Transportation Research Part A 158 (2022) 19–43

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Analysis of the barriers to the adoption of zero-emission vehicles in Spain

Abel Rosales-Tristancho [a,*], Raúl Brey [b], Ana F. Carazo [b], J. Javier Brey [c]

[a] *Department of Statistics and Operational Research, Universidad de Sevilla, Avenida Reina Mercedes s/n, 41012, Seville, Spain*
[b] *Department of Economics, Quantitative Methods and Economic History, Universidad Pablo de Olavide, Carretera de Utrera, Km 1, 41013, Seville, Spain*
[c] *Engineering Department, Universidad Loyola, Avenida de las Universidades s/n, 41704, Dos Hermanas, Seville, Spain*

ARTICLE INFO

Keywords:
Zero-emission vehicles
Barriers
Cluster analysis
Survey
Spain

ABSTRACT

This paper investigates Spanish drivers' perceptions of the main barriers existing in Spain to the purchase of zero-emission vehicles (ZEVs). Following a comprehensive literature review in this field, this paper quantifies, by means of a survey conducted in Spain of 1474 Spanish drivers, the drivers' desired levels for each barrier to consider ZEVs in their next purchase decision to replace their current usually-used car.

The analysis of these reported levels with latent class cluster models revealed the existence, in the sample, of groups of consumers with homogeneous preferences regarding the barriers. These groups differ in terms of individuals' characteristics, the car to be replaced, and journeys made with it. The most flexible groups comprise individuals with a significant knowledge of ZEVs, which underscores the importance of educational policies for the promotion of the use of ZEVs.

The desired levels of the barriers for each group are confronted with the current status of the barriers for certain ZEVs. This comparison reveals that Fuel Cell Electric Vehicles (FCEVs) would have great potential if they received government support, because their only barriers are economic (purchase price and fuel availability). This paper also quantifies the effects that purchase incentives and infrastructure investment policies could have in terms of higher FCEV penetration rates.

1. Introduction

Zero-emission vehicles (ZEVs) are motor vehicles that do not produce direct tailpipe emissions. These vehicles can be divided into two groups: electric vehicles that store energy in a battery (Battery Electric Vehicles or BEVs), and electric vehicles in which energy is stored in the form of hydrogen (Fuel Cell Electric Vehicles or FCEVs). They are considered solid alternatives to overcome most of the problems associated with the use of fossil fuels in the transportation sector (European Commission, 2011, 2014; Han et al., 2014; Ou et al., 2018; Shaheen et al., 2020; Wesseling et al., 2014; Zhang and Cooke, 2010).

Over the past decade, new ZEV models have appeared, and are being mass produced. However, their market penetration remains less than 5% in most countries (European Alternative Fuels Observatory, 2021). There are still several barriers that make individuals reluctant to purchase these vehicles compared to fossil-fuel-powered vehicles. Of course, the barriers are not necessarily the same for

* Corresponding author.
E-mail address: artristancho@us.es (A. Rosales-Tristancho).

https://doi.org/10.1016/j.tra.2022.01.016
Received 30 April 2021; Received in revised form 24 October 2021; Accepted 28 January 2022
Available online 24 February 2022
0965-8564/

FCEVs and BEVs, as they have different characteristics, performance levels, and associated infrastructure.

In order to attain a successful penetration of ZEVs, it is therefore necessary to study how these barriers make difficult their choice in the various stages of the car-purchase decision process. Evidence (Hauser, 2014) suggests that, in markets with many alternative products (such as the car market), consumers reduce the cost of their decision process using a two-stage process (Fu et al., 2017; Gensch, 1987; Horowitz and Louviere, 1995; Kaplan et al., 2009; Manski, 1977; Paleti, 2015; Simon, 1955; Suzuki, 2007; Swait and Ben-Akiva, 1987; Xu et al., 2015), where they first apply a number of non-compensatory heuristics to discard the alternatives that they will not consider (consideration-set formation stage), and subsequently they compare the remaining alternatives (the consideration set) to make a decision (final-choice stage). The motivation for this two-stage formulation is that consumers often use decision rules for the consideration set that differ from those for the final choice (Hauser et al., 2009).

