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Electric vehicle recharging options in urban areas: Discrete choice modeling to estimate user preference

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ABSTRACT

Electric mobility has grown in recent years, and this requires a proper charging infrastructure according to the needs of users and all stakeholders involved in the decision-making processes. To support user-centric planning of recharging infrastructure in cities, this study investigated user behavior in charging activities. We analyzed user choices regarding different charging options during routine activities: private and public infrastructures near home or near work, and equipped parking areas available close to other places (such as shopping centers). A stated choice survey was used to collect data from European cities for a discrete choice experiment. Models were specified, calibrated, and then analyzed in key scenarios for cities to analyze user charging choices according to the main factors (such as the cost and time for charging) and show the effect of different policies on the use of public charging points. Furthermore, segmentation analysis was performed to evaluate the effect of specific socioeconomic characteristics of users on their choices. According to the scale of the attributes obtained, the most influential factor was the charging cost. The effect of price neutralization was more significant for public charging options close to home and work, whereas comfort improvements were more effective for parking areas.

1. Introduction

Europe aims to be carbon neutral by 2050, with an intermediate target of a 55 % reduction in GHG emissions by the year 2030 through decarbonization of all sectors (European Green Deal (COM (2019) 640 final) and Climate Law (COM (2020) 80 final)). The transport sector is responsible for nearly a quarter of Europe's greenhouse gas emissions and road transport in particular accounts for the largest share (European Environment Agency). Road transport is not only responsible for climate change-inducing emissions but also for air pollution. The European Public Health Alliance estimated the health costs of air pollution caused by road transport in Europe to be €67 to €80 billion annually. Electric mobility is one of the solutions selected for road transport to achieve environmental sustainability goals. However, the shift from traditional vehicles powered by internal combustion engines (ICE) to battery electric vehicles (BEVs) requires an adequate charging infrastructure system that can be planned, designed, or provided by public authorities in synergy with other operators such as charging point operators (CPO) or distribution system operators (DSO), as described in Section 1.1. According to several studies, public charging infrastructure as an alternative to private home charging is only required in a few densely populated urban areas. The potential market for public charging infrastructure can be meaningful and overcome private infrastructure demand in metropolitan areas, including the largest portion of the non-residents' demand (Liu et al., 2022). Other studies suggest that home charging is the most influential factor in choosing to purchase an electric vehicle (EV) even though public charging infrastructure is essential for long trips and those living in apartments without private parking (Brückmann & Bernauer, 2023). Adenaw and Krapf (2022) argued that it was precisely the public charging points that were a means to enable and promote BEV. This aspect is relevant to mobility electrification and is also considered in the methodology proposed in this study, where users can choose both types of charging alternatives in different locations (home or work), as explained below.

1.1. Charging infrastructure eco-system

The charging infrastructure ecosystem is a complex network of interconnected stakeholders, technologies, and policies that work together to enable widespread and convenient charging for electric vehicles. Collaboration and coordination among all these entities are required to ensure the growth and sustainability of electric mobility.

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The key aspects to be considered with respect to charging infrastructure, are the charging station typologies (low power, fast, and ultra-fast), charging standards (connectors typology, power supply), grid integration (integration of charging infrastructure with the electrical grid), physical infrastructure (locations, electrical infrastructure, and permits), payment and billing systems (credit cards, mobile apps, and RFID cards), network management (monitoring and maintenance), roaming and interoperability, regulatory and policy considerations (permit processes, incentive programs, and public-private partnerships), and scalability. To address the technical, financial, regulatory, and operational challenges, real collaboration and decision support tools are necessary among the multiple stakeholders involved. The primary stakeholders in this ecosystem are the Public Authorities (PAs), who are in charge of transport and mobility and create policies, regulations, and incentives to promote the installation of charging stations; the charging point operators (CPOs), who operate one or more charging stations on their account and are therefore, responsible for the installation, operation and service thereof; the electromobility providers (EMPs) who are the providers of the charging services on a contractual basis. An EMP thus provides access to charging stations for vehicle users via charging cards or apps. The other stakeholders are the roaming network operators (RNOs), who are responsible for managing the platform for the exchange of charging data between the CPOs and the EMPs among different nations, and the power grid operators (PGOs), who are the operating managers (and sometimes owners) of energy distribution networks. Interoperability between players represents a crucial element in the mobility electrification sector. For this purpose, stakeholders should be able to share information on dedicated platforms to ensure the availability of increasingly extensive and detailed data. An example of this is the Italian PUN[1] (*Piattaforma Unica Nazionale*), a platform that aims to ensure uniform and consistent access conditions for electric-charging infrastructure-related information. Through such tools, the quality of studies and analyses that use modeling techniques can be improved by exploiting wider data resources and overcoming the limits imposed by a lack of information.

1.2. Aim of the study

This study aimed to identify the main factors influencing user choices in urban charging, considering the specific role of public charging networks over the available options. It is still not completely clear whether the development of electric mobility can be independent of an adequate public charging infrastructure network to justify the investments in this direction, considering the range of features for public recharge. This topic is specifically investigated by exploring system conditions, such as pricing policies for charging and improving comfort when using charging points (for example reducing the charging time or booking in advance the charging operations), which make it more appealing to the public.

To achieve this objective, the chosen model has been designed with a simple structure, with a limited number of attributes based on data that are expected to be easily available to support the decision-makers involved in public infrastructure, as described in Section 1.1. To analyze and predict user choices in urban charging activities, five types of charging options were considered according to their location (near home, work, or in other parking areas) and accessibility (private or public), and compared with a discrete choice model calibrated with data obtained from a stated choice (SC) survey.

This research activity was developed in the context of the H2020 EU-funded project titled INCIT-EV (Large demonstratIoN of user CentrIc urban and long-range charging solutions to boosT engaging deployment of Electric Vehicles in Europe), in which data is collected to understand the future needs of electric vehicle drivers and their expectations of the proposed advanced charging solutions. A decision support system (DSS) that aims to support municipalities, authorities, agencies, and other stakeholders in planning the optimal charging station framework in a city and estimating the impact of previously planned scenarios was developed for the project (Macaluso et al., 2023). The calibrated urban charging preference models presented in this study are valuable inputs, called user charging behavior data, for the DSS module which simulates the charging habits of EV drivers.

1.3. Related works

In literature, discrete choice experiments have been largely used to investigate the factors that influence charging activities by considering different formulations and data. In Wolff and Madlener (2019) a DCE was performed to investigate users charging preferences, assuming attributes such as charging location, charging duration, charging technologies, waiting time, cost, and share of renewables in the electricity mix used for vehicle charging. These attributes were also included in our model; however, the investigated charging alternatives were quite different. They distinguished between recharging at home and at work and added two alternatives at the roadside: for the first option, the user visits solely for recharging; for the second option, the user recharges while performing other activities (shopping). The dataset used was collected only in Germany, and the model revealed an intrinsic preference for home charging and a meaningful effect on the charging cost and waiting time. Similar to our study, the analysis was also conducted on specific consumer categories (such as EV owners) to detect possible differences in their perceptions because of their experience with charging choices. User experience was addressed by Liu et al. (2018), who used a genetic algorithm to optimize vehicle-charging strategies to maximize user satisfaction in terms of convenience and profit. An SC survey (2831 respondents) was conducted to detect user charging preferences based on attributes such as waiting time, charging cost, charging time, and facilities, by Brückmann and Bernauer (2023). The attribute effect, estimated by the average marginal component effects (AMCEs) method, evidenced the importance of waiting time for users who accepted higher costs to avoid queuing time, and that the socio-economic characteristics of respondents had a considerable influence on varying perceptions of the user. The general framework and objective of the study were similar to those of our study; nevertheless, the methodology presented meaningful differences. The model was calibrated assuming two charging options while in our study, five location-based alternatives for logit formulation have been assumed. In Budnitz et al. (2022) a stated choice experiment was performed to investigate user preferences for an overnight charging service in a residential neighbourhood. The options offered to respondents were on-street or car park charging, characterized by attributes such as charging fees, payment frequency, walking time, security measures, and walking experience. The binary logit model calibration results revealed that the intrinsic preferences for charging on the street or in a car park were similar, while the most effective factors were cost, walk time, and experience (from car to home). This study proposed an interesting analysis to detect user preferences between on-street and car park charging, while our study proposes a more high-level charging choice between the five charging options based on location and service accessibility.

