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User Adoption of Electrified Powertrains: Identification of Factors Through Discrete Choice Modelling

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Abstract: This study identified the main factors affecting car selection decisions through discrete choice experiments based on a large dataset collected in four European countries in 2023 using stated choice questionnaires. The choice set includes six current and popular car powertrains with factors related to vehicle features, user characteristics, and specific geographical contexts, which can influence the adoption of vehicles with electrified powertrains. An easily applicable multinomial logit model was first proposed to explore the effects of selected attributes and the model's ability to reproduce user preferences with different incentive policies, geographical contexts, and energy prices. A mixed logit model and a segmented multinomial logit model were introduced to consider the sample's heterogeneity. The first captures the preference dispersion among respondents related to incentives and operational costs. The second, which specifically classifies users based on car market segments, showed a greater variation in factors related to the purchase cost and battery range. The models estimate the weight of nine factors, offering support for targeted policy recommendations. Cost-related factors confirm their relevance in choices, and the analysis shows that users who want to enhance their vehicle range by 1 km are willing to pay approximately EUR 80.

Keywords: discrete choice experiment; electric vehicles; stated preference; EV adoption

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1. Introduction

Electric mobility is a solution for road transport that contributes to achieving the sector's environmental sustainability goals; it does so by improving air quality and reducing greenhouse gas emissions. The European Green Deal [1] aims to achieve a carbon-neutral European Union (EU) by 2050, and a shift toward using electric vehicles (EVs) is one of the main goals planned for the next few years. This is consistent with the decarbonisation process of all sectors, especially transportation, which is responsible for nearly a quarter of Europe's greenhouse gas emissions. Nevertheless, the percentage of new EV registrations in Europe, including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), although growing rapidly in recent years, was only 21.5% on average in 2022 [2]). Moreover, this growth is not homogeneous across Europe; some countries, especially in the north, have reached peaks of 80%, but more than half of the European countries have a percentage of new EV registrations well below 20% [3].

1.1. Literature Review

Discrete choice experiments (DCEs) are widely used to investigate the factors influencing EV adoption. Numerous experiments have been conducted at the urban level using local datasets or by considering larger areas, such as countries. Several studies have proposed different modelling formulations to estimate the diffusion of EVs in urban areas and to investigate the effects of variables such as the sociodemographic characteristics of the population, personal opinions, and travel-related information.

A literature review was conducted using Google Scholar and Scopus. The latter was searched using keywords such as "battery electric vehicles", "plug-in electric vehicles", "consumer preferences", "penetration", "adoption", "discrete choice model", "mixed logit model", and "stated choice/preference".

The analysis of related studies focuses on three main factors:

- How is the SC survey structured? What alternatives are offered? What attributes are investigated?
- Which models of the logit types have been used, and what are the alternatives?
- What are the main findings?

A synthetic view of the characteristics of the surveys contained in the past literature is proposed in Appendix A. Most research was conducted in China, Republic of Korea, and the US. Surveys carried out within the EU relate to only two countries (Italy and Germany), and none offer a European perspective. Considering the alternatives, most surveys proposed choice scenarios in which the EV alternative (BEV or PHEV) is proposed against an ICEV, whereas only [4,5] included hydrogen fuel cell vehicles (HFCVs), which is not, however, the focus of this study.

When considering directly measurable attributes, monetary costs—namely, purchase, maintenance, and fuel costs—are the most recurrent barriers to EV adoption, with particular emphasis on purchase price. The authors of [6] highlighted the key role of the purchase cost difference between zero-emission or emission-reducing technologies and emission-emitting technologies in EV adoption. Incentives on purchase and utilisation (i.e., access to TLZ, bus lanes, free parking, or tax exemptions) can partially or completely mitigate the negative effect of the purchase price [7–10]; however, sometimes they are not even sufficient [11]. Thus, many authors proposed recommendations that were addressed to policymakers. As an example, the authors of [12] suggest new financing schemes (such as soft credits) to allow more consumers to afford the upfront cost, whereas the authors of [10] propose a "free fuel" incentive, i.e., free or discounted energy tariffs. They explore the potential disparities in the impact of EV purchase incentive policies in different contexts, exhibiting the greater effectiveness of purchase incentives in low-income, low-traffic, and low-density cities. In contrast, incentives for utilisation are more effective in high-income, high-traffic, and high-density areas. An interesting approach is taken by the authors of [13], who quantify the average equivalent value that public authorities should grant every year to keep the BEV adoption rate constant. Possible aspects of the market dynamics of the electric vehicle sector, such as battery production, which can be affected by the adopted supply chain logic [14], sourcing, and recycling, can influence vehicle costs and, thus, end-user choices. Furthermore, price volatility, particularly in energy, fuel, and raw materials, significantly impacts vehicle adoption decisions, as it can alter consumer perceptions and the economic feasibility of such investments [15,16].

After the purchase price, the availability and reachability of charging infrastructure is the second highest barrier to EV adoption, as it is perceived to be insufficient by most of the interviewed individuals [8,17–19]. This issue is partially related to range anxiety, i.e., the belief that a single charge is not sufficient, even though some opinions are in opposition. In fact, on one side, the authors of [8,11,20,21] suggest that the autonomy range, together with a reduction in charging time, is the most urgent technical upgrade to be carried out in the EV market in order to enhance adoption in their own countries, i.e., China and the US. In contrast, the authors of [19,22], who carried out studies in Italy and Germany, found that the driving range has started to be perceived as reliable. Other related attributes are the car segment [23] and the lack of availability of large-size EV options [24].

Finally, the relationship between the adoption and perception of environmental issues should also be noted. The authors of [5,25] found that Korean consumers are positively pushed toward EVs if the energy required for vehicle recharging comes from renewable sources. Meanwhile, the authors of [17,26,27] found the same results only in specific subgroups, mainly younger and higher-income individuals. Moreover, a novel and effective proposal would be the use of personal carbon trading (PCT) and tradable driving credit (TDC) proposed by the authors of [28].

The effects of the users' socioeconomic characteristics and personal attitudes on EV adoption are explored in the literature [29–31]. Collecting socioeconomic data is good practice for checking the consistency and representativeness of the sample. However, these data can be integrated into models such as mixed logit (MXL) and latent class models (LCMs). These models can catch psychological traits that would otherwise be neglected. It was observed that several socioeconomic factors have a crucial influence on EV penetration and diffusion in a society. Some are quite expected, such as "opposing with the upfront purchase price and marginal driving cost" [32] or the lower sensitivity of low-education classes relative to environmental issues [17]. Other approaches are instead more interesting, such as those regarding the social norm, as explored by the authors of [30,33,34], or common perceptions [35]. This information is also used to segment EV adopters into classes [7,27] in order to address target policies for each group.

1.2. Research Contribution and Structure of This Study

This study aims to extend the knowledge of user preferences for cars with alternative powertrain technologies, identifying the principal factors that may influence choices. How do attitudes shift with respect to adopting an EV change depending on the size of the city and with respect to opportunities to charge EVs using public infrastructure? Can users be incentivised to buy electrically powered vehicles? Is it more effective to discourage vehicles that use internal combustion engines (ICEs) than to incentivise EVs? How do these factors change for different vehicle market segments (for example, small or large vehicles)? The discrete choice model (DCM) application, estimated using data from state choice (SC) surveys, attempts to answer these timely questions by identifying the factors influencing choices and estimating their weight. The SC survey allows us to investigate user preferences for a phenomenon that is not common in the real world by proposing a series of adoption choice situations between two hypothetical cars with different powertrains described via a list of attributes.

Most surveys used to collect data offered an alternative EV option (BEV, PHEV, or both) compared to traditional ICE vehicles. This study extends the analysis of user preferences by explicating the most popular and current alternatives for vehicle powertrains, including their typical features. The choice set includes six alternatives, including hybrid electric vehicles (HEVs), biofuel-powered ICEVs (BIOICEVs), and natural gas and liquefied gas (LPG/NGV) vehicles.