The previous literature in this field has largely focused on the study of the effects of the barriers in the final-choice stage (Ferguson et al., 2018; Hackbarth and Madlener, 2013, 2016; Hidrue et al., 2011; Kormos et al., 2019; Ščasný et al., 2018; Sheldon et al., 2017). However, given the very low penetration of these vehicles into the transportation sector, attention should also be paid to their effect in the consideration-set formation stage. This stage is crucial for policy-makers and car manufacturers to ascertain how to entice consumers into considering ZEVs. Given the very high number of car alternatives in the market, the inclusion of ZEVs in the consideration set considerably increases the odds of their sale (Hauser et al., 2009).

In this consideration-set formation stage, consumers could consider some minimum or maximum acceptable levels (cutoffs) for the barriers to consider purchasing ZEVs. Attribute cutoffs play a key role in this stage because they provide the basis for two very common non-compensatory rules applied to consideration-set formation (Chen and Hwang, 1992; Dzyabura and Hauser, 2011; Hauser, 2014; Huber and Klein, 1991; Pham and Higgins, 2004; Truong et al., 2015): the conjunctive rule and the Elimination-by-Aspects (EBA) rule. In the conjunctive rule, the consideration set is formed by all the alternatives that meet the attribute cutoffs, whereas in the EBA rule, the consumer removes the alternatives in order of attribute importance if they fail to meet the cutoffs. In terms of consideration sets, deterministic EBA is indistinguishable from the conjunctive rule (Dzyabura and Hauser, 2011; Hauser, 2014; Hauser et al., 2009; Hauser et al., 2014; Moe, 2006). Applications of these heuristics to consideration-set formation in car-purchase decisions include those by Bakken (2006), Kim and Ratchford (2012), Paulssen and Bagozzi (2005), Punj and Brookes (2002), and Xu et al. (2015).

Given the very low penetration of these vehicles into the transportation sector in Spain (0.11% of the total fleet in the case of BEVs in 2019, and only two FCEVs sold up until that year) (European Alternative Fuels Observatory, 2021), it appears that Spanish drivers could be using certain cutoff levels for the barriers (for example, until the price difference of a ZEV with respect to its conventional vehicle counterpart falls below a certain amount, or until they perceive a sufficiently convenient alternative recharging/refuelling infrastructure). Through a survey of 1474 Spanish drivers, this paper focuses on the threshold levels of the main barriers, as identified in the literature, that Spanish drivers use to consider purchasing ZEVs. Individuals' heterogeneity in the perception of these barriers is modelled using latent class cluster models. Finally, identified groups are characterised by several non-parametric tests in terms of various covariates (socio-economic and mobility characteristics of drivers, drivers' attitudes, and their knowledge).

To the best of our knowledge, this is the first paper in this field that analyses the relationships between stated cutoff levels for different barriers with latent class cluster models. This approach is very informative for any region in the early stages of the transition to ZEVs, since it provides information on the minimum requirements people demand in order to consider the purchase of these vehicles. Furthermore, this approach enables the identification of groups of people with different requirements for these minimums and, therefore, it provides information on the probable timing of their purchase of ZEVs and on the actions that need to be implemented to bring a particular group into the market.

The structure of this paper is as follows. Section 2 provides a comprehensive review of the literature on barriers to the adoption of ZEVs, Section 3 describes the sample and the questionnaire. Section 4 contains the model employed to analyse the data. Section 5 presents the results, and Section 6 provides the discussion. Finally, the last section summarises the conclusions.

2. Literature review

The study of these barriers has been conducted from various viewpoints. In this paper, we classify the existing literature into two groups: the papers that aim to identify the main barriers to the adoption of ZEVs within the population; and the papers that study the effect of these barriers in ZEV purchase decisions.

2.1. Identification of the main barriers

This section goes through different approaches based on consumers' perceptions that have been utilised in the identification of the main barriers that hamper the penetration of ZEVs into the market (see Fig. 1).

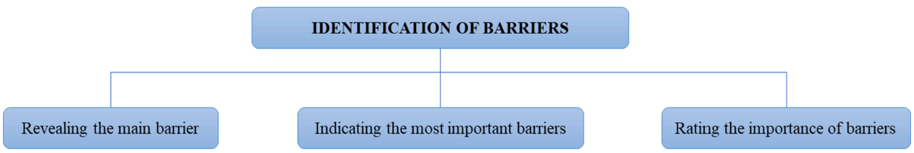

Fig. 1. Various approaches to the identification of the main barriers.