Several studies, such as that of Xu et al. (2017), have focused on the areal distribution of charging demand. For example, Berkelmans et al. (2018) proposed a model based on cross-nested and mixed logit formulations to estimate the spatial charging demand distribution in an urban area, based on a specific dataset of charging sessions of publicly accessible charging points within Amsterdam, which is a different approach than using data from an SP survey. Other studies have aimed to predict charging distribution using different methods, such as fuzzy-based formulation (Xydas et al., 2016) or decoupled demand forecasting based on the autoregressive integrated moving average (ARIMA) method (Amini et al., 2016). A meaningful aspect is the electric

[1] https://www.gazzettaufficiale.it/eli/id/2023/05/22/23A02948/SG

network load caused by the EV demand effect (Zheng et al., 2020) particularly focusing on the peak time and daily charging event distribution (Lopez et al., 2021). In demand estimation, several studies used agent-based models (Daina et al., 2017) which allowed the detection of different user types (residents, visitors, taxis, and shared vehicles) (Wolbertus et al., 2021). Furthermore, these models were also implemented using specific tools such as MATSim (Waraich et al., 2013). A modal choice simulation framework based on Triandis' theory of interpersonal behavior was proposed (Nguyen & Schumann, 2020). They investigated scenarios similar to ours, including the variation in the charging price, although they estimated the charging demand (kWh) without distinguishing between the types or locations of the infrastructure (private, public, home, or work).

A widely discussed topic that is directly linked to charging demand estimation, is charging station placement strategy, particularly for urban areas where an optimized solution is required. They also focus on public infrastructure and the relevance of specific factors, highlighted in this paper, such as the charging power. Several studies have focused on the public charging infrastructure and proposed optimal charging station placement schemes considering the estimated charging demand based on a deterministic approach (Pan et al., 2020) and infrastructure characteristics influencing user behavior (Adenaw & Krapf, 2022). He et al. (2015) proposed a tour-based equilibrium framework to assess the optimal location of public charging stations considering budget limits. This method was implemented using an iterative procedure to obtain the equilibrium placement solution. An important aspect of charging placement was represented by the different typologies of charging points in terms of charging power, which could affect user choices (Globisch et al., 2019), and user preferences could vary depending on the context. For example, slow charging was acceptable in locations where vehicles were parked for longer periods (Anderson et al., 2018). Fast-charging infrastructures required an optimized location scheme to meet user needs (Philipsen et al., 2016) and were based on factors such as station development cost, EV energy loss, and electric grid loss.

This work proposes a easily transferable modelling tool across different cases. The developed models have a simple structure but are based on large datasets: over twenty thousand observations were collected across four different European countries. Furthermore, considering that data were collected in 2023, the observation appears to be extremely recent and this is consistent with the current situation of electric vehicle models in the market. Indeed, observations carried out even five years ago have detected behaviours affected by the limited vehicle models available in that specific period. This study focuses on describing mathematical models of user behavior regarding the routine planning of charging operations (such as at home or during work time), whereas many studies concentrate on charging demand in terms of in spatial locations. Moreover, various factors associated with electric vehicle charging operations are included and some have received few explorations in existing literature, such as the introduction of enhanced services (i.e., booking charging operations or charging wireless). Finally, this work provides not only the estimation of specific factors influencing user charging behavior, but also updated results to be compared to those already obtained in other studies, such as the effect of charging costs.

The following section will provide details on the dataset used, the calibration and specification of the discrete choice models, and the investigation of the effects of possible segmentations of the sample based on certain socioeconomic characteristics. The models described will then be applied in different scenarios to demonstrate their use and to analyze the effect of certain incentive policies for public charging. The main results are summarized in the concluding section.

2. Methodology

To understand and predict consumer choices in expected and future scenarios in the field of electric mobility, an SC questionnaire was developed to collect data and feed three discrete choice experiments. The SC approach proposes that respondents complete several choice tasks in predefined scenarios, including selecting one or more alternatives from a limited set. These alternatives are described by a selected set of attributes for each task, across a range of prespecified levels, to define and characterize the options to be compared. Using the collected datasets, two models are calibrated assuming the multinomial logit (MNL) structure and the nested logit (NL) structure (Section 3.1). Furthermore, disaggregated versions of the models are presented in Section 3.2 introducing a user segmentation based on defined users' features. Finally, the calibrated models are used to compare several explorative scenarios in Section 4.1 to better understand the effect of specific attributes on users' charging preferences. Fig. 1 shows schematically the steps of the proposed methodology, described in detail in the following sections.

2.1. Formulation of discrete choice model

In this study, discrete choice models are proposed by considering well-known logit formulations. These models are based on the principle of utility maximization, in which users choose the alternative with the highest utility value. In the proposed models, the alternatives are represented by the different charging options available, and the utility of choosing a specific charging option (alternative) describes the value that users assign to each option when compared during the selection process. Random utility is composed of a systematic component and an error component and can be evaluated as follows:

$$U_i = V_i + \varepsilon_i = \beta^* x_i + \varepsilon_i \tag{2.1}$$

where U_i is the random utility of an alternative i; V_i is the systematic part of the utility; ε_i is the error term; β is the vector of model parameters; and x_i is the vector of attributes of alternative i.

In this case, utility is defined as a non-dimensional quantity and is computed as the sum of products between attributes and associated β parameters. To respect the non-dimensionality of the utility, the β parameters assume the inverse of the unit associated with the corresponding attribute. In this study, the base formulation considered was the multinomial logit model (MNL), in which the error terms of all alternatives were independent and identically distributed (IID) as a Gumbel distribution. The formulation of the multinomial logit model provides an estimation of the probability *p(i)* of selecting each alternative *i* in the defined set of choices *j* as follows:

$$p(i) = \exp(V_i) \Big/ \sum_j \exp(V_j) \tag{2.2}$$

The second proposed formulation is the nested logit model (NL), which differs from the MNL because more levels of choice are considered when introducing a nested structure. In the NL model, the alternatives are divided into nests (Nm), and their error terms are independent if they are in different nests. The nested logit enhances the multinomial logit because it introduces a correlation between the alternatives included in the same nest. In the NL, the probability of selecting alternative *i* is expressed as the product of the probability of selecting the related nest *k* and the conditional probability of selecting alternative *i* in the nest.

$$p(i) = p(k)^* p(i|k) \tag{2.3}$$

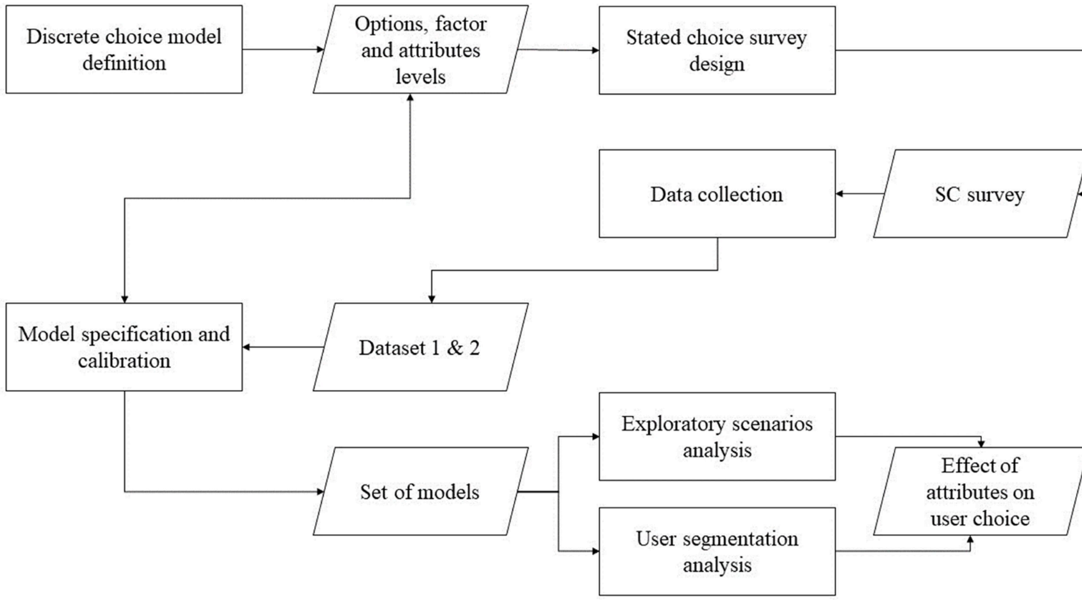

Fig. 1. Schematic representation of the methodology.

$$p(i) = \exp\left(\mu_k * \ln \sum_{i \in k} \exp(V_j)\right) \Big/ \sum_h \exp\left(\mu_h * \ln \sum_{i \in h} \exp(V_j)\right) * \exp(V_i) \Big/ \sum_{i \in k} \exp(V_i) \tag{2.4}$$

where μ_k is the nest coefficient related to nest k.