Secondly, the literature shows that Europe is underrepresented among the most analysed countries. The survey used for the modelling process was obtained with the support of the H2020 EU-funded project INCIT-EV (https://www.incit-ev.eu/, accessed on 22 January 2025), in which data collection was performed to understand future EV drivers' needs and expectations in order to propose advanced charging solutions. The dataset used in this study was collected from four European countries: Italy, Spain, the Netherlands, and Estonia. The selection was based on the active participation of project partners in these areas. A European perspective on EV adoption was examined and added to the actual scientific literature while exploring different diffusion levels of electric mobility (typically more established markets in the Nordic countries than in the south). The four countries included in the analysis have different characteristics (income level, sensitivity to sustainability, technological progress, etc.) that can be useful in extending the models obtained across other European regions with similar socioeconomic conditions in order to approximate their preference for EV adoption.

Electric mobility scenarios have varied greatly in recent years since new car models have been introduced in the market; they have also varied due to new players in the industry, with rapid changes in their features, including price, range, and the technology implemented. For this reason, the date of the distributed survey is a relevant point in this study because the "picture" obtained is updated and based on a large sample of participants that can help estimate reliable models. Thus, the data used in this study are recent (collected in 2023) and much larger than the average used in previous research (n = 16,735 choice scenarios). This can provide a more accurate and broader overview of the European situation in supporting policymaking at the European level. According to the project's objectives, to provide tools that policymakers can use in different European countries, this study consistently uses established methodological approaches that are widespread in the literature and easily applicable. Given the meaning of the attributes and parameters used in the model, the defined method is easily interpretable and simplifies understanding and applicability for a wide range of researchers.

After providing an introduction and problem statement, Section 2 of this study describes the methodology used, including identifying factors influencing users' choices in vehicle adoption, data collection through the SC survey, and estimation techniques for the DCM. Subsequently, the obtained results are analysed in Section 3 and further explored through specific applications, such as the sensitivity analyses of parameters and an investigation of random parameters and segmentation models.

2. Methodology

This study proposes quantitative models estimated using data from SC questionnaires, which asked respondents to select their preferences from a predefined set of alternatives. To define the situation as realistically as possible, six options were provided according to the most currently adopted powertrain systems for cars: ICEV, LPG/NGV, BIOICEV, HEV, PHEV, and BEV. The final version of the survey contained an initial set of questions to integrate the socioeconomic variables in the sample. The structure of the survey and pilot tests has been described by the authors of [36]. The factors relevant to users' choice of vehicle were identified at a preliminary stage by reviewing the relevant scientific literature and then refining the selection with the involvement of INCIT-EV project partners. Two pilots were helpful in better defining the levels of each attribute or the addition of new factors, as the extensions of socioeconomics questions, for example, were managed with more details at a later stage [36].

The model investigates the effect of selected factors on the probability of a particular choice being made among a set of alternatives, which was initially estimated by assuming a multinomial logit (MNL) formulation. Although the adopted structure cannot include any covariance among alternatives and assumes identical distributions for random utilities, its main advantage is its easy applicability and transferability. As explained in Section 1.2, the proposed modelling approach is based on an established and widely used MNL model with a simple formulation and good flexibility for greater replicability. This is further enhanced by required common and generally available data, even in different and resource-constrained contexts, ensuring broad applicability across varying scenarios. In addition, a further model was estimated with the MXL formulation to consider behavioural heterogeneity among individuals, assuming random distributions for selected parameters.

2.1. Identification of Factors for User Adoption

Vehicle size is a key factor affecting adoption choices [23]. If considered in the survey, more targeted responses can be obtained, as the respondent selects the preferred and probably best-known type of car and the related choice situation. Three market segments for cars were included in the study based on 45% of total model sales in 2019 [36]:

- Car segment B: Subcompacts (such as Ford Fiesta, Renault Clio, and Volkswagen Polo)
- Car segment C: Compacts (such as Volkswagen Golf, Ford Focus, and Skoda Octavia)
- Car segment D/E: Mid-size and large (such as Volkswagen Passat, Mercedes C-series, and BMW 5-series).

Other factors that may influence choices are related to certain vehicle characteristics, such as the range a vehicle can cover with a single full charge/refuel (RANGE, proposed between 100 and 800 km, depending on the powertrain and car segment) and the minimum time duration for charging operations allowed from the vehicle (CHARGINGTIME, between 15 min and 2 h) to charge 50% of the battery [26]. This latter value was chosen because, typically, the state of charge (SOC) is maintained between 20% and 80% to maximise the health state of the battery. Factors related to purchase and vehicle use costs are commonly included when modelling user preferences [37,38]. This study tailored the purchase costs (PRICE) for the three car segments based on current average prices. These costs also incorporate some aspects of market dynamics, particularly for EVs. For example, the production costs or those associated with batteries directly influence the market price of electric vehicles, and we can assume that they are contained in them. The other car-related costs are operating costs (OPERCOST), which include only the expenditure for fuel, electric energy, or a mixture of both in covering 100 km. The three options proposed for operative costs are the baseline price (current market price) and their possible increases (+25%) or decreases (−25%). Although OPERCOST represents a variation and does not define a cost, the survey proposed this attribute as a monetary value to facilitate the user's understanding of this point. Incentives may also influence user choices [31,39,40]. The most common incentive for purchase (PURCHINCENT) is a price discount, whereas for utilisation (UTILINCENT), incentives include free parking and free access to limited traffic zones (LTZs). The proposed attribute levels also include the "disincentives" for ICEVs. These attributes are defined according to the most popular push and pull strategies for promoting e-mobility, i.e., measures that render less sustainable choices (push) less attractive and encourage positive behaviours (pull). As vehicle-related factors are relevant in choices, other elements may also play a role, such as the socioeconomic characteristics of the user. Population features such as the average income (INCOME) and education level (EDUCATION) may have a meaningful effect on powertrain choice if people with higher incomes can afford the higher costs of EVs, and the educational level affects awareness of the environmental impact of car usage. Finally, choices can be influenced by geographic conditions such as city characteristics and size (CITYSIZE) or the diffusion level of public charging infrastructure [32]. The latter can be defined as a percentage of public spaces, car parks, shopping centres, and petrol stations equipped with a charging point for EVs (DIFFUSION). Table 1 shows the defined levels for each factor related to the vehicle's characteristics.

Table 1. Level description of identified factors included in the experiment.

Car Features	Levels Description
Engine	ICEV (gasoline/diesel) Bio-fuel ICEV LPG/CNG ICEV (gas) HEV (hybrid electric vehicle) PHEV (plug-in HEV) BEV (battery electric vehicle)
Price [EUR] (PRICE)	15,000 20,000 25,000 30,000 35,000 40,000 45,000 50,000 60,000 70,000
Operating cost per 100 km (only fuel/energy) (OPERCOST)	+25% Baseline −25%
Incentive on purchase (PURCHINCENT)	Disincentive (taxes based on CO_2 emissions and engine power) None Low (EUR 3000 with scrapping) Medium (EUR 6000 with scrapping) High (EUR 10,000 with scrapping)
Incentive on utilisation (UTILINCENT)	None Limited (in Italy, access and free parking in LTZs) High (in Italy, access to bus lane, LTZs, free parking)
Range (with a single full refuel/recharge) (RANGE)	200 km 300 km 400 km 500 km 600 km 700 km 800 km 1000 km
Charging time (to recharge 50% of the battery) (CHARGINGTIME)	2 h (slow charging) 1 h (accelerated charging) 30 min (fast charging) 15 min (ultra-fast charging)
Diffusion of infrastructure in public spaces (petrol stations, parking, malls, etc.) equipped with charging points (DIFFUSION)	Only home/work private charging 1 out of 5 (20%) 1 out of 2 (50%) 3 out of 4 (75%) All (100%)

2.2. Stated Choice Survey

The SC survey was designed based on car-related attributes and their levels (Figure 1). Respondents were asked to choose the car segment they were most likely to use or buy at the beginning of the survey. Then, each respondent faced a series of choice situations between two vehicle alternatives (A and B) and had to choose which car they would buy or use. The alternatives were described using the values of attributes, which were adapted based on the car segment selected by the user in the preliminary question. The interviewees were requested to provide details of their socioeconomic characteristics.