In this context, several authors have studied the importance of the barriers for consumers by asking them to reveal the main barrier they encounter (Adhikari et al., 2020; Andriosopoulos et al., 2018; Barisa et al., 2016; Chachdi et al., 2017; Egbue and Long, 2012; Iribarren et al., 2016; Zhang et al., 2018). The results obtained in these papers are summarised in Fig. 2. In the case of BEVs, the most frequently mentioned barriers are the lack of public charging infrastructure (34% of individuals in Barisa et al., 2016; 13.6% in Adhikari et al., 2020), the limited range (32% of students and 40.5% of faculty members of the University of Perugia, Italy, in Andriosopoulos et al., 2018; 33% in Egbue and Long, 2012; 37.8% in Zhang et al., 2018), and the higher purchase price compared to conventional vehicles (52% in Chachdi et al., 2017). Other barriers related to the performance and features of the car/battery (including charging time) are often mentioned in several of the papers. In the case of FCEVs, purchase price (34.63%) and fuel availability (22%) emerge as highly relevant barriers (Iribarren et al., 2016).

Likewise, other authors have asked individuals to indicate the most important barriers (not only one), normally without a limit to the number of barriers to be specified (Bühler et al., 2014; Cellina et al., 2016; Ciarapica et al., 2013; Hardman et al., 2016a, 2017; Noel et al., 2020). Some of the results obtained from this approach are shown in Fig. 3. Limited range arises again as a highly significant barrier for BEVs, and reaches the highest percentages in several papers (65% in Cellina et al., 2016; 59.9% in Noel et al., 2020). In Bühler et al. (2014), this factor is not only the most commonly mentioned barrier, but also the only factor increasing its percentage from 56.4% (T0) to 70.5% (T1) following 3 months of driving a BEV. In Ciarapica et al. (2013), range also reached high percentages (68.7%), although the most frequently mentioned barrier was the higher purchase price (70.5%). Other factors such as infrastructure and, with much lower percentages, charging time and safety/reliability are included by consumers in the list of barriers for BEVs. The lack of infrastructure is again the most commonly mentioned barrier for FCEV adoption in Hardman et al. (2016a, 2017) (63.3% and 63.2%, respectively).

A third approach consists of asking individuals to rate, on a scale, the importance of a given set of barriers in their ZEV purchase decision (Berkeley et al., 2018[1]; Ciarapica et al., 2013[2]; Hardman et al., 2016a[3], 2016b[4]; Haustein and Jensen, 2018[5]; Larson et al., 2014[6]; Lebeau et al., 2013[7]; She et al., 2017[8]). Results from this approach are shown in Fig. 4. In this figure, the absence of a barrier in a particular paper is not relevant, as the barriers to be rated are chosen by its authors. Therefore, the focus should be placed on the relative ratings between those barriers that have been included.

For BEVs, on considering a 5-point scale, purchase price received the highest mean rating in Berkeley et al. (2018) (4.3), Ciarapica et al. (2013) (4.3), Larson et al. (2014) (4.28, tied with reliability), Lebeau et al. (2013) (4.1), Hardman et al. (2016b) (3.4) for the group of high-end adopters, and Haustein and Jensen (2018) (3.7, tied with public infrastructure) for conventional car users. Limited range is the top-rated barrier in Hardman et al. (2016b) for the group of low-end BEV owners (4.4). Finally, safety is considered the most important barrier in She et al. (2017) (4.9). As in previous figures, the lack of public infrastructure is very highly rated in the papers in which it was included. It is also worth mentioning the importance given by consumers in various papers to the charging time of the BEVs: this barrier features among the top three highest-rated barriers in certain papers.

For FCEVs, Hardman et al. (2016a, 2016b) shows the results of a survey conducted on participants in an FCEV trial. When rating barriers of FCEVs were compared to conventional vehicles and BEVs, participants top-rated the higher purchase price (4.6 and 4.2 on a 5-point scale, respectively): this barrier is rated more than one point higher than the second-highest-rated barrier.

Kim et al. (2020) use AHP to identify the main adoption barriers in order to explain the slow market diffusion of BEVs in Korea. They asked experts and drivers with prior knowledge of BEVs to evaluate different barriers to market diffusion of BEVs, by means of pairwise comparisons, on a 9-point scale. They found that charging concerns (which included lack of charging infrastructures, a limited driving range, and long charging time) constituted the most important barrier. The burden of costs, which includes the initial car costs, was the second-most important barrier for drivers and the third for the expert group (the second-most important barrier for the group of experts being the existence of insufficient policies to promote the adoption of BEVs). Finally, Noel et al. (2020) interviewed experts from Denmark, Finland, Iceland, Norway, and Sweden to identify the main barriers that electric vehicles face and their interconnections. From these interviews, they obtained a list of 53 different categories of barriers, with range, price, public charging infrastructure, and consumer mental barrier or knowledge in the top 4 (mentioned by more than 40% of the experts). Connections between barriers were studied by analysing transcriptions of the interviews with NVIVO software.