The nested logit model allows capturing correlations among different alternatives, making it more effective in describing preferences when such correlations are not negligible. In our work, we explored both multinomial and nested formulations for the two collected datasets to understand, with the support of observations and the calibration procedure, whether including the correlation among alternatives was important. Indeed, the nested logit was disregarded for the sake of computational simplicity, in case the nest coefficient was close to 1.

2.2. Identification of influencing factors

An essential aspect of discrete choice experiment design is the identification of factors that can influence respondents' choices. The selection of variables to include in the analysis was the result of a process focused on discussions among project partners and their expectations, and even more on evidence from previous studies. In our work, we aimed to focus on the high-level location of the charging points by considering aggregated options, such as public access to parking areas, proximity to homes or workplaces, or private use at home or work. In real life, more complex alternatives than the five high-level locations are available for users, combining the used features to define charging options. However, the selected options can represent the typical and most common situations, which can be also easily presented to users in surveys and modelled consequently. A similar approach is used to define the levels of attributes, which cannot cover all the possibilities but represent significant values. Among the key attributes selected in the experiment, the cost of charging operations plays a well-known role in user choices (Brückmann & Bernauer, 2023; Budnitz et al., 2022). In this work, the charging price of different alternatives was estimated by collecting information available in the involved countries during the months before the survey. Through discussions among project partners, a price range was defined based on the quality of the charging service to include and characterize the various alternatives available, taking into account real-world factors including, beyond the observed cost, the possibility of subscription rates or variations in the cost of electricity. Several studies highlighted also the significance of charging time in the decision-making process (Wolbertus & van den Hoed, 2020; Yang et al.,

Table 1
Charging infrastructure characteristics in the experiment (choice attributes and attribute levels).

Charging point features	Levels description
Charging point typology	1. Parking area equipped with charging point 2. Home (private) 3. Near home (public) 4. Work (private) 5. Near work (public)
Charging time (to recharge 50 % of the battery)	1. 4 h (Home charging) 2. 2 h (Slow charging) 3. 1 h (Accelerated charging) 4. 30 mins (Fast charging)
Charging price per 100 km	1. <3 € (with periodic subscription) 2. 3 € (−50 % than average EU price at home) 3. 6 € (average EU price at home) 4. 18 € (x3 than average EU price at home)
Possibility of reservation	1. No 2. Yes, optional
Waiting time	1. Less than 10 mins 2. From 10 to 30 mins 3. More than 30 mins
Comfort and ancillary services	1. None, only the charging point 2. Covered charging point 3. Food and shops (in place or nearby)
Energy from renewable sources	1. No 2. Yes
Connection technology	1. Wired 2. Wireless

2020). This variable also includes the charging power of the infrastructure, which the duration of the operation depends on. Despite the importance of this attribute experienced in other studies, it is not expected a fundamental role since this work focuses on charging operations integrated into planned daily activities and potentially long durations (e.g., working time). Another factor related to charging time is the expected waiting time to be served at charging points (Hassler et al., 2021; Huang & Kockelman, 2020; Wang et al., 2021). To explore innovative features of charging points and understand their role in attracting users, we have integrated some of the services that can be provided, such as the possibility of reservations, the availability of wireless charging, and the presence of ancillary services, such as shops, near the charging point (Visaria et al., 2022). In Table 1 the selected attributes and the considered levels are reported.

2.3. Survey design

To perform the SC survey and obtain a proper dataset, a discussion was conducted among the project partners involved in INCIT-EV to define the preliminary specification of the model, which included factors assumed to be influential in alternative selection discussed in Section 2.2. The survey structure and pilot tests developed before the final version of the experiment are reported in La Gamba et al. (2022). Pilots were used to refine values and levels of attributes such as price and waiting time. For instance, the waiting time values are expressed by a defined scale (low, medium, high) that was translated for the users in minutes for greater simplicity. Nonetheless, this is a categorical variable. The categorization was done by defining thresholds that we hypothesized would change the user's perception. These threshold values are the result of discussions with partners and of the analysis in pilot surveys. The first established value is 10 mins, lower waiting times are perceived as insignificant and comparable to the typical time spent in a potential queue waiting to refuel at a gas station or searching for parking. A waiting time exceeding 30 mins gives the respondent the impression of a very onerous wait. An intermediate class was also included between these two values. Although it would have been possible to create more levels, we decided not to exceed the three levels discussed to simplify the choice process of respondents in the survey. The SC design involved planning daily activities and deciding how to fit the need to recharge EVs into the daily schedule. The design of the choice scenarios was supported by Ngene, a software used for creating discrete choice experiments with various available approaches. In this study case, the selected approach was the fractional factorial D-efficient Bayesian design with binary choice situations (two alternatives for each choice task). Specific settings to manage survey design characteristics such as orthogonality, correlation structure, and balance of attribute levels were selected. Particularly, 60 choice situations were included and 10 blocks were generated to enhance attributes level balance. The combinations of attribute levels presented to participants were carefully regulated by imposing criteria to prevent the inclusion of unrealistic feature combinations. For this purpose, several conditions were specified:

Table 2
Ngene general settings for survey design.

Ngene design settings	
Alternatives	2 (A, B)
Rows	60
Block	10
Efficient design	multinomial logit, d-efficient

Conditions	if (A.CHARGING_TIME<*B*.CHARGING_TIME, A.CHARGING_PRICE<B.CHARGING_PRICE),
	If (A.CP_TYPOLOGY=2, A.CHARGING_PRICE<B.CHARGING_PRICE and A.CHARGING_PRICE<B.CHARGING_PRICE)
	if (A.CP_TYPOLOGY=2, A.ANCILLARY_SERVICES=0 and A.RESERVATION=0)

- The alternative with a lower charging time must have a higher charging price
- Home private charging option, if available, always has a higher charging time and lower charging price with respect to the other option
- The attributes related to ancillary services and the possibility of reservation are nullified for the home private charging option.

Table 2 includes a summary outlining the software settings.

The choice situations presented to respondents involve selecting between two possible charging alternatives, each with their respective attributes. Each interviewee is presented with 5 different choice situations. The questionnaire assumed that the respondent had been informed of the availability of both alternative charging options (existing infrastructure within 500 m also according to Adenaw and Krapf (2022)). In the proposed choice situations, values with units of measurement were presented (such as recharge time expressed in hours) to make it easier for the respondent to understand. However, during the modeling process, attribute values were converted into a dimensionless-value scale of levels to simplify the calibration, interpretation, and comparison of estimated parameters. To ensure greater awareness on the part of the interviewee, the questionnaire was translated into the official languages of the countries where it was administered. In Fig. 2 an example of a choice task proposed to respondents is shown.

2.4. Description of datasets

Data was collected in two rounds during the INCIT-EV project, resulting in two datasets used for the calibration shown in this study, which are summarized in Table 3. The first data collection was done in the last months of 2022 in four European cities (Amsterdam, Turin, Tallin, Zaragoza) including territories that are not strictly urban; 4532 responses were collected from approximately 900 users. The second dataset (16,735 responses from approximately 3350 users) was obtained with the same SC structure as the previous but with the addition of a set of questions related to the socioeconomic characteristics of the sample submitted in early 2023, in four European countries (Italy, Spain, Estonia, and The Netherlands). The two different and not comparable datasets were used to investigate different calibrations of the models that considered whether the collected data comprised socioeconomic characteristics, or whether it was aimed only at the urban environment or extended to the entire country, influencing the complexity of the model. For both datasets, the respondents were mostly drivers; however, not all were electric car drivers and they were equally distributed across the four countries. In Table 3 the main characteristics of the sample are summarized. Furthermore, additional information is reported: with the term "availability" it was possible to check the number of times the five alternatives were proposed to respondents in SC surveys to verify that, in both datasets, the five alternatives were homogeneously present. According to the sample description (Table 3), the sample is representative of the population (4 selected EU countries) as regards the gender distribution (51.1 % female and 48.9 % male).[2] As regards the age distribution the first class is more represented compared to the population (13 % of people between 18 and 29 in the four countries). The last feature of the sample can be explained by the method used for data collection (web-based survey) by the company involved in the diffusion of the surveys.