	A	B
Vehicle typology	BEV	BIO-FUEL ICEV
COSTS AND INCENTIVES		
Purchase price	45,000€	35,000€
Operating cost per 100 km	3.38 €	4.6 €
Incentives on purchase	10.000€ with scrapping (to be deducted from purchase price)	None
Incentives on utilization	None	None
RECHARGING/REFUELING OPERATION		
Range with a single recharge/refuel	400 km	800 km
Charging time to recharge 50% of the battery	1 hour	Not Applicable
ELECTRIC VEHICLES CHARGING INFRASTRUCTURE		
Diffusion in terms of public spaces equipped with charging points. It describe the scenario in which to imagine buying the car (even if the vehicle is not electric)	3 OUT OF 4 (75%) Scenario with 75% of public spaces (parking lots, malls, petrol stations, …) equipped with electric charging points	

Figure 1. Example of choice task in proposed web-based survey (levels refer to car segment C).

The design of the choice scenarios, developed as part of the INCIT-EV project, was supported by Ngene 1.3 (ChoicheMetrics, Sydney, NSW), a software tool used to design DCEs utilising various methodologies and settings. For this design, the method selected was the Bayesian D-efficient fractional factorial design, setting 60 rows. Ngene was used to manage various survey design features, including orthogonality (10 blocks added), correlation structure, and the balance of attribute levels. The tool also ensured that the combinations of attribute levels presented to participants were realistic by setting criteria to exclude unrealistic combinations; for instance, the incentives for purchasing an ICEV were limited and lower than those related to EVs. Participants had to imagine that they were in the situation of having to purchase a new vehicle. Figure 1 provides an example of a choice task presented to respondents, showing all details of options A and B. In the questionnaire, attributes were expressed in commonly used units to help participants better understand the differences among the options. However, during data analysis, these units were converted to scale levels to facilitate the interpretation of the results after the estimation process. Specifically, each attribute level was associated with coding to preserve the linear and ordinal variation in attributes (for example, each price value is associated with a corresponding code in units of EUR/EUR 10,000).

The distribution of the web-based survey was outsourced to a specialised agency using appropriate panels of respondents in the European countries involved. Respondents were rewarded for participating in the experiment. Data collection occurred in January and February 2023 and included 16,735 responses from approximately 3350 users from Italy, Spain, Estonia, and the Netherlands. The survey was translated into the official languages of the four countries to ensure that participants could properly understand it. This decision also impacted the number of countries chosen for the economic feasibility of data collection. These countries were selected due to the presence of project partners in the area and to explore different contexts in the spread of the EV market. For example, it is known that e-mobility is more widespread in Nordic countries than in southern

Europe, such as Spain and Italy, and users may have different perceptions of the factors influencing their purchase choice. The respondents made choices based on their preferences, considering the cost-related attributes, vehicle features, and policies discussed in Section 2.1. Table 2 shows the main characteristics of the collected sample. The authors of [41] report some preliminary statistical analysis results of the collected dataset before modelling and the relationship between alternative preferences and socioeconomic characteristics. For example, participants with a high income (above EUR 5000/month) selected BEVs 40% of the time when available among the alternatives, compared to only 30% for those having an income lower than EUR 2000/month. A similar gap is observed when analysing the variable related to respondents' education levels. Individuals with at least a high school diploma tend to choose BEVs more frequently when offered (43%) than other respondents (31%). In addition, the size of the user's city of residence also seems to influence their choices. Specifically, those living in small cities with fewer than 100,000 inhabitants chose BEVs in only 30% of cases when offered, compared to 43% among the residents of cities with over 500,000 inhabitants.

Table 2. Main socioeconomic features of collected sample.

Question	Options	% of Sample
Driving License	No	14%
	Yes	86%
Electric Vehicle Owners	No	88%
	Yes	12%
Charging Infrastructure Owners	No	91%
	Yes	9%
Country	Italy	25%
	Spain	25%
	Estonia	25%
	Netherlands	25%
Gender	Not declared or non-binary	0.3%
	Male	45.4%
	Female	54.3%
Age (years)	18–29	37%
	30–39	27%
	40–49	18%
	50–59	12%
	60–69	5%
	70+	1%
Context	Urban	62%
	Suburban	21%
	Rural	16%
City size (CITYSIZE)	Very small city (less than 50,000 inhabitants)	35%
	Small city (50,000–200,000)	28%
	Medium city (200,000–500,000)	19%
	Medium–large City (500,000–1,500,000)	9%
	Large city (more than 1,500,000)	8%

Table 2. *Cont.*

Question	Options	% of Sample
Income (per month) (INCOME)	<EUR 1000	11%
	EUR 1000–2000	31%
	EUR 2000–3000	24%
	EUR 3000–4000	16%
	EUR 4000–5000	8%
	EUR 5000–7000	4%
	EUR 7000–10,000	2%
	>EUR 10,000	2%
Education (EDUCATION)	Primary school	3%
	Secondary school	19%
	High school	39%
	Bachelor degree	26%
	Master's degree	10%
	Doctorate	3%

2.3. Discrete Choice Model's Formulation

The collected data were used to build and estimate different versions of DCMs. These models were based on utility maximisation [42,43], in which users chose the alternative with the highest perceived utility value. The proposed model includes six car powertrain types in the set of alternatives. The utilities describe the value users ideally assign to each alternative i when compared during the selection process. Perceived utility U_i is composed of a systematic component V_i (usually obtained as a linear combination of attributes for each alternative x_i) and a random component, which can be expressed as follows:

$$U_i = V_i + \varepsilon_i = \beta x_i + \varepsilon_i$$

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

Assuming the formulation of the MNL model, the estimate of probability $p(i)$ related to each alternative i can be obtained as a function depending on the associated utilities from the defined set of choices:

$$p(i) = \exp(V_i) / \sum_j \exp\left(V_j\right)$$

The MNL model is a commonly adopted modelling option, but it has some limitations that can be accepted according to the aim of the analyses. For example, this model assumes that all individuals have the same preference coefficients for choice alternatives, thus ignoring behavioural heterogeneity among users. In addition, it does not consider possible correlations among alternatives in the modelling process. To explore a more advanced modelling approach that addresses these issues, the MXL model was chosen to account for user behavioural heterogeneity. This approach investigates heterogeneity by assuming it affects the systematic component of utility rather than the stochastic term, which can be analysed using alternative methods [44]. Unlike the MNL model, which assumes independence among errors and applies the IIAs (independence of irrelevant alternatives) property, the MXL model allows for more realistic alternative relationships through a flexible stochastic component [43]. This type of model, using numerical integration techniques such as Monte

Carlo simulation, allows the accurate estimation of model parameters by including individual variability. User behavioural heterogeneity is captured by enabling coefficients to vary randomly across individuals, and this flexibility helps mitigate covariance problems. This is carried out by modelling selected parameters as random distributions [45,46], which can be normal, log-normal, uniform, triangular, and other functions [44]. The probability that an individual n chooses alternative *i* in the MXL model is given as follows:

$$p(n,i) = \int \frac{exp(X_{n,i}\beta)}{\sum_{j=1}^{J} exp(X_{n,j}\beta)} f(\beta|\theta) d\beta$$

where the following are defined:

- $f(\beta|\theta)$ represents the probability distribution of random parameter β;
- θ represents the parameters of the random parameter distribution.