2.2. Effects of the barriers in ZEV purchase decisions.

Papers described in this section aim to analyse the influence of different barriers in the consideration or choice of ZEVs.

Several authors have paid attention to the effects of the levels of the barriers on the willingness to purchase ZEVs by asking individuals about their willingness to consider the purchase of ZEVs for some particular levels of certain barriers or the levels required in order to consider their acquisition (Brey et al., 2017; Chachdi et al., 2017; Ciarapica et al., 2013; Egbue and Long, 2012; Larson et al.,

[1] 5-point Likert scale (1: no concern at all; 5: really serious concern).
[2] 1, the factor is a barrier; 2, otherwise.
[3] 5-point Likert scale (1: far worse; 5: far superior).
[4] 5-point Likert scale (1: far superior; 5: far worse).
[5] 5-point Likert scale (1: very dissatisfying; 5: very satisfying).
[6] 5-point scale (1: very low; 5: very high).
[7] 4-point scale (1: not important disadvantage; 4: crucial disadvantage).
[8] 5-point Likert scale (1: not impeditive; 5: strongly impeditive).

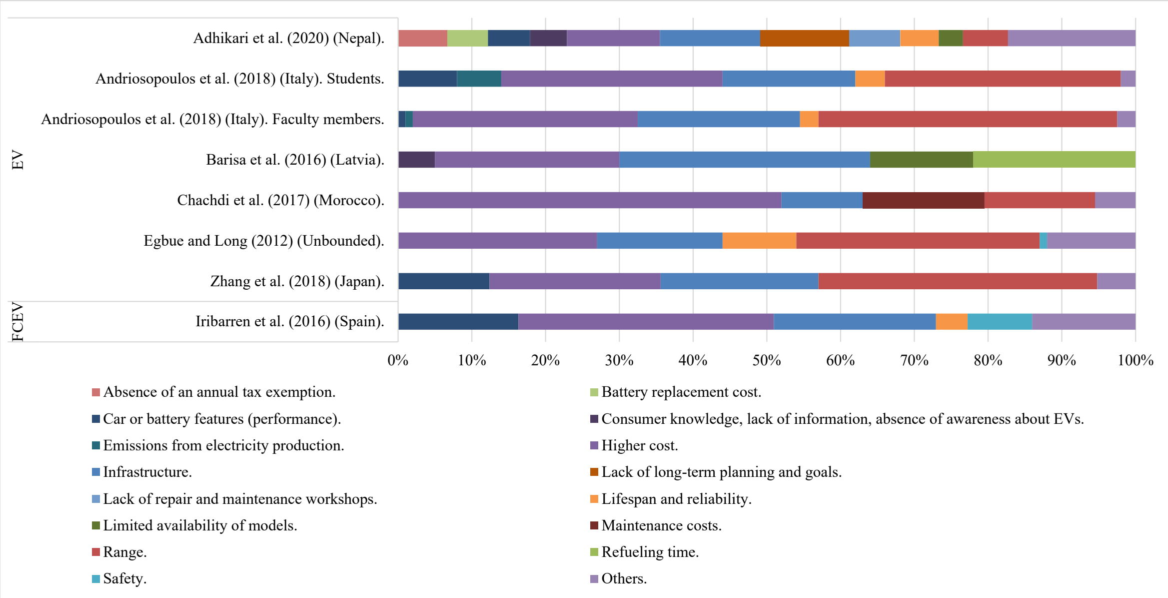

Fig. 2. Most-relevant barriers.

2014; Lebeau et al., 2013; Lipman et al., 2018; Martin et al., 2009).