2.5. Evaluation process for model definition

Once the dataset has been collected and the modelling structures defined, it is crucial to obtain a reliable model specification refined by

[2] Data obtained from the average data of the 4 countries (source: Eurostat)

	A	B
Charging station typology	Near home (public)	At work (private)
Charging price per 100 km	6 € (average EU price at home)	Less than 3 € (with periodic subscription)
Charging time to recharge 50% of the battery	1 hour	2 hours
Possibility of booking	Yes (optional)	No
Waiting time before having access to a charging point	10 - 30 minutes	10 - 30 minutes
Comfort and ancillary services	Food and shops (in place or nearby)	Food and shops (in place or nearby)
Energy from renewable sources	Yes	No
Connection technology	Wired	Wireless

Fig. 2. Example of a choice task in survey.

Table 3
Main characteristics of the datasets.

		Dataset 1	Dataset 2
Driving license	No	13 %	14 %
	Yes	87 %	86 %
EV Owners	No	87 %	88 %
	Yes	13 %	12 %
CI_owners	No	88 %	91 %
	Yes	12 %	9 %
Country	Italy	32 %	25 %
	Spain	24 %	25 %
	Estonia	22 %	25 %
	Netherlands	22 %	25 %
Gender	Not declared or non-binary	NA	0.3 %
	Male	NA	45.4 %
	Female	NA	54.3 %
Age (years)	18–29	NA	37 %
	30–39	NA	27 %
	40–49	NA	18 %
	50–59	NA	12 %
	60–69	NA	5 %
	70+	NA	1 %
Context	Urban	100 %	62 %
	Suburban	NA	21 %
	Rural	NA	16 %
City size	Very small city (less than 50,000)	NA	35 %
	Small city (50,000 – 200,000)	NA	28 %
	Medium city (200,000 – 500,000)	22 %	19 %
	Medium – large city (500,000 – 1500,000)	78 %	9 %
	Large city (more than 1500,000)	NA	8 %
Availability	Parking area	34 %	34 %
	Private Home	41 %	38 %
	Public Home	47 %	47 %
	Private Work	44 %	46 %
	Public Work	34 %	35 %

calibration. To achieve this, starting from the expected formulation that includes the selected attributes in 2.2, an iterative refining process was adopted, adjusting the specifications further by comparing the results of experimented versions. The calibration procedures were conducted using Biogeme 3.2.10, basing parameter estimation on the maximum likelihood principle. The collected dataset was used to explore several model specifications and logit structures. Indeed, through model design and a refining operation, only some of the previously identified variables were included in the final versions of the models. Some variables were excluded due to their lack of significant impact. For instance, in model ID8 the variable “waiting time” was not included since it exhibited a low *t*-test indicator value. This indicator is directly connected to the standard error associated with the estimated parameter and a low value indicates an inadequate significance of the parameter.

To compare modelistic structures’ performance in reproducing user choices and selecting a representative model, Table 4 presents a synthetic overview of the specifications of a part of trial experimental models. The table includes synthetic information for each model trial as the dataset used (see Section 2.1), sample size, structure type of the logit model if nested (NL) or not (MNL), total number of attributes selected for inclusion in the model, and total number of estimated parameters, which may be common among alternatives if they included the same attributes. Quality indicators for the model are also listed in Table 4; the number of parameters with low significance or unexpected signs, a parameter consistency score evaluated based on the number of critical parameters estimated and their error severity, and the Bayesian Information Criterion (BIC)[3] value are useful for comparing models built with the same dataset.

[3] BIC is an information criteria-based relative-fit index that was developed as an approximation of marginal densities based on two basic components required for its computation: deviance and a penalty term. (Boykin et al., 2023)

Table 4
Model characteristics and comparison.

ID	Dataset	Sample size	Model Type	Alternatives Attributes	Parameters estimated (ASC included)	Critical parameters	Parameter consistency	BIC
1	1	4532	MNL	19	9	1	medium +	6149
2	1	4532	NL	15	11	2	medium	6152.5
3	1	4532	NL	14	10	0	medium +	6153.4
4	**1**	**4532**	**NL**	**17**	**11**	**0**	**high**	**6146.7**
5	2	14,248	NL	15	11	3	medium	19,560.9
6	2	14,248	MNL	20	10	1	medium +	19,547.3
7	2	14,248	MNL	23	11	2	medium+	19,555.7
8	**2**	**14,248**	**MNL**	**22**	**10**	**0**	**high**	**19,541.4**

Several trials were conducted using the two collected datasets and their partial extracts, as described by the sample size. The process implemented in this phase was to modify the specifications and structure of the model step-by-step to enhance the quality of the previous trials. For both collected datasets, different model formulations (MNL, NL) were tested considering the approximations that each model includes, their simplicity of application and the case that options may be not independent. The dependence between alternatives is, at least in this case, relative and not always easily identifiable. To establish the dependency among options and to define the most suitable formulation of the models, we used a refinement and testing process based on the significance of model parameters and goodness-of-fit measures. In the estimations related to dataset 1, a significant correlation between private and public alternatives was evident, leading to the choice of the nested formulation. Nevertheless, in the calibrations concerning dataset 2, the nested models presented issues related to the quality of estimated parameters (such as in ID5) and exhibited a relatively low level of correlation among alternatives. Consequently, it was decided to select the multinomial formulation, which, despite neglecting the correlation, ensures more reliable parameters and easier applications. Although the two datasets were collected through a similar survey, they respond to the calibration process in different ways, exhibiting a different level of correlation among the alternatives and thus leading to distinct model formulations. The models selected from the set of experiments were identified as ID 4 and ID 8 and are marked in bold in Table 4. These two models were calibrated on two different datasets, particularly Model ID 4, referring to Dataset 1 and Model ID 8, referring to Dataset 2, and, as previously explained, had two different structures: NL (Model ID 4) and MNL (Model ID 8). These models were considered the best in our experiments because no critical parameters were observed in either model and the BIC value comparison with the same dataset-built models confirmed a better fit. Therefore, further analyses were performed considering these two versions of the model.

Fig. 3 shows the number of attributes included in the utility formulation of each alternative in the model trials presented in Table 4. In most specifications, the alternatives that include more attributes are public access (Park-area, Publ-home, Publ-work) because several attributes such as the presence of ancillary services (*ANCSERVICES)* or waiting time (*WAITINGTIME*) are related only to public charging options. Furthermore, in Fig. 3, the total number of parameters estimated in the model calibration phase is shown to provide a synthetic indicator of the model complexity and the subsequent effort required to implement and manage the model which increases consistently with the number of parameters included.

In Fig. 4 the frequency of the required attributes in each model is reported, considering that the maximum number of appearances for each attribute is the same as the number of alternatives (five). Several attributes such as charging price and use of renewable energy (*RENENERGY*) were always included in the utility of alternatives of the models, resulting in consistency and significance. Other variables, such as connection type (*CONNECTION*) and possibility of reservation (*RESERVATION*), were included in the later experiments when the trials were conducted for the new specification. The attributes related to charging time (*CHARGINGTIME*) and waiting time (*WAITINGTIME)* were initially included in the alternative's utilities; however, the charging time resulted to be significative only for models referred to Dataset 2, while the waiting time significance was acceptable for models calibrated using observations from Dataset 1. This result, which suggests that the weight of attributes related to time, both charging and waiting, does not indicate their primary relevance, is not in conflict with our

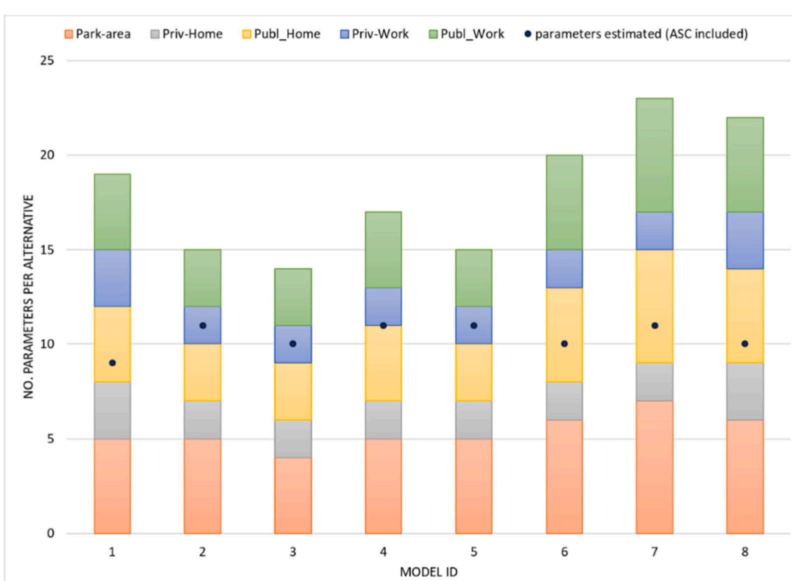

Fig. 3. Number of attributes per alternative and the total parameters estimated (without ASC) for each model.