3. Results

Using the estimated MNL model (assuming preference homogeneity among users), three explorative scenarios were investigated to understand the effects of specific attributes included in the model in order to estimate user choices. The preference heterogeneity in user choices was examined by estimating a random parameter model (MXL). The heterogeneity was assumed to affect the systematic component of the utility by randomising three of the selected factors. Finally, the sample's variety was also investigated using a segmented MNL model based on the three car type classes (seg. B subcompact, seg. C compact, and seg. D/E mid-size/ large).

3.1. Multinomial Logit Model

The MNL model was specified and estimated based on data collected with the SC survey, shown in Section 2.2, and the model formulation in Section 2.3. Additionally, a direct measure derived from the estimated parameters is presented in Section 3.1.2. In fact, the willingness-to-pay (WTP) analysis on the RANGE parameter was included to determine how much users are willing to pay for an increase in vehicle autonomy, which is a key factor for adopting BEVs.

3.1.1. Model Specification and Estimation

A fundamental step in model building involves specifying the model by selecting a linear combination for the systematic utilities associated with each alternative, including its key attributes. The definition and description of each variable are included in Section 2.1, and the detailed levels for vehicle-related attributes are reported in Table 1. The socioeconomic variables included were CITYSIZE (five levels based on the number of inhabitants), EDUCATION (six levels based on educational level), and INCOME (monthly income in EUR, eight levels) (see Table 2 for the details). For the proposed model, the utilities were defined as follows:

$$V_{ICE} = ASC_{ICE} + \beta_{price} \times price_{ICE} + \beta_{opercost} \times opercost_{ICE} + \beta_{purchincent} \times purchincent_{ICE}$$

$$V_{BIOICE} = ASC_{BIOICE} + \beta_{price} \times price_{BIOICE} + \beta_{opercost} \times opercost_{BIOICE} + \beta_{purchincent} \times purchincent_{BIOICE} + \beta_{utilincent} \times utilincent_{BIOICE}$$

$$V_{LPGNGV} = ASC_{LPGNGV} + \beta_{price} \times price_{LPGNGV} + \beta_{opercost} \times opercost_{LPGNGV} + \beta_{purchincent} \times purchincent_{LPGNGV} + \beta_{utilincent} \times utilincent_{LPGNGV}$$

$$V_{HEV} = ASC_{HEV} + \beta_{price} \times price_{HEV} + \beta_{opercost} \times opercost_{HEV} + \beta_{purchincent} \times purchincent_{HEV} + \beta_{utilincent} \times utilincent_{HEV}$$

$$\begin{gathered} V_{PHEV} = ASC_{PHEV} + \beta_{price} \times price_{PHEV} + \beta_{opercost} \times opercost_{PHEV} + \beta_{purchincent} \times purchincent_{PHEV} + \beta_{utilincent} \times utilincent_{PHEV} \\ + \beta_{citysize} \times citysize + \beta_{education} \times education + \beta_{income} \times income \end{gathered}$$

$$V_{BEV} = \beta_{price} \times price_{BEV} + \beta_{opercost} \times opercost_{BEV} + \beta_{purchincent} \times purchincent_{BEV} + \beta_{utilincent} \times utilincent_{BEV} + \beta_{chargingtime} \times chargingtime_{BEV} + \beta_{range} \times range_{BEV} + \beta_{citysize} \times citysize + \beta_{education} \times education + \beta_{income} \times income$$

The model was estimated using Biogeme 3.2.10, an open-source Python package designed for the maximum likelihood estimation of parametric models, particularly DCMs. This tool allows for the estimation of the β-parameters of the model according to a defined specification, formulation, and dataset. Table 3 presents the estimation results.

Table 3. Estimated β-parameters of MNL model and main goodness-of-fit indicators.

β-Parameter	Value	Rob. Std Err	Rob. *t*-Test	Rob. *p*-Value
ASC_1 (ICEV)	1.16	0.142	8.2	2.22×10^{-16}
ASC_2 (BIOICEV)	0.78	0.14	5.57	2.56E-08
ASC_3 (LPGNGV)	1.45	0.141	10.3	0
ASC_4 (HEV)	1.31	0.138	9.53	0
ASC_5 (PHEV)	0.82	0.0917	8.94	0
B_CHARGINGTIME	0.0064	0.00921	0.695	0.487
B_CITYSIZE	0.0606	0.0243	2.49	0.0127
B_EDUCATION	0.028	0.029	0.964	0.335
B_INCOME	0.0516	0.0194	2.66	0.00775
B_OPERCOST	−0.062	0.00729	−8.51	0
B_PRICE	−0.176	0.029	−6.06	1.38×10^{-9}
B_PURCHINCENT	0.0345	0.0133	2.6	0.00936
B_RANGE	0.139	0.0193	7.21	5.78×10^{-13}
B_UTILINCENT	0.0424	0.0196	2.16	0.0307

Sample size: 12,064; null log-likelihood: −8362.128; final log-likelihood: −8034.407; BIC: 16,200.39.

Considering the statistics computed for the obtained solution, all the estimated parameters are coherent with the expected signs. Indeed, it is possible to observe the negative values of parameters associated with costs, such as OPERCOST or PRICE. In contrast, positive values are exhibited in PUCHINCENT, UTILINCENT, INCOME, EDUCATION, and RANGE. All the attributes are statistically significant, except for the charging time attribute (CHARGINGTIME), which exhibits the lowest estimated value (close to zero and positive sign consistent with the expectations) and the minimum absolute value of the *t*-test indicators. This attribute is not related to charging infrastructure but is used to approximate the maximum vehicle charging power. As shown in Figure 1, it was presented in the questionnaire as the time needed to charge 50% of the battery in order to facilitate user responses. The attribute was included in the model to explicitly consider this factor, which is commonly used in the literature, and highlight its negligible weight in car adoption preferences as observed during the survey.

In contrast, the attribute related to charging infrastructure diffusion (DIFFUSION), which was initially included in the initial model's specification, was excluded from the final version of the model because its associated parameter exhibited low significance (the observed *t*-test value was approximately 0.54, with a standard error larger than the estimated parameter, and it was significantly lower than one, which is typically considered as the threshold). Moreover, the negative sign estimated, disagreeing with the expectations, confirmed this modelling decision. This parameter is not directly related to a technical characteristic of the vehicle but rather to the charging infrastructure. During the survey, the percentage of public spaces equipped with infrastructure was presented (Figure 1), and the dataset analysis in [41] shows how this variable exhibits unexpected behaviour. Indeed, while preferences for BEVs increase as expected with moderate levels of public charging infrastructure availability, they decrease significantly and unexpectedly when the availability reaches higher levels. These results suggest that maybe the levels of this attribute were not clearly described and highlight potential issues in the survey that would require further investigation. For these reasons, this attribute related to the diffusion level of charging infrastructure was excluded from the final version of the model. The estimated parameters of the MNL model shown in Table 3 were obtained with a new model estimation method that did not include DIFFUSION in the parameter's list. However, estimating the model by excluding a parameter included in the choice tasks could impact the values of other parameters as it might consider, albeit minimally, the effects. Indeed, the decision process of some users, even if marginally given the obtained results, may have been influenced by this variable, and this effect could affect the estimation of the other parameters included in the model. Nevertheless, its exclusion was deemed preferable based on the considerations mentioned above.