Regarding the existence of public refuelling infrastructure, Martin et al. (2009) asked individuals about their maximum willingness to deviate from their normal route to refuel FCEVs (see Figs. 5a and 5b) and ascertained that 89% are willing to accept deviations of more than 5 min, but only 29% are willing to accept deviations of more than 15 min (see Fig. 5a). As an alternative question, Brey et al. (2017) used the percentage of existing stations that should offer hydrogen to refuel and the maximum distance to the closest station offering hydrogen. They found that acceptance rates higher than 50% could be achieved when availability of the fuel is at least 20% of that of the conventional stations (see Fig. 5b), or when the driving time to the closest hydrogen station is less than 10 min.

For the range (see Fig. 6), Chachdi et al. (2017) indicated that 62% of the sample would be satisfied with a range higher than 200 km for BEVs, while 38% would accept a range between 100 and 200 km. Egbue and Long (2012) found that 32% requested a minimum range of between 0 and 100 miles (160.93 km) to consider the purchase of a BEV, 23% a range between 100 and 200 miles (160.93 and 321.87 km), and 45% a range greater than 200 miles (321.87 km). The average minimum range desired was 215 miles (346 km). Lebeau et al. (2013) enquired as to the acceptable level of range for BEVs and found that 10.4%, 32.6%, 49.5%, and 71.1% of the sample were satisfied with less than 200 km, 300 km, 400 km, and 500 km, respectively.

In Martin et al. (2009), the percentages of acceptance were 4%, 22%, 23%, and 42% for ranges of FCEVs in the intervals 0–120 km, 120–240 km, 240–360 km, and 360–480 km, respectively. Lipman et al. (2018), asking about the range of 440 km reached by the Toyota Highlander "FCHV-adv", found that 26% of the sample considered that was "very limiting" or "slightly limiting", whereas the rest of the sample stated that it was adequate for their needs.

Fig. 6 summarises these results for the case of range. This figure shows that ranges of approximately 400 km are sufficient to attain acceptance rates higher than 50% in the population.

The effect of charging time has also been studied for BEVs following this approach (see Fig. 7). This barrier is not relevant in the case of FCEVs as they have similar performance to conventional vehicles in terms of refuelling time. The effect of this barrier in a BEV purchase decision will depend on the desired recharging behaviour of the driver. The refuelling paradigm for all BEV owners does not necessarily have to be the same as for those of conventional vehicles, since they can recharge their BEVs at home. Home or workplace charging is expected to be a crucial factor for these vehicles (Lebeau et al., 2013). Therefore, this barrier will be mainly relevant for those owners of BEVs that wish to charge their BEVs away from their home or their workplace. For slow charging, consumers are willing to accept longer charging times, probably because this charging type is associated with home charging and night charging (Lebeau et al., 2013): 70.4% is willing to accept up to 4 h to recharge. For fast charging, more closely linked to en-route charging, consumers demand much shorter charging times. According to Chachdi et al. (2017), 78% of the sample accept a charging time between 30 and 60 min, 14% up to 120 min, and only 8% are willing to accept periods longer than 120 min. In Egbue and Long (2012) and Lebeau et al. (2013) (for fast charging), charging-time requests are more severe: 86% and 34% of their samples want to charge their vehicles in no more than 15 min.

This approach has been extensively used to study the effect of purchase price. The results are summarised in Fig. 8. However, this figure must be interpreted with caution because willingness-to-pay responses are highly contingent on the willingness-to-pay scenario used in each study. Therefore, these results are not easily comparable.

Ciarapica et al. (2013) asked respondents how much extra they would be willing to spend on an electric vehicle (BEV, HEV or PHEV). According to this author, 25.3% of the sample would be willing to pay up to €2,000 extra for a BEV, 44.6% would pay between