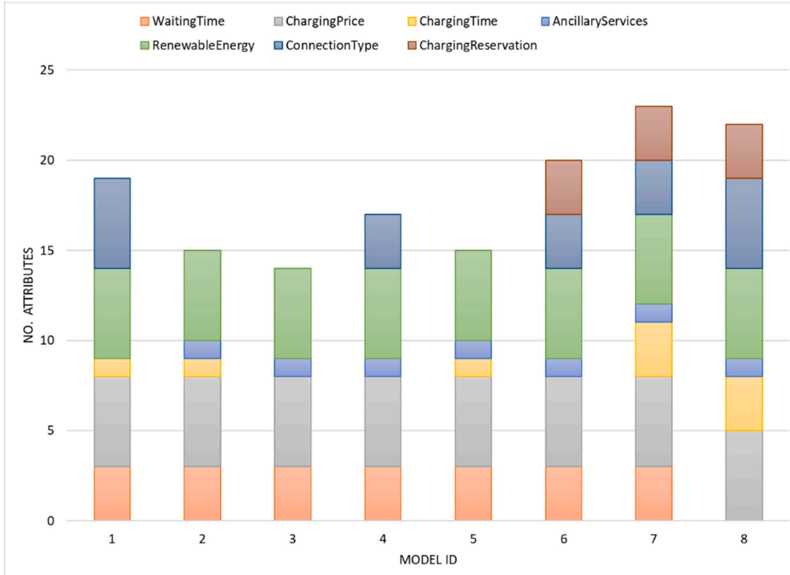

Fig. 4. Frequency of attributes in each model.

expectations. Indeed, as already mentioned it must be considered that the charging operations analysed in this paper occur during planned daily activities in an urban area with a generally long duration (e.g., hours at the workplace). As confirmed from Fig. 4, attributes can be included in all alternative utilities, or only in the selection for which they are considered influential. This is the case for attributes relevant to public charging options, such as the possibility of reservation or the presence of ancillary services (*ANCSERVICES)*, which generally do not influence the choice of private options. Other attributes, such as the availability of wireless connection (*CONNECTION*), present higher significance of the associated parameter if included in the utility formulation of all the alternatives and not only the selection of them as explored in initial attempts. This means that the availability of the wireless connection will provide the same increase in the utility for any options and can potentially be associated with all alternatives. This type of effect can also occur for RENENERGY, whose effect is independent of the alternatives because it is present as a dummy variable across multiple alternatives. However, during the development of explorative scenarios, it is possible to selectively activate these dummy variables only in some charging options (Section 4.1).

3. Results

3.1. Specification and calibration of selected models

As introduced in Section 2.5, one of the two models selected was Model ID 8, which is based on a multinomial logit formulation and calibrated using Dataset 2. For this model, the specification of alternative utilities is defined as

- $V_{parking} = ASC_{parking} + \beta_{cprice} * cprice_{parking} + \beta_{ancserv} * ancserv_{parking} + \beta_{renenergy} * renenergy_{parking} + \beta_{ctime} * ctime_{parking} + \beta_{connection} * connection_{parking} + \beta_{reservation} * reservation_{parking}$,
- $V_{privhome} = ASC_{privhome} + \beta_{cprice} * cprice_{privhome} + \beta_{renenergy} * renenergy_{privhome} + \beta_{connection} * connection_{privhome}$,
- $V_{pubhome} = ASC_{pubhome} + \beta_{cprice} * cprice_{pubhome} + \beta_{renenergy} * renenergy_{pubhome} + \beta_{ctime} * ctime_{pubhome} + \beta_{connection} * connection_{pubhome} + \beta_{reservation} * reservation_{pubhome}$,
- $V_{privwork} = ASC\_{privwork} + \beta_{cprice} * cprice_{privwork} + \beta_{renenergy} * renenergy_{privwork} + \beta_{connection} * connection_{privwork}$,
- $V_{pubwork} = ASC_{pubwork} + \beta_{cprice} * cprice_{pubwork} + \beta_{renenergy} * renenergy_{pubwork} + \beta_{ctime} * ctime_{pubwork} + \beta_{connection} * connection_{pubwork} + \beta_{reservation} * reservation_{pubwork}$.

The model was calibrated and refined using an open-source Python package designed for the maximum likelihood estimation of parametric models (*Biogeme 3.2.10)*. The values obtained for the selected parameters are reported in Table 5, along with the classic statistical indicators, i.e., robust standard error (Rob. Std err), robust *t*-test (Rob. *t*-test) and robust p-value (Rob. p-value). In addition, the goodness of fit measures of the model are also reported. There is no ideal value for the indicators as ρ^2, since it allows a relative comparison among different

Table 5
Estimated parameters for model ID8.

Parking	PrivHome	PubHome	PrivWork	PubWork	B-parameter	Value	Rob. Std err	Rob. *t*-test	Rob. p-value
x					ASC_parking	−0.144	0.0666	−2.16	0.0306
	x				ASC_privhome	0.462	0.0537	8.6	0
		x			ASC_pubhome	0.139	0.0357	3.89	0.000101
			x		ASC_privwork	0.216	0.0612	3.53	0.000411
x					B_ANCSERVICES	0.123	0.0419	2.93	0.0034
x	x	x	x	x	B_CHARGINGPRICE	−0.06	0.00587	−10.2	0
x	x	x	x	x	B_CONNECTION	0.0217	0.0175	1.24	0.214
x	x	x	x	x	B_RENENERGY	0.0597	0.0176	3.39	0.000701
x		x		x	B_RESERVATION	0.0948	0.0375	2.53	0.0115
x		x		x	B_CHARGINGTIME	0.0285	0.0117	2.43	0.0152

Sample size: 14,248; Estimated parameters: 10; $\rho^2 = 0.145$; $ll = -9722.897$ **AIC** $= 19465.79$; **BIC** $= 19541.44$; .

specifications of the same model structure and dataset. Indeed, in the calibration and refining process conducted on both models using the two datasets, the rho value was only one of the determining factors in choosing the best model versions. Specifically, the process of refining the model specifications described in Table 4, was done separately for the two datasets with two model forms.

The parameters associated with the variables are significant, considering the value of *t*-test, and consistent with expectations in terms of signs. Indeed, the parameter for price is negative, whereas it is positive for the other attributes. Considering the attribute scale, the most influential factor was the charging price (*CHARGINGPRICE*). In addition, the effect of ancillary services (*ANCSERVICES*) on parking alternatives and other comfort attributes related to public charging options is significant.

An alternative solution was proposed for Model ID 4. This model was calibrated using Dataset 1 (4532 observations) assuming a nested logit formulation. The specification of the alternative utility was defined as:

- $V_{parking} = ASC_{parking} + \beta_{cprice} * cprice_{parking} + \beta_{ancserv} * ancserv_{parking} + \beta_{renenergy} * renenergy_{parking} + \beta_{wtime} * wtime_{parking} + \beta_{connection} * connection_{parking}$
- $V_{privhome} = ASC_{privhome} + \beta_{cprice} * cprice_{privhome} + \beta_{renenergy} * renenergy_{privhome}$
- $V_{pubhome} = ASC_{pubhome} + \beta_{cprice} * cprice_{pubhome} + \beta_{renenergy} * renenergy_{pubhome} + \beta_{wtime} * wtime_{pubhome} + \beta_{connection} * connection_{pubhome}$
- $V_{privwork} = ASC_{\_privwork} + \beta_{cprice} * cprice_{privwork} + \beta_{renenergy} * renenergy_{privwork}$
- $V_{pubwork} = ASC_{pubwork} + \beta_{cprice} * cprice_{pubwork} + \beta_{renenergy} * renenergy_{pubwork} + \beta_{wtime} * wtime_{pubwork} + \beta_{connection} * connection_{pubwork}$

A nested structure (Fig. 5) was introduced to consider the possible correlation between alternatives that allowed charging at home or nearby (private near home, public near home) and alternatives that included a charging event in a location different from home (equipped parking area, private near work, public near work).

The calibration results for Model ID 4 are listed in Table 6. As in Model ID 8, all parameters are significant and coherent with the expected signs. Considering attribute scales, the charging price is the most influential factor, as expected. Notably, the magnitude of nest coefficients, meaning the coefficient related to "home" alternatives, presents a higher value concerning the coefficient related to "not-home" alternatives, revealing a general preference for alternatives that allowed charging nearer home.