3.1.2. WTP Analysis for Vehicle Range

Estimating model parameters renders conducting analyses that provide a deeper understanding of user preferences possible. Among these, the WTP is a key metric that quantifies the amount consumers are willing to pay for specific improvements in product attributes. This measure is particularly important as it helps assess users' values with respect to different features, guiding product development and pricing strategies [47]. In this analysis, we focus on evaluating the WTP for enhancements in the range of autonomy of EVs [21]. The RANGE factor was chosen for this analysis because the limited perceived range is one of the main barriers to the adoption of EVs, directly affecting consumer confidence and choice. Unlike other attributes, range affects daily usability and overall vehicle value perception, making it a critical factor in EV adoption. The WTP for each unit of increase in range is calculated as a ratio between the coefficient of the variable of interest (β_range) and the coefficient for price (β_price), considering the unit measures assumed for the variables in the estimation process. The calculation of WTP with the ratio of the selected attribute parameter to the estimated marginal utility of income, i.e., the negative price parameter, is possible because the utility considered is linear [47]. This evaluation assumes the homogeneity of user preferences:

$$WTP = -\frac{\beta_{range}}{\beta_{price}} = -\frac{(0.139)}{(-0.176)} = 0.789 \left[\frac{10^2 €}{\text{km}}\right] = 78.9\ \frac{€}{\text{km}}$$

To account for the uncertainty associated with the estimate, the standard error (SE) of the WTP was calculated as follows:

$$SE(WTP) = \sqrt{\left(\frac{SE(\beta_{range})}{\beta_{price}}\right)^2 + \left(\frac{\beta_{range} \times SE(\beta_{price})}{{\beta_{price}}^2}\right)^2}$$

The estimated standard error of the WTP is 16.9. To provide a range of truthful values for the WTP, a 95% confidence interval was computed:

$$WTP = 78.9\ \pm 16.9\ \frac{€}{\text{km}}$$

The calculated WTP value represents the price range that users are willing to pay to increase the vehicle's autonomy range. The obtained result is, on average, consistent with similar estimated values in the literature, ranging from values exceeding EUR 100/km, particularly in northern European countries [48,49], to slightly below EUR 40/km [21,22]. The result obtained is, therefore, intermediate to these extreme values in the literature. The WTP can offer valuable insights for pricing strategies and EV development by highlighting consumers' importance relative to range autonomy.

3.2. Investigation of the Effect of Attributes on Users' Behaviour

Despite the positive results related to the estimated β-parameters, a possible model limitation is that EVs have limited diffusion in the market. Therefore, collecting data with revealed preferences (RPs) was not useful. It is challenging to gather meaningful insights about their typical features from actual market data, and as is the case in this study, datasets collected by an SC survey are frequently considered. However, there may be disparities between respondents' stated preferences and their actual behaviour in real market situations [50]. This bias could be particularly pronounced in decisions regarding EV adoption because many consumers may not be familiar with EV alternatives or their unique characteristics. Moreover, considering the limited time budget during surveys, providing a full description of EVs to respondents was not feasible. Taking into account the possible bias, the proposed model was applied to explain the effect of variations in specific attributes on user choices rather than to predict the share of EVs in future scenarios. Research relying on stated preference data is considered less reliable for estimating market share. However, it can still offer valuable insights into the relative significance of various decision-making factors [40,51]. The estimated model was applied to selected scenarios to test it, highlighting the effect of city-related factors on the car powertrain-type choice (Section 3.2.1). A sensitivity analysis was performed in a typical city, thus blocking context-related factors, to investigate the effects of possible incentive and disincentive policies (Section 3.2.2) and market changes in electricity and fuel costs (Section 3.2.3).

3.2.1. Effect of Geographical and Socioeconomic Conditions

The proposed application compares how the choice among six powertrain alternatives may change under several geographical conditions. These differ based on the size of the city and two specific population features, namely, education and income. For this purpose, three hypothetical contexts with different city and population characteristics were considered (Table 4. Characterisation). The geographical conditions were designed by assuming a joint increase in the values associated with the connected attributes in order to limit the number of presented cases and explore reasonable and consistent scenarios.

Table 4. Characterisation of charging features among defined geographical conditions.

Geographical Conditions	City Size	Education	Income [EUR/Month]
C1	very large	medium–high	3000–4000
C2	medium	medium	2000–3000
C3	very small	medium–low	1000–2000

With the values of the other attributes required for the estimation maintained constant, the model was applied to the three presented geographical conditions. Figure 2 exhibits the simulation results. According to expectations, the analysis shows that inhabitants of larger cities are more inclined to adopt cars equipped with electric powertrains (PHEV or BEV) than those of a medium or small city. A stated preference for LPG/NGVs is clear from Figure 2 in all geographic contexts analysed, and this is probably because the category includes more types and often presents helpful conditions, especially from an economic point of view.

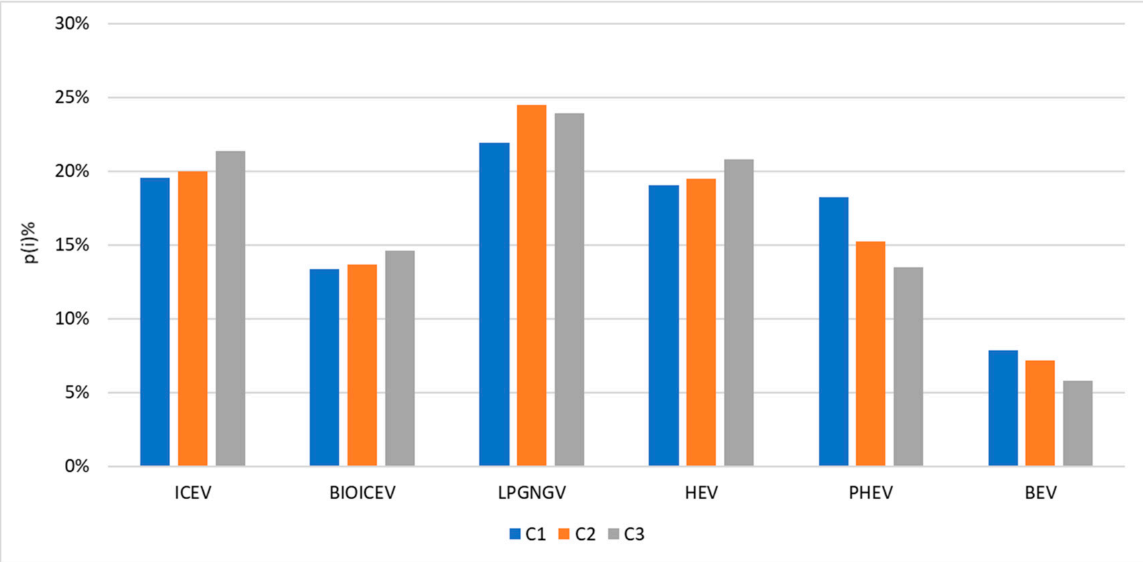


Figure 2. Distribution of powertrain adoption preferences for different geographical conditions.

3.2.2. Effect of Purchase and Utilisation Incentives

For each geographical condition, a sensitivity analysis was conducted to investigate the influence of specific policies or powertrain attributes on the purchase of EVs. For this purpose, three incentive scenarios were assumed in one defined geographical context. In particular, to analyse the role of incentives, the previously defined geographical context "C2" was considered to represent a common situation in Europe (average wages in Euro Area: EUR 2066/month; average city size: 228,970 inhabitants [52]): medium-sized city (200,000–500,000 inhabitants) and standard levels of education and income of the population. Powertrain-type-related attributes, such as price and operative costs, were included with standard and fixed values. Four scenarios were defined for this specific application:

- The baseline scenario does not include any incentives or disincentives.
- The scenario "Inc_purch" includes a disincentive (taxes) on purchase for ICEVs and economic incentives of different levels for HEVs (limited), PHEVs (medium), and BEVs (high).
- The scenario "Inc_util" provides incentives during use. PHEVs are encouraged with incentives, such as access to and parking in LTZs, while BEVs also have access to bus lanes and free parking.
- The scenario "Inc_purch+util" combines the incentives of the two previously described scenarios.

Considering the built scenarios, the model was evaluated for its ability to respond to these actions. The impact of incentives increases the preferences for PHEVs and BEVs by 1% and decreases the adoption of ICEVs by up to −1.2%. Analysing the variation compared to the base scenario in more detail (Table 5), the impact of purchase incentives is greater than that of utilisation incentives for electrified powertrains. The effects of both incentive strategies are different for BEVs and hybrid solutions: The discount for purchase produces the same result (+0.5%) even if the discount level is different, whereas the different incentive levels for use produce different benefits (+0.4% for BEVs, +0.1% for PHEVs, and negative for HEV). Regarding policymaking, the cost of introducing bonuses for utilisation could be much lower and, in any case, would produce an increase of almost one percentage point in the choice of BEVs.

