Additionally, public charging infrastructures are used differently depending on their location [112]. In [106] state that public charging along the streets accounts for 62.86% of all sessions, while charging near work is 27.84% of the total, and charging sessions near home makes up 9.3%. Public and corridor charging stations are the least used types of infrastructure [26,113]. The overall analysis of charging demand reveals that the likelihood of using public charging within a given area is proportional to the average number of cars per family and inversely

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proportional to the percentage of private homes in the 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 conducted 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 time [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 time, with inactivity percentages ranging from about 40 to 75% [78,79,113]. The idle time, i.e., the period an EV is parked without charging, last on average 4 hours, although it depends on the CP 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 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 the recharge depends on various factors, including geographical and social variables (work start and end times, commuting rate, etc.). However, a peak can usually be observed in the morning when leaving for work and later when arriving at work, and in the evening when returning home, especially for slow charging [104,128] and domestic [143]. 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 average [106,137]. In [81], they find 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 charge occur less than once a day and with periodicity of approximately 24 hours [78,79], although Yang et al. [81] reports an average number of charges in days of use of 1.1. At home, about 70% of cars charge 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, 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 [1,55,75,139,140], but there is no unanimity which alternative between 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 stations usage also depends on the vocation of the areas where they 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 the 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 by 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 cause inconvenience to 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 under 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 hours, which is primarily associated with charging at work. The second is the daytime behavior, with an average duration of 1.5 hours. The third and fourth behaviors are afternoon and evening charging, with an average duration of 4.5 and 15 hours, respectively. These charging behaviors are mainly identified with home charging [89]. The 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 is 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 charges their EV based on price and need, while the second type recharges their vehicle whenever there is an opportunity. The third type considers 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] classifies EV charging behavior during weekdays, weekends, and holidays for a month in 2018. The findings show that the largest group of users recharge their EVs primarily during weekdays after dawn, with slow recharges and small amounts of energy. Meanwhile, on weekends, most users start 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 has 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 study also found that charging sessions are generally shorter on weekdays and in the morning than in the afternoon. Cars with higher capacity batteries show longer dwell times and are more likely to recharge at home. At DC chargers, dwell times are the lowest, and the initial state of charge (SOC) is more than 20% lower than other chargers, 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 beyond daily routine [39,40].

3.5. Autonomy and Charging Anxiety

The perception of SOC is closely linked to the evaluation of the 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 studies place emphasis on battery SOC, charging time and prices. The battery SOC is considered among the most influential factors when modeling the charging choices [28,30,38,45,84,130,131], although its distribution at the beginning of the charge seems to depend on the type of charging infrastructure used: the higher the power, the lower the initial SOC [131]. 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 the battery, but connect the vehicle as soon as they have the opportunity. This tendency is particularly true for home or private charging, especially for overnight charging [101]. Morning charging near multi-family homes occurs with a lower initial SOC than charging at single-family homes [116], and public charging, especially fast ones, has the lowest initial SOC values [105,116,128]. Users tend to overestimate the importance of the battery SOC in the charging decision, particularly for short trips [47], and tend to charge the battery at 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 the charging behavior characterization: risk aversion leads to focus 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 the battery [58]. Technological knowledge, driving experience, and risk aversion play a positive role in alleviate 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 to maximize 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 to analyze the various factors that affect their private charging behavior. 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. The study found that the 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 in choosing slow charging at home or work. Another survey conducted by Anderson et al. [43] among approximately 4,000 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 the vehicle charged as long as they were home and avoided ending the charge if it caused delays in 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 to 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.

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According to the concept of User-Battery Interaction (UBIS) analyzed by Franke and Krems [65], the psychological approach to charging users is different for those with low and high UBIS. Users with low UBIS have a lower awareness of the battery level of their devices. Thus, they tend to recharge based on contextual triggers rather than on the battery charge level, which is the case for users with high UBIS. Moreover, the survey revealed that personality traits such as self-control, low impulsivity, and greater competence towards 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. The study also found that free charging outside of the home reduces the use of home charging and is positively correlated with trip planning. People who consider travel as a necessity or have flexibility in their travel plans tend to charge outside home, while those who don't plan their travel choices much tend to charge their vehicles mostly at home.

Recently, the service experience at the charging stations has been recognized as influential in the charging decision process [45,62,98]. Analyzing the impact of the service level of charging stations on user choice, it emerges that the high satisfaction score of previous users and the short queue time attract more EV drivers [62]. The 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 income, and (2) those who consider multiple factors such as range, parking time, and charging fee, 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 the charging price are likely to be more satisfied with private charging infrastructure.

Furthermore, the choice of charging at public charging stations is directly influenced by the weather conditions [98], environmental conditions, comfort, or any faults at the EVSE, [45] which means 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 to reduce peak demand and make 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, 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.

The effectiveness policies capable of influencing charging choices is of strong interest to local or national authorities. Applying a tax is generally effective in inducing users to move their car when it runs out of charge. However, the behavior is not unique, but three categories stand out: subjects sensitive to the application of the tariff, users who move the car regardless of the tariff, and those who do not move the car, regardless of the established fee level [73]. The latter may be more sensitive to the scarcity of other parking opportunities, and mostly drivers who rely on charging at public infrastructure. Indeed, a pilot experiment on dedicated neighborhood charging shows that potential users of electric vehicles value charging options combined with parking and bookable within the city, especially because parking is a problem felt among users of electric and non-electric vehicles [70].

Another strategy for indirectly controlling charging is to act on its price. The work in [74] examines user response to dynamic charging pricing. Respondents could choose whether to book now with a guaranteed price or wait for a better rate but taking on the risk of an increase in costs, with a known probability. Most of 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 leads to a significant reduction of 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's 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, both for public, commercial, or private vehicles. Examining what influences private charging behavior is possible through user surveys and analysis of mobility and charge data. Due to the vastness of this topic and the difficulty in isolating the impact 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 the private users charging behavior is far from being exhaustive, which can be ascribed to various reasons, among which there are:

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 the 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 the social and cultural frame and the topographical structure of the urban environment. According to research, personal safety, socio-demographic 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 the 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 from EV in future scenarios, some aspect of the investigation should be considered:

3. Inferences of EV 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 operation [147,148].

These topics can be further explored with new and more comprehensive data available and combining different information sources, such as mobile apps for charging management and reservation. A promising line of study employs users' reviews to obtain information on charging preferences and user needs, also for the optimal design of charging infrastructure and services [54,61]. Using this data can help examine the possible obstacles and desires in the usage of the infrastructure, especially public ones, by various users, with special attention to the most fragile categories. It is also interesting to inspect the relationship between charging behavior and infrastructure technology to comprehend the different use of the same type of structure that emerges from some studies. These

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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.

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