3.2. Extending models with user segmentations

The described models did not include any user-related variables; only the attributes describing the features of the alternatives were considered. In the specification of the models, we did not include socioeconomic attributes (available for dataset 2), such as gender or electric vehicle ownership, in the utility functions because of the low significance of the associated parameters. However, we decided to further analyze these variables using the approach of user segmentation. To improve the ability of the model to detect user choices, an analysis was conducted, by including the effect of socioeconomic variables on modeling of user behavior. This analysis does not aim to improve the proposed model but rather focuses on performing a sensitivity analysis to more deeply understand potential heterogeneities in choices among individuals belonging to segments of the population. The variables identified for this purpose were:

- EV owner (whether the respondent already owns an electric vehicle).
- Gender of the respondent (male/female; others were excluded for simplicity)

In contrast to attributes describing the quality of alternatives, socioeconomic variables did not vary across alternatives because their role was to capture the heterogeneity of preferences in different population classes.

For the mentioned socioeconomic variables, two segments of users were considered, particularly the classes of EV "owners" and "non-owners" and the classes of "male" and "female." Among these classes, we expect significant behavioral differences. Indeed, the experience of electric vehicle owners leads them to attribute different importance to certain factors compared to non-experts (Sovacool et al., 2018). The limited knowledge regarding the characteristics of different charging opportunities among individuals with no experience with electric vehicles is one of the critical points in observing their behavior. Nevertheless, the current number of owners of EVs in Europe is still quite low and gathering data only from this category could reduce the sample size. To mitigate this issue, the choice experiments of the survey were proposed also to EV non-owners, trying to effectively describe the hypothetical choice situation. To explore the heterogeneity in choices between these two categories and clarify how the experience might diversify user behavior, this variable was selected for this analysis. Also, differences in preferences are expected between men and women (Csillak & Kamenz, 2023). For instance, women appear to be more attentive to sustainability (Kawgan-Kagan, 2020), whereas men demonstrate a preference for high-performance vehicles and newer technologies (Sovacool et al., 2019; Vivi & Hermans, 2022).

In the model-building step, a new form of model was calibrated separately for the two segmentation variables. A set of parameters was associated with each level of the attribute used to segment the population (e.g., owner, non-owner), obtaining two parameters for each model variable. Maintaining the same specification proposed in Model ID8 (dataset 2), two new models with segmented parameters were calibrated. The result is thus composed of two models, each having two parameters for every variable, one for each population class. Fig. 6 shows the calibrated segmented parameter values for both the proposed models.

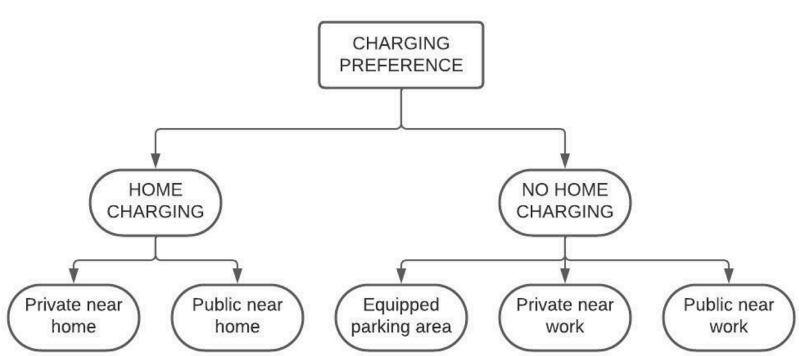

Fig. 5. Nested logit structure diagram (Model ID 4).

Table 6
Estimated parameters for Model ID4.

Parking	PrivHome	PubHome	PrivWork	PubWork	B-parameter	Value	Rob. Std err	Rob. *t*-test	Rob. p-value
x					ASC_parking	−0.0268	0.112	−0.239	0.811
	x				ASC_privhome	0.134	0.0867	1.54	0.123
		x			ASC_pubhome	0.307	0.0653	4.71	2.51E-06
			x		ASC_privwork	0.11	0.08	1.38	0.168
x					B_ANCSERVICES	0.136	0.0716	1.9	0.0575
x	x	x	x	x	B_CHARGINGPRICE	−0.123	0.0133	−9.29	0
x		x		x	B_CONNECTION	0.057	0.044	1.3	0.195
x	x	x	x	x	B_RENENERGY	0.177	0.0293	6.03	1.69E-09
x		x		x	B_WAITINGTIME	−0.0522	0.0171	−3.06	0.00223
	x	x			MU_home	1.85	0.859	2.15	0.0315
x			x	x	MU_nohome	1.28	0.272	4.72	2.34E-06

Sample size: 4532; Estimated parameters: 11; $\rho^2 = 0.035$; $ll = -3030.398$ **AIC** $= 6082.796$; **BIC** $= 6153.404$; .

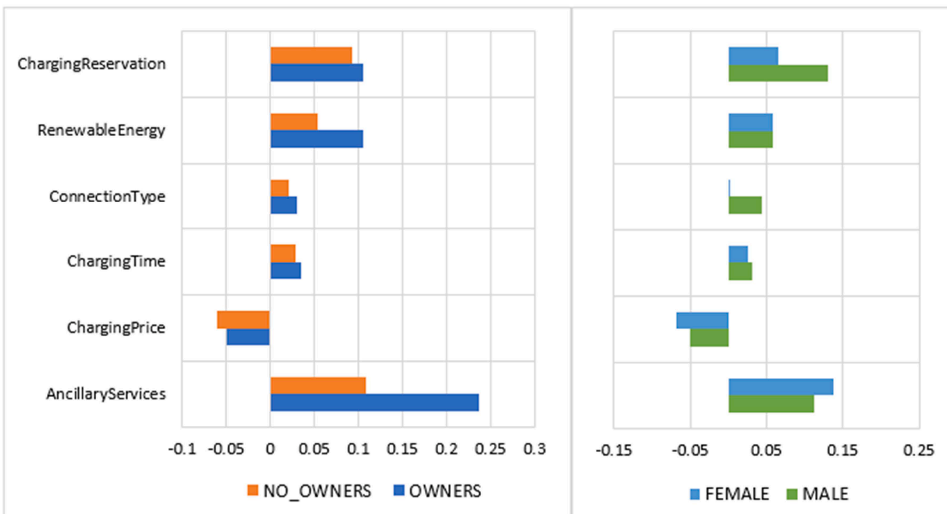

Fig. 6. Comparison of estimated parameters for the two experiments (Model ID 8).

Observing the parameter values for the model with ownership-related segmentation, it appears that the preferences of non-owners are more affected by charging prices, whereas owners were more influenced by attributes related to comfort and sustainability, such as connection type or the availability of electricity produced by a renewable energy source. This aspect can be justified by the experience of EV owners with fixed-cost subscriptions or other types of opportunities for charging, which decreases the importance of the net charging price, as proposed in the SC survey. However, non-owners with less experience were more influenced by this attribute. This result confirms that there are considerable differences in taste and perception of alternatives between the categories of "owners" and "non-owners." Nevertheless, in the considered sample, the two classes were not homogeneously represented (only 12 % were EV owners). Therefore, population segmentation was not introduced in the model to mitigate the estimation error caused by the lower sample rate for EV owners. Meaningful results were also

Table 7
Estimated segmented parameters.

OWNERSHIP SEGMENTATION			*GENDER SEGMENTATION*		
β-parameter	Value	Rob. Std err	β-parameter	Value	Rob. Std err
ASC_1	−0.143	0.0666	ASC_1	−0.147	0.0663
ASC_2	0.463	0.0538	ASC_2	0.463	0.0535
ASC_3	0.14	0.0358	ASC_3	0.139	0.0357
ASC_4	0.217	0.0612	ASC_4	0.217	0.061
B_ANCSERVICES_NO_OWNERS	0.108	0.0428	B_ANCSERVICES_FEMALE	0.137	0.0472
B_ANCSERVICES_OWNERS	0.237	0.0784	B_ANCSERVICES_MALE	0.112	0.0488
B_CHARGINGPRICE_NO_OWNERS	−0.0611	0.0062	B_CHARGINGPRICE_FEMALE	−0.0687	0.00786
B_CHARGINGPRICE_OWNERS	−0.0491	0.0175	B_CHARGINGPRICE_MALE	−0.0496	0.00857
B_CHARGINGTIME_NO_OWNERS	0.0281	0.0121	B_CHARGINGTIME_FEMALE	0.0265	0.0135
B_CHARGINGTIME_OWNERS	0.0344	0.023	B_CHARGINGTIME_MALE	0.0319	0.0142
B_CONNECTION_NO_OWNERS	0.0209	0.0185	B_CONNECTION_FEMALE	0.00186	0.0235
B_CONNECTION_OWNERS	0.0307	0.0525	B_CONNECTION_MALE	0.0433	0.0258
B_RENENERGY_NO_OWNERS	0.0543	0.0187	B_RENENERGY_FEMALE	0.0578	0.0238
B_RENENERGY_OWNERS	0.106	0.0521	B_RENENERGY_MALE	0.0588	0.026
B_RESERVATION_NO_OWNERS	0.0937	0.0388	B_RESERVATION_FEMALE	0.065	0.0459
B_RESERVATION_OWNERS	0.106	0.0912	B_RESERVATION_MALE	0.131	0.0497

obtained from the parameter calibration of the gender-related segmentation model. The perception of public charging options was more positive for males, whereas females appeared to be more confident about private charging alternatives. The attributes related to the presence of ancillary services in parking areas and the charging price had a greater influence on females, whereas the magnitudes of other parameters related to comfort, such as charging time, connection type, and possibility of reservation, reveal a higher influence on the choices of males. In this case, the two population segments were homogeneously represented in the sample and the differences in the parameter values were generally lower in the other segmentation experiments.