Table 5. Variation in adoption preferences in different incentive scenarios compared to baseline scenario.

Alternatives	ICEV	BIOICEV	LPGNGV	HEV	PHEV	BEV
Baseline [p(i)]	20.7%	14.6%	23.4%	19.5%	14.1%	7.7%
Inc_purch [Δp(i)]	−0.9%	−0.2%	−0.3%	0.4%	0.5%	0.5%
Inc_util [Δp(i)]	−0.1%	−0.1%	−0.2%	−0.1%	0.1%	0.4%
Inc_purch+util [Δp(i)]	−1.2%	−0.4%	−0.6%	0.2%	0.9%	1.0%

3.2.3. Effect of Fuel and Energy Costs

The operating costs in the model only consider fuel, electric energy, or a mixture of both depending on the vehicle type. However, they are used to investigate the effects of possible variations in market prices for vehicle power supply by setting the operating cost attribute value. In geographical condition "C2", the explorative scenarios were analysed to evaluate the effect of an increase in fuel cost ("Op_fuel+") and in electricity cost ("Op_energy+"). As expected, the increase in the cost of fuel increased the choice of electric-powered vehicles by 1%, whereas a decrease in traditional engine use is more moderate at approximately 0.5% (Table 6). In the scenario "Op_energy+", the increased cost of electricity has a smaller positive effect on the share of ICEVs. The impact of increased operational costs on PHEVs is particularly interesting. It might be expected that the impact on PHEVs would be similar because of their dependence on both energy sources. In contrast, fluctuations in fuel costs reveal their importance concerning energy-related issues. The change in fuel costs caused an increase of 1% compared to a decrease of 0.6% caused by an increase in electricity costs.

Table 6. Variation in adoption preferences under different operative cost conditions compared to baseline scenario.

Alternatives	ICEV	BIOICEV	LPGNGV	HEV	PHEV	BEV
Baseline [p(i)]	20.0%	13.7%	24.5%	19.5%	15.2%	7.2%
Op_fuel+ [Δp(i)]	−0.5%	−0.4%	−0.6%	−0.5%	1.0%	1.0%
Op_energy+ [Δp(i)]	0.4%	0.3%	0.5%	0.4%	−0.6%	−0.9%

3.3. *Estimation of Random Parameter Model*

The analyses presented in Section 3.2 are based on the multinomial formulation in 3.1, which neglects behavioural heterogeneity among individuals. A more complex modelling formulation (MXL) was estimated to explore this aspect. This model type considers randomness in one or more parameters, represented by probability density functions. In this case, initially, a normal distribution was adopted, and to select the parameters to be randomised, experiences reported in the literature were first used, supported by an iterative process of testing the variables and keeping fixed parameters that reduced their significance when randomised. Indeed, to limit the computational time, not all parameters can be set as random (more than 6 h, Table 7). These evaluations were conducted by observing the robust *t*-test and robust *p*-value values associated with the mean and standard deviation of the random parameters.

The final selection of randomisation is for the parameters "OPERCOST," associated with changes in fuel and electricity costs; and "PURCHINCENT" and "UTILINCENT", associated with incentive policies. This approach highlights the heterogeneity of users that impact the choices considering these factors. The parameters of the MXL model were estimated by assuming the formulation presented in Section 2.3 using the Monte Carlo simulation technique. Specifically, the estimation was iterated several times by increasing the number of draws for numerical simulations until a stable solution was reached (in this case, 2000 draws). The increase in the number of draws assumed for Monte Carlo simulations results in a consequent increase in the computational time. The use of a normal distribution as a random function aimed to observe the behaviour of the parameter with greater flexibility. To further refine the estimation of the MXL model, an additional experiment was conducted by adopting a truncated normal distribution for the parameter OPERCOST. This approach ensures the negativity of the estimated parameter, aligning with the expectation that users should perceive costs negatively. This adjustment reflects the intuitive understanding that users consistently associate costs with a disutility. Table 7 shows the estimated parameters of the MXL formulation with an increasing number of draws, different random parameter distributions assumed, and a comparison with previous MNL results.

Table 7. Estimated parameters for MNL and MXL models with a different number of draws.

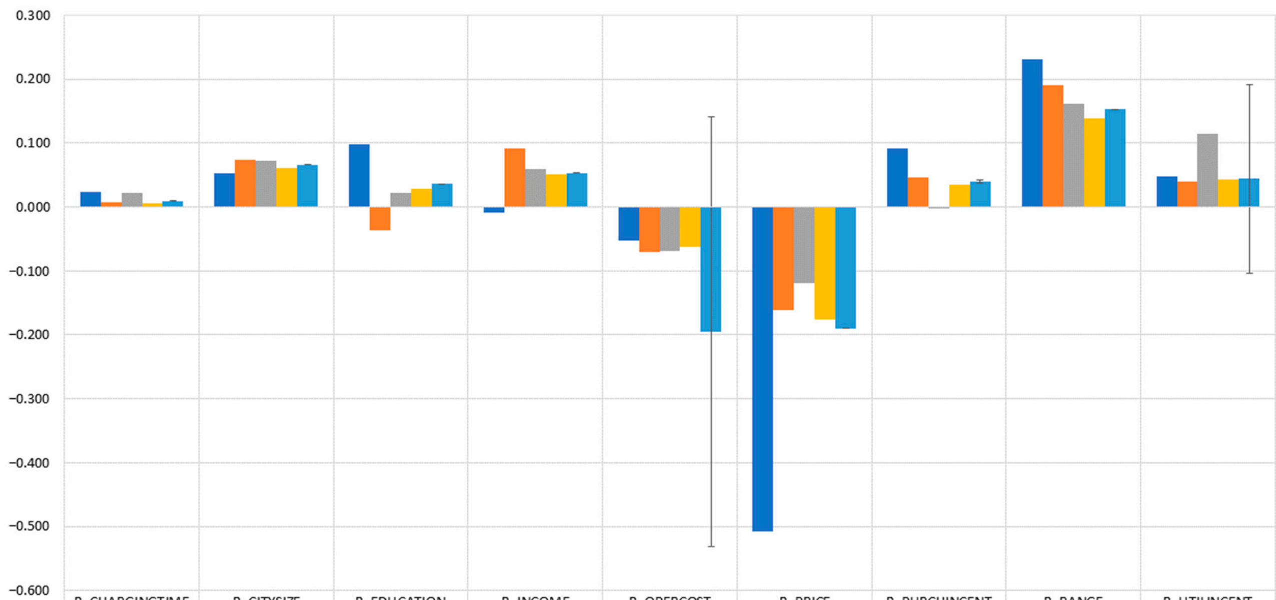
	MNL	**MXL (Draws = 1000)**	**MXL (Draws = 2000)**	**MXL (OPERCOST Distributed Using Truncated Normal) (Draws = 2000)**
B-parameter	Par. value (*t*-test)	Par. value (*t*-test)	Par. value (*t*-test)	Par. value (*t*-test)
ASC_1	1.16 (8.2)	1.32 (7.21)	1.28 (7.09)	1.28 (6.66)
ASC_2	0.78 (5.57)	0.894 (5.17)	0.863 (5.09)	0.852 (4.93)
ASC_3	1.45 (10.3)	1.66 (8.36)	1.61 (8.11)	1.62 (7.33)
ASC_4	1.31 (9.53)	1.5 (8.01)	1.46 (7.78)	1.45 (7.25)
ASC_5	0.82 (8.94)	0.951 (7.32)	0.92 (7)	0.911 (6.47)
B_CHARGINGTIME	0.0064 (0.695)	0.00682 (0.62)	0.00742 (0.692)	0.00951 (0.836)
B_CITYSIZE	0.0606 (2.49)	0.068 (2.42)	0.0661 (2.42)	0.0662 (2.4)
B_EDUCATION	0.028 (0.964)	0.0346 (1.02)	0.0339 (1.02)	0.0365 (1.06)
B_INCOME	0.0516 (2.66)	0.0562 (2.48)	0.0542 (2.46)	0.0534 (2.45)
B_OPERCOST_mean	−0.062 (−8.51)	−0.0745 (−6.49)	−0.0727 (−6.24)	−0.195 (−2.99)
B_OPERCOST_std	-	0.172 (2.52)	0.166 (2.26)	0.336 (1.91)
B_PRICE	−0.176 (−6.06)	−0.197 (−5.75)	−0.192 (−5.67)	−0.19 (−5.56)
B_PURCHINCENT_mean	0.0345 (2.6)	0.0391 (2.43)	0.0389 (2.47)	0.0398 (2.46)
B_PURCHINCENT_std	-	−0.18 (−1.62)	0.114 (0.72)	−0.002 (−0.016)
B_RANGE	0.139 (7.21)	0.16 (6.42)	0.155 (6.24)	0.153 (5.95)
B_UTILINCENT_mean	0.0424 (2.16)	0.0414 (1.75)	0.0417 (1.83)	0.0439 (1.89)
B_UTILINCENT_std	-	−0.375 (−1.76)	−0.287 (−1.11)	−0.147 (−1.89)
Sample size = 12,064				
ll(0) = −8362.128	ll(f) = −8034.407	ll(f) = −8031.116	ll(f) = −8030.907	ll(f) = −8033.159
Optimisation time:	0:00:04 h	2:01:07 h	4:00:34 h	6:43:46 h