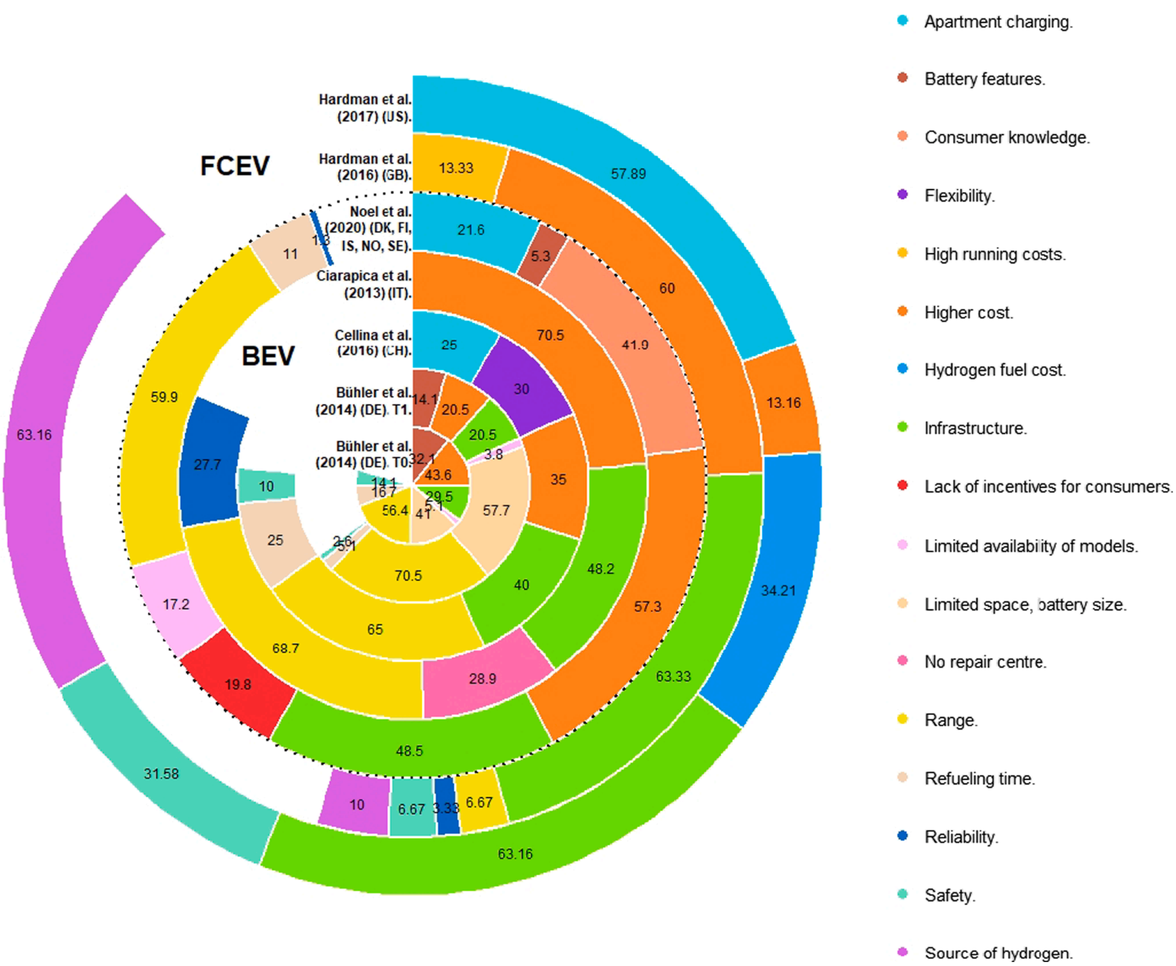

Fig. 3. Percentage of respondents citing each barrier.

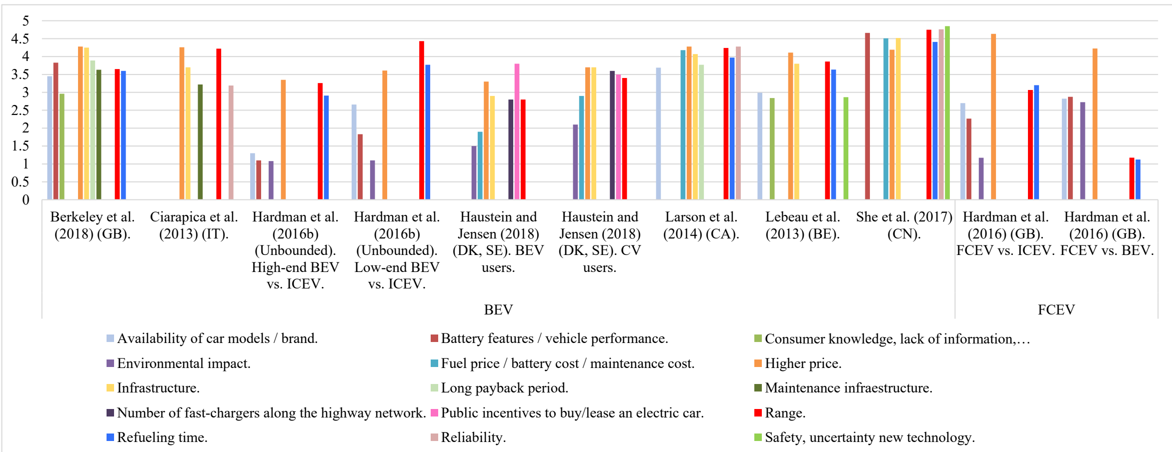

Fig. 4. Factors evaluated on a 5-point scale (see footnotes 1–8).