The values of the parameters calibrated for the two experiments are detailed in Table 7.

4. Model analysis and discussion

In this section, the previously presented calibrated models are applied assuming different scenarios and attribute level combinations to investigate the effect of specific attributes on users' charging preferences. Before proceeding to this application, it is necessary to clarify an existing limitation. Electric vehicles have a limited presence in the market; therefore, it is challenging to gather meaningful data related to EV users' charging behavior. Consequently, datasets collected through SC surveys, as in this study, are often utilized. However, there might be disparities between what respondents express as their SC during the interview and their actual behavior in real charging situations (Beck et al., 2016). This bias could be particularly significant when it comes to decisions regarding electric vehicle charging operations, as many users may not be well-informed about the different charging options available. As a result, research relying on stated preference data is generally considered less reliable for estimating users' preferences. Nevertheless, it can still provide valuable results related to the relative importance of different factors influencing decision-making (Ben-Akiva et al., 1994) (Cherchi & Ortúzar, 2006). For these reasons, the models proposed in this study have been applied to evaluate the impact of variations in specific attributes on users' choices, rather than to predict the actual charging behavior of users in urban areas. Therefore, in this section, the application scenarios are considered to extend the knowledge of the influence of attributes on users' charging preferences.

4.1. Explorative scenarios for urban areas

The two models selected (ID 4 and 8, see Table 4) were applied to different explorative scenarios (Table 9) to evaluate the effect of different policies on the use of public charging points according to the preferences detected and interpreted by the logit models. First, a baseline scenario was created to simulate a typical situation in a European city, where the cost of public recharging is approximately twice that of private recharging, and there are usually no comfort services available for public recharging (ancillary services, wireless connectivity, reservation possibilities, fast charging, or use of renewable energy) (Table 8).

A possible way to understand whether public charging can be more appealing to users is price control. To explore the flexibility of the shift from private to public, the price difference between the alternatives was neutralized by equalizing it to 0.4 €/kWh, according to the current packages and subscriptions available in the market. In this scenario (*Neutral_Price*), no variation aimed at improving the comfort of public charging was included, as in the Comfort+ scenario in which public charging infrastructure quality is improved. In particular, the test was focused on the effect of specific enhancements on public charging demand, such as increasing the power of the infrastructure (charging time), which, despite impacts on the cost for operators. The scenario "Comfort+" includes also additional services at public infrastructures, such as food and shop facilities (only for parking areas), the possibility to book the operation, and to charge wirelessly. Additionally, the use of renewable energies in charging is introduced. Table 9 summarizes the attribute levels characterizing the scenarios (where not specified the values of the levels are as given in Table 8). Therefore, the two actions were simulated without overlapping to observe their effects separately.

4.2. Modeling behavior for charging activities under different conditions

The application of the selected models (ID 4 and 8) in the proposed scenario (Table 9) enabled the simulation of user charging preferences under different conditions. The relevant results are shown in Fig. 7 and summarized as follows.

- According to Model ID 8, in the *baseline scenario,* private charging is the first choice of users, particularly home private charging with a percentage of approximately 28 %. In the nested logit model (ID 4), on the other hand, the private home option is opted for by 30 % of users, followed by the public option, but still close to home, with approximately 25 % of choices.
- Charging location in a *parking area* appears to be more sensitive to comfort improvement than price neutralization. In both models, the preference for charging in parking areas increases by 4.5 % and 3.5 % owing to comfort improvements and price neutralization, respectively.
- The two models show different behaviors regarding *public charging options* close to home or close to work. In Model ID 8, the benefits of improved comfort had a higher impact concerning price control policy for public alternatives. In Model ID 4, the charging preferences changed differently for the public option that was close to home or work. In the former case, the choice increased by 2 %, by improving comfort, and by over 4 % by equalizing the price; in the latter case, the increase is smaller.
- Similarly, the two models show the sensitivity of *private charging* in the public charging incentive exploratory scenarios, with reductions of slightly less than 5 %.

In general, the MNL calibrated with Dataset 2 shows only minor differences between recharging at work or home, whether public or private, compared to the NL calibrated with Dataset 1, which shows a stronger preference for home recharging, both private and public.

4.3. Effect of user segmentation in modeling

The effect of heterogeneity on the perceptions of different user classes may be included in the modeling to better describe and predict their choices. In Section 3.2 this issue was considered by introducing two

Table 8
Reference values for a typical scenario.

Attribute	Parking	PrivHome	PubHome	PrivWork	PubWork
ANCSERVICES	covered charging point				
CHARGINGPRICE(€/100 km)	5.6	2.8	5.6	2.8	5.6
CONNECTION	wired	wired	wired	wired	wired
B_RENENERGY	no	no	no	no	no
B_RESERVATION	no		no		no
B_CHARGINGTIME	slow		slow		slow

Table 9
Scenario characteristics.

Scenario	Public_ Price [(€/kWh] (€/100 km)	Private_ price [(€/kWh] (€/100 km)	Ancillary services (park-area)	Connection Type (public)	Renewable energy (public)	Reservation (public)	Charging time (public)
Baseline	0,7 (5.6)	0,35 (2.8)	covered CP	wired	no	no	slow
Neutral_Price	0,4 (3.2)	0,4 (3.2)	covered CP	wired	no	no	slow
Comfort+	0,7 (5.6)	0,35 (2.8)	food and shops	wireless	yes	yes, optional	fast

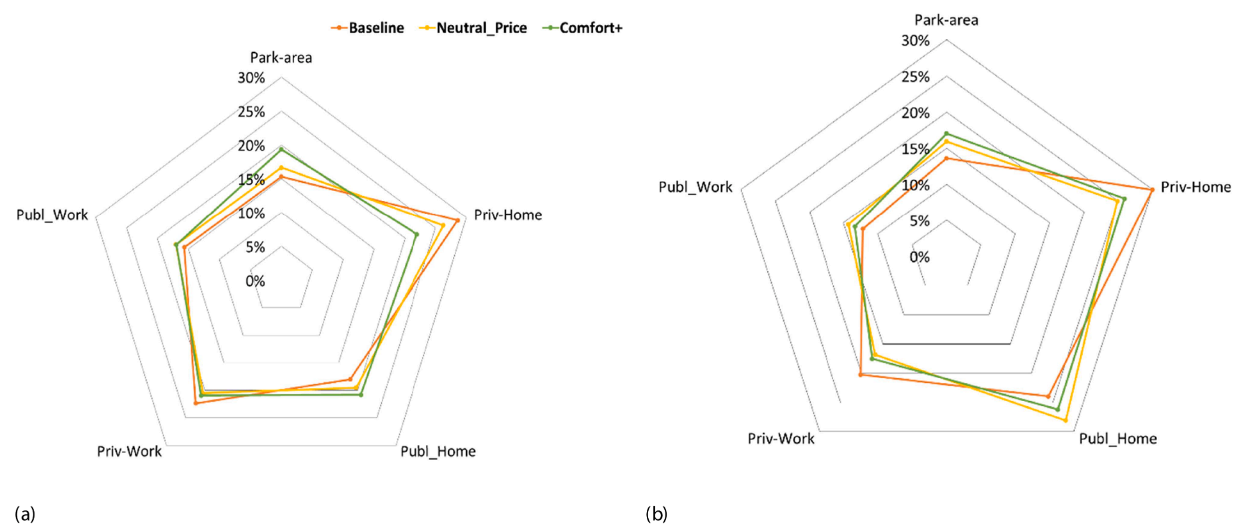

Fig. 7. User charging preferences: (a) multinomial logit model [ID 8] and (b) nested model [ID 4] in three different scenarios.

socioeconomic attributes and analyzing their effects separately. The role of user segmentation was investigated by considering the calibrated multiclass models presented in Section 3.2. For this experiment, the aforementioned *Comfort+* scenario was considered as a reference for comparison and multiclass models were applied to estimate the demand for user classes, particularly male/female and EV owners/non-owners.