3.4. Modelling Choice Including Car Market Segmentation

As mentioned, at the beginning of the survey, before the SC answers, users were first asked to choose the vehicle category they were interested in; then, the key features of all alternatives proposed in the DCE were adapted to the selected class (for example, purchase price). Therefore, the effect of heterogeneity on the perception of users interested in different car market classes may be included in modelling to better analyse their choices using the class-based segmentation of observations.

The class-segmented model is based on the MNL formulation proposed in Section 2.2, with the nine parameters estimated independently for each car market segment (B—subcompacts, C—compacts, and D–E—mid-size and large). The Biogeme Python package applies segmentation to the selected model.

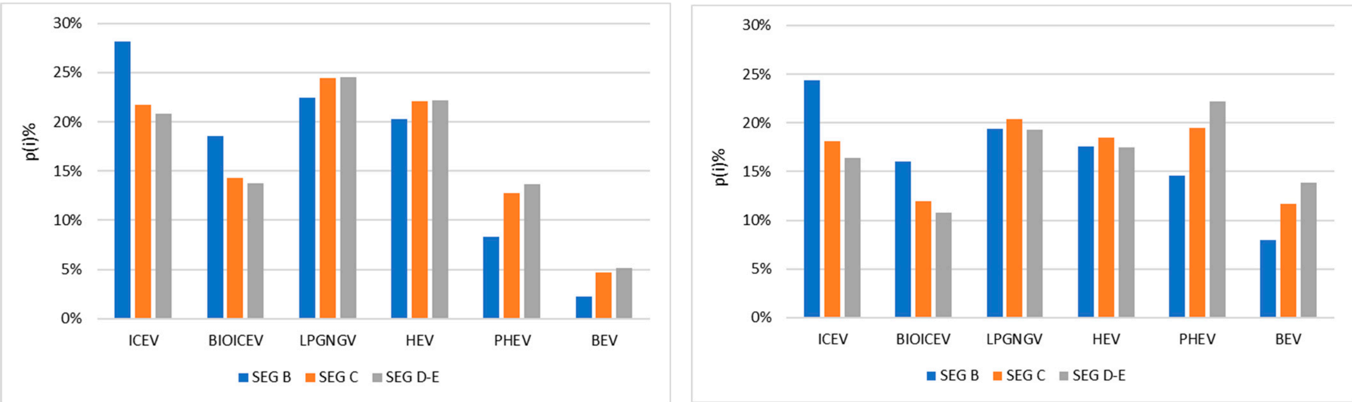
Figure 3 shows the estimated parameters in the disaggregated model compared with the aggregated versions (MNL and MXL). The parameters related to costs (B_PRICE, B_PURCHINCENT, and B_UTILINCENT) exhibited meaningful differences among the three car segment classes. Whereas the operative cost-related parameter (B_OPERCOST) values are similar, the price strongly influences the segment B vehicle class according to expectations. Indeed, buyers of small cars may be more interested in saving money than buyers who prefer executive cars. For the same reason, segment B's parameter related to purchase incentives is still higher. In contrast, utilisation incentives have a greater effect on segment D–E buyers, who may be more interested in comfort and extra services (bus lane access and parking in LTZs). The segmented model based on vehicle classes and the MXL model presents different parameter variabilities, thus showing user heterogeneity. For example, the price attribute (B_PRICE) shows considerable variability among the three segments, but this was not significant in the randomisation of the MXL model. The more complex MXL model captures sample heterogeneity, while the simpler MNL model segmentation succeeds in focusing on differences in the choice of specific classes of users. The two approaches thus result in two different outcomes depending on the objective chosen.



	B_CHARGINGTIME	B_CITYSIZE	B_EDUCATION	B_INCOME	B_OPERCOST	B_PRICE	B_PURCHINCENT	B_RANGE	B_UTILINCENT
SEG B	0.023	0.052	0.098	−0.009	−0.053	−0.508	0.092	0.231	0.048
SEG C	0.007	0.074	−0.037	0.092	−0.070	−0.161	0.046	0.190	0.039
SEG DE	0.021	0.072	0.022	0.059	−0.069	−0.119	−0.002	0.161	0.115
MNL	0.006	0.061	0.028	0.052	−0.062	−0.176	0.035	0.139	0.042
MXL	0.010	0.066	0.037	0.053	−0.195	−0.190	0.040	0.153	0.044

Figure 3. Estimated β-parameters of aggregated (MXL and MNL) and disaggregated models (SEG B, SEG C, and SEG DE).

The segmented model was then applied to test the effect of selected classes on vehicle adoption preferences. This application requires knowledge of the attribute values for all considered car market segments, which could discourage replicability in other contexts. For this reason, analyses on the aggregate MNL model, such as those related to the impact of incentives or fluctuations in fuel costs, were not replicated with the disaggregated model. Instead, a decision was made to conduct an analysis related to the estimates obtained for the different classes of vehicles, assuming two extreme contexts and attribute sets. Thus, two scenarios were defined: a worst case where geographic conditions (city size and population features) and other factors such as operating costs and incentives were unfavourable to BEV adoption, and a best case where, on the contrary, attribute set levels would push the choice toward electric vehicles. Figure 4 shows the results for the three market class segments. Segment D–E buyers are more inclined to adopt an EV, whereas segment B users tend to adopt more traditional engines in unfavourable and favourable contexts. Users who chose the middle car segment (C) have preferences similar to those of the D–E class in the unfavourable scenario, while they differ more in the favourable scenario.



(**a**) (**b**)

Figure 4. Vehicle adoption preferences for market class segment in unfavourable (**a**) and favourable (**b**) BEV cases.