€2,000 and €4,000, 22.3% between €4,000 and €6,000, and 7.8% more than €6,000.

Larson et al. (2014) asked "How much more in initial purchase price would you be willing to pay for an electric vehicle (BEV or PHEV) compared to a "conventional'' car?". They formulated this question without and with additional information on fuel and

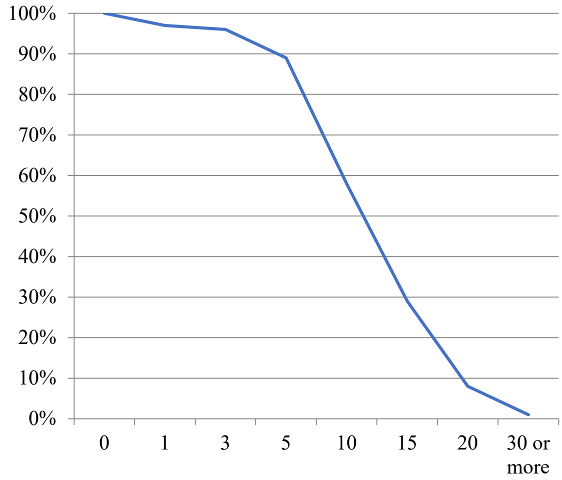

Fig. 5a. Cumulative percentage of tolerance of extra travel time to refuelling station (min). (Martin et al., 2009).

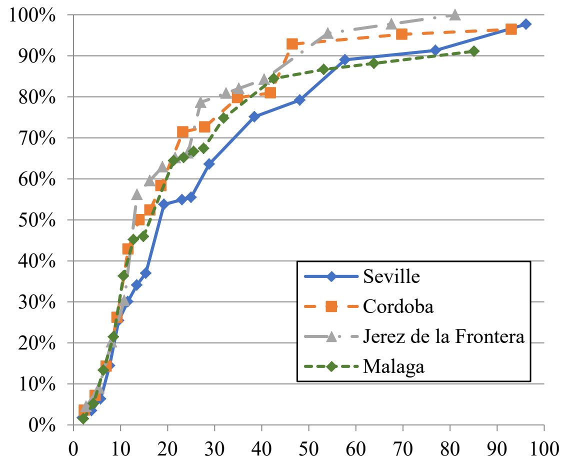

Fig. 5b. Acceptance percentage based on percentage of alternative fuel stations against existing conventional stations (%) (Brey et al., 2017).

lifetime cost savings to three different groups: experienced users, students, and the general population. In this exercise, without additional information on cost savings, they found that the percentage of respondents in the general population unwilling to pay more for an electric vehicle than for its traditional fuel counterpart was approximately 51% (of which 12.3% would not buy a BEV at any price), whereas around 26% would be willing to pay $5,000 extra for it. Lebeau et al. (2013) formulated a similar willingness-to-pay question for BEVs and obtained 73% and 12%, respectively.

Martin et al. (2009) asked participants of a “ride and drive” clinic held in California with FCEVs how much more they would be willing to pay, compared to their current gasoline vehicle, for a vehicle operating comparably to the vehicle they currently owned but with no air-quality impacts (including emission from fuel production). The results showed that 7% percent of the sample was unwilling to pay more for such a vehicle, but 44% would pay $5,000.

Within this context, the most commonly used approach by far to identify the main barriers and analyse their effect in the choice stage of the consumer’s car-purchase decision is the use of stated-preference discrete-choice modelling (Achtnicht et al., 2012; Pernollet et al., 2019). Individuals are faced with various car options characterised by certain attributes (including barriers and/or policy measures) with different levels, and they are then asked to express their preferences for the different car options through choices. Discrete-choice models are subsequently utilised to analyse the implicit trade-offs between attributes that consumers made when revealing their preferences. By assuming that individuals have compensatory preferences over the set of attributes in the levels considered, this approach enables the marginal relative importance of the different attributes for consumers in their car-purchase decision to be obtained (Byun et al., 2018; Choi et al., 2018; Cirillo et al., 2017; Ferguson et al., 2018; Giansoldati et al., 2018; Hackbarth and Madlener, 2016; Huang and Qian, 2018; Ito et al., 2019; Kormos et al., 2019; Ščasný et al., 2018). If these trade-offs are analysed with respect to a monetary attribute (usually purchase price), then it is possible to obtain estimates of the mean of consumers’ willingness to pay for marginal changes in the levels of the barriers (Byun et al., 2018; Choi et al., 2018; Cirillo et al., 2017; Ferguson