The results of this experiment are shown in Fig. 8 for the identified classes and aggregated samples. The estimated demand for the male/female multiclass reveals a preference for public charging by males, whereas a slightly increased demand for private home charging by females is observed (Fig. 8a). Nevertheless, despite these slight differences, the overall demand followed a similar trend, making the modeling of this user classification unnecessary. A different situation was observed for multiclass EV owners/non-owners (Fig. 8b). In this case, the behavioral differences between the two classes were relevant. A meaningful preference for charging in equipped parking areas of EV owners was detected, whereas non-owners were less aware of this alternative and preferred other charging options, particularly private home charging (26 % of non-owners demand). A higher proportion of EV non-owners in the sample (approximately 88 %) renders the overall demand shift closer to that of the non-owner class. This effect should be considered because it could influence the estimation of real demand, which was, actually generated by EV owners. If this is not considered, using the aggregated version of the model, a potential underestimation of the demand for public charging can occur. For this reason, the disaggregated model version, including BEV ownership class, can provide

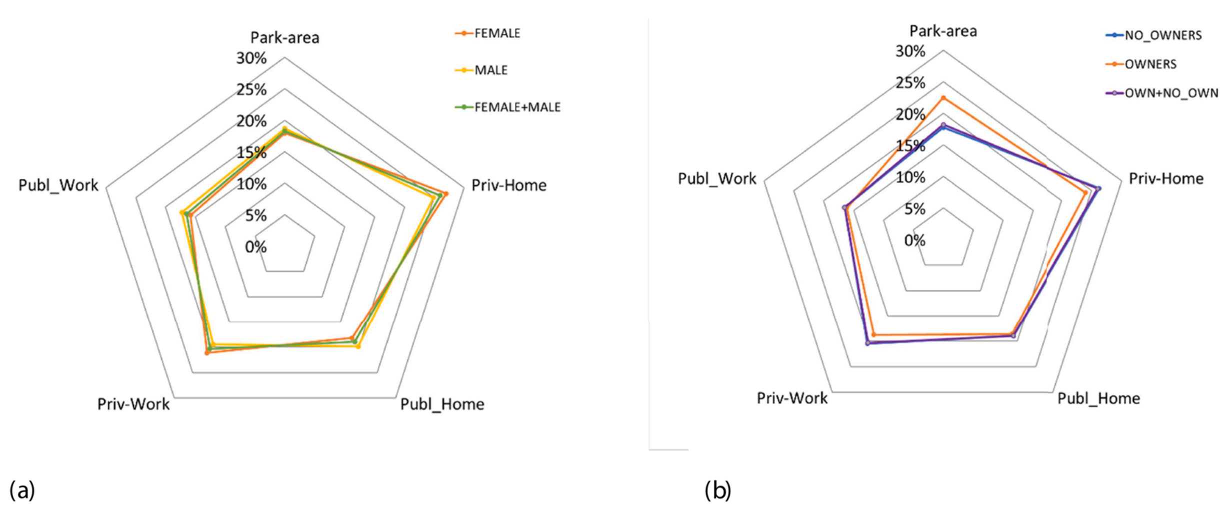

Fig. 8. Percentage of charging preference in multiclass analysis (Comfort+ scenario, model ID 8).

flexibility for application also in case the electric vehicle diffusion may significantly change. For example, assuming an increase from 10 % to 100 % of EV owners in the population, a shift higher than 5 % is estimated from private homes to parking area recharging options. As expected, an intermediate result was estimated for the case of 50 % of EV owners.

5. Conclusion

To support a user-centric design of the recharging infrastructure for urban charging activities, this study proposed a modeling approach to reproduce user behavior. Five options were identified, which had private or public access and were near home, work, or in parking areas. A SC survey was used to collect data for a discrete choice experiment to analyze and connect user choices to the main factors, such as the price or time required for charging.

An iterative process of calibrating and redefining the discrete choice models, starting from the preliminary versions used to conduct the two surveys, generated two models with different characteristics. One was a nested logit model (ID 4) with a more complex modeling structure and included correlations between alternatives, resulting in fewer attributes to estimate. The sample size was smaller, without socioeconomic characteristics, and limited to an urban environment. The other was a more linear multinomial logit model (ID 8) that included a larger number of attributes for the alternatives; it was calibrated using a larger dataset involving users from all across the selected countries and their main socioeconomic characteristics. An additional formulation based on Model ID 8 was proposed by introducing user segmentation, which better reproduced user behavior; however, the complexity of the mathematical formulation increased, requiring a wider knowledge of user characteristics. For example, the introduction of population segmentation based on EV ownership in the model could reduce the estimation error caused by the considerable differences in taste and alternative perceptions between categories. The results showed that non-owners consider charging price to have higher relevance, whereas EV owners are more influenced by attributes related to comfort and sustainability, such as the connection type or the availability of electricity produced by renewable energy sources while selecting charging options. In addition, non-owners appeared less confident about public charging options than owners who had acquired more experience with these alternatives.

The two selected models (ID 4 and ID 8) were applied in different explorative scenarios to demonstrate how different policies, such as price controls and actions aimed at improving the comfort of public electric charging, can affect the use of public charging points. The percentage of users who preferred recharging their electric vehicles closer to home or work, whether public or private, was not very different in the multinomial logit model, whereas it was more unbalanced towards home recharging in the nested model (55 % of home charging, both public and private). Regarding possible actions to improve public charging options, the effect was positive for all public alternatives, with an increase of between 2 and 4 %. The effect of comfort improvements, including the creation of ancillary services, wireless connections, and the use of renewable resources, was greater for charging options in parking areas. Price neutralization had a greater impact on public charging options close to home or work, although the percentage increase was comparable to that of the comfort incentive.

Finally, the behavioral differences between owners and non-owners were also investigated in the model application, revealing a meaningful preference of EV owners for charging in equipped parking areas, whereas non-owners were observed to be less aware of this alternative and preferred other charging options, particularly, private home charging. The presented models and the examples of their applications can be used in a decision-making process, depending on the data available for a specific city and the modeling complexity chosen to simulate the charging behavior of urban users. Planners can leverage some of results to implement actions aimed at managing charging demand. For example, investments can be oriented to improve the quality of public charging stations in parking areas instead of implementing pricing strategies, which seems to be more effective to attract users in public charging stations near home. Also, the choice of the most suitable charging power to install in public infrastructure is one of the critical aspects of policy actions in electric mobility. Lower-power devices are indeed less expensive but require more time to users. Decision-makers could explore these options based on the expected demand, which may be influenced by a higher-quality service. However, these observed effects, as highlighted by the calibrated models, are affected also by the specific situation of the charging infrastructure described by other attributes. The different charging locations (home, work, other parking facilities) are seen more as part of the user's charging routine than as a specific physical location. Nevertheless, various recommendations on infrastructure placement can also be drawn. For instance, by utilizing the model in residential areas, it is possible to understand whether the potential installation of public charging stations with specific characteristics (and therefore a specific cost for operators) could be attractive to residents who may choice between private home charging and, indeed, public charging near home.

In the presented modelling approach the dependent variable represented by the 5 charging options should be seen as a spatial and time attribute to represent the choice of users during daily schedule. In future work, we might consider applying the model with an agent-based technique (such as Monte Carlo simulation), sampling individuals and recharge options following specific attribute distributions. This approach can model individual's behaviours enhancing the approach based on average values. For instance, in situations in which the same option for charging can be provided with different electric powers. In this case, the frequency of a specific charging option during sampling is expected to be consistent with its diffusion. Future developments will also involve the implementation of models using DSS tools to support the planning of urban charging infrastructures. Finally, using the results obtained from the survey, the specifications and calibration of a model to describe electrified vehicle adoption are ongoing.

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CRediT authorship contribution statement

Lorenzo Sica: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Angela Carboni:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Francesco Deflorio:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Cristiana Botta:** Writing – review & editing, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

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Data availability

The data that has been used is confidential.

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