4. Discussion and Conclusions

A DCM is estimated to analyse the role of different factors in users' choices for adopting EVs, with a choice set of six powertrains (ICEVs, BIOICEV, LPG/NGV, BEV, PHEV, and HEV). Using these specific alternatives ensures a comprehensive set of choices aligned with the market to enhance the realism of the scenarios presented to respondents. Several typical attributes are included, such as range, price, and the characteristics of the urban area, including city size, average income, and education. The parameter related to the maximum car charging power presented by the minimum charging time (CHARGING) shows the lowest estimated and minimum absolute *t*-test values. This commonly used and relevant factor in the literature has no significant effect on the dataset used in this study. This result can be interpreted by analysing certain contextual elements. For example, a correlation between the vehicle's purchase price and the market class is possible. Higher-end vehicles usually offer lower charging times. Since the attribute levels were adjusted to the realistic values based on the chosen vehicle class, the charging time value may have been less influential for the respondents. Furthermore, the charging time, although related to the vehicle's performance, is more linked to charging infrastructure. The respondents perhaps tend to underestimate this parameter's importance because of their limited access to high-power charging networks. A greater diffusion of high-powered charging infrastructures enabling vehicle-charging capabilities could influence users' perception of this attribute. The supply of charging infrastructure deserves in-depth analyses, in addition to the users' charging behaviours and preferences, and it is a subject of other ongoing studies. Charging preferences regarding power and location must be analysed to properly guide policymakers in their charging infrastructure network design process.

The effect of some parameters was investigated in detail with three applications of the estimated MNL model. The first application was conducted by assuming three geographic contexts to investigate the effects of city-related attributes (population size, average income, and level of education) on EV adoption. These characteristics significantly influence the diffusion of EVs. Large cities with a population with high income and education provide a favourable environment for electrified mobility, as expected. This result highlights how the geographic context, which is synthetically defined by city size, income level, and the average education level of the population, influences users' choices, and thus should be considered during policy definitions aimed at incentivising the adoption of EVs. Then, the model was tested in an average geographic context, a medium-sized city with a medium-income and educated population, to assess the effect of purchase and utilisation incentives (free access to restricted zones of the city and free parking). The effect of utilisation incentives is not the same for three electric powertrains (HEV, PHEV, and BEV), which are realistically effective only for BEVs. Significant and variable changes in electricity and fuel costs have been observed in recent years. The application of this model allows the exploration of scenarios that consider changes in the market costs of vehicle fuels. Increasing fuel costs appear to have a greater effect than changes in electricity costs. This result may suggest that policies that disincentivise the use of fossil fuels may be more effective in pushing toward the adaptation of EVs.

The MNL model is an easily interpretable modelling option that assumes that all individuals have the same preference coefficients for choice alternatives, thus ignoring user behavioural heterogeneity. To explore a more advanced modelling approach to address these issues, an MXL model was estimated. Incentives (for use and purchase) and operating costs are the three parameters that showed significance after randomisation. Although the MNL model has this limitation, it enables segmented analysis by dividing users into classes according to a specific characteristic. Vehicle adoption preferences can vary among the three market class segments included in the experiment (subcompact, compact, and large cars). According to the MNL model with car market segmentation, higher segment users are more interested in purchasing BEVs than the lower segment, which prefers traditional powertrains. In addition, the weight of some factors analysed changes greatly among the three vehicle market segments. For example, the weight of the purchase price is much more influential for users who typically choose vehicles from the cheapest considered segment (B). Participants who choose high-class (seg D–E) vehicles give greater weight to incentives for use, and vice versa, they are not influenced by purchase price benefits. This result shows, as in the case of the geographical context, that the type of car segment should be considered to define targeted and, consequently, more effective incentive policies. The two methods that investigate sample heterogeneity allow different results based on the chosen objective. In particular, the MXL model is a tool that captures the dispersion of preferences within the sample of users, assuming random distributions for the parameters used in the linear function of the systematic utility. Meanwhile, the simpler MNL model's segmentation highlights differences in the choices estimated for predefined user groups. This dual analysis of user heterogeneity, with different complexities and outcomes, can provide a new and useful contribution to EV adoption research as it shows the versatility of methodologies and increases their replicability. The proposed MXL model allows for the investigation of heterogeneity affecting the systematic component of utility by randomising a subset of coefficients (incentives and operating costs). Other methodologies analyse instead the heterogeneity related to the stochastic component of utility, which does not emerge in the MXL model [44]. The results obtained with the MXL model may differ and have different policy implications from models that analyse stochastic heterogeneity. The easily interpreted and applicable MXL model may not consider all variabilities in individuals' choices, which are also caused by variations that cannot be explained by the observable variables included in the systematic term of the utility. The estimated model analysing heterogeneity for the large dataset collected allows for good robustness and reliability, but it also requires significant computational time, which was contained by limiting the selection of parameters to be randomised to three.

The estimated DCMs evaluate the effects of the main vehicle characterising factors in users' choices in four European countries for adopting different powertrains. This can provide a synthetic understanding of relevant aspects influencing decision-making, which can support the development of targeted policy recommendations. The weights and attributes of the proposed models derive from user choices, and thus show the possible elements that can be used to guide policy choices. Indeed, defining and applying fixed policies that can be generalised to different contexts are not recommended. However, investigating the role of factors, including socioeconomic features, in a modelling approach can provide flexibility for identifying the set of actions with the expected effects consistently.

Future research, starting with the models obtained in this analysis, could investigate in more detail the applicability and design of incentive and disincentive (push and pull) policies in various typical contexts. The supply of charging infrastructure deserves in-depth analysis, in addition to the users' charging behaviours and preferences, which are investigated in other ongoing studies. New technological opportunities, including vehicle-to-grid (V2G) solutions, were not investigated in this survey but could have a specific effect on user choices. V2G technology can accelerate EV adoption because it can change the business model [21]. In fact, V2G technology allows EVs to communicate with the power grid to draw electricity for charging or to deliver stored energy to the grid. Bi-directional energy flow allows EVs to act as mobile energy storage units, enabling advantages for operators and better electricity tariffs for the user. Moreover, V2G improves the stability of the power grid by ensuring the resilience of charging points.

In addition, technological car improvements toward vehicle automation enable more optimised driving styles that can reduce energy consumption. These more virtuous driving behaviours can increase a vehicle's driving range, which was found to be an influential factor in EV adoption in our analysis.

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Appendix A

Table 1. Literature review analysis (MNL = multinomial logit; ML = mixed logit; LC = latent class; RPL, RPM = random parameters logit; ICLV = integrated choice and latent variable).

Reference	Model 1	Model 2	BEV	PHEV	ICE	Other	Purchase Price	Maintenance Cost	Charging Time	Fuel Cost	Battery Changing Cost	Utilization Incentives	Purchase Incentives	Range	Diffusion of Charging Infrastructure	Previous Experience	Environmental-Related Attributes	Other Attributes
[17]	LC		x	x	x		x	x		x				x			x	Acceleration; Vehicle size
[25]	ML		x				x		x					x			x	Autonomous driving functions available
[11]	ML		x	x	x		x	x	x	x	x	x		x				Annual tax exemption
[22]	MNL	RPL	x		x		x		x	x		x		x	x			
[53]	ML	LCM	x	x	x		x			x				x	x			
[7]	MNL	LCM	x	x	x		x	x	x					x	x			Replaceable battery, V2G availability
[8]	ML	LCM	x	x	x		x			x		x		x	x			
[20]	ML		x	x	x		x		x	x			x	x	x			Acceleration
[24]	ML		x	x	x		x			x					x			Smart car options
[27]	ICLV		x				x			x		x				x	x	Risk aversion
[4]	cluster-based-MNL	ML	x		x	HFCV												
[54]	RPM	LCM	x				x		x	x	x		x	x	x			Depreciation rate; carbon trading income; Brand
[9]	MNL		x															NO SP
[13]	BN		x		x							x	x					Restriction's policy
[37]			x		x		x		x	x				x			x	Vehicle value after 3 years
[5]	ML		x		x	HFCV	x		x	x				x	x		x	
[12]	LCM	LM	x		x	HEV	x			x		x			x			Risk aversion
[21]	ML		x				x		x			x		x				V2G availability
[18]	ML		x	x	x		x	x		x		x	x	x	x			
[19]	LCM		x	x	x		x			x		x		x	x			Power
[55]	ML			x			x		x	x	x			x	x			
[56]	ML		x	x	x		x		x					x		x		Maximum speed; Observability

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