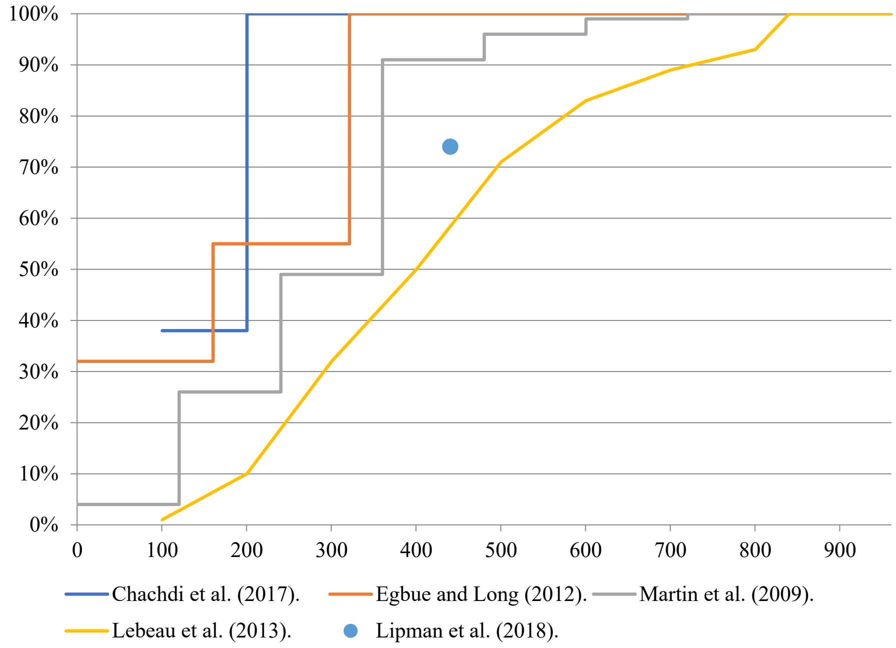

Fig. 6. Cumulative percentage of minimum required range (km).

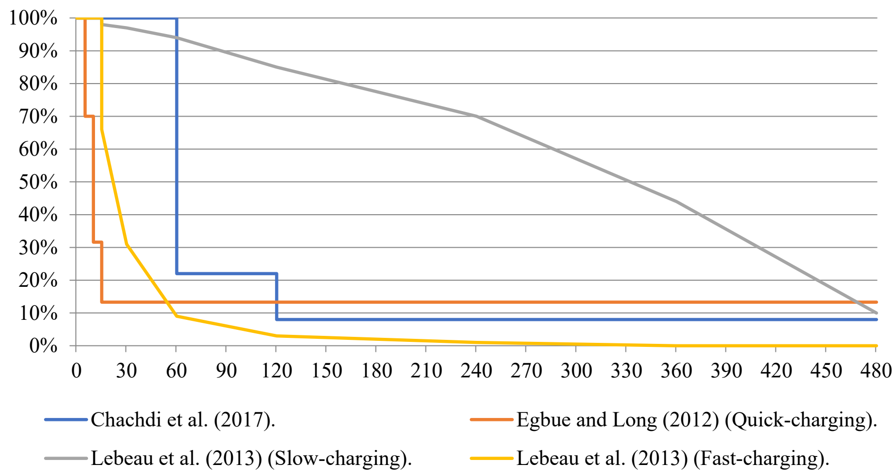

Fig. 7. Cumulative percentage of maximum recharging time tolerated (min).

et al., 2018; Hackbarth and Madlener, 2016; Huang and Qian, 2018; Kormos et al., 2019; Ščasný et al., 2018).

2.3. Consumers' heterogeneity.

Naturally, not all consumers perceive the different barriers similarly and there are individuals who are more flexible regarding the levels of the different barriers and are therefore more willing to consider the purchase of ZEVs. These differences may be due to individual attitudes towards the environment or new technologies (Axsen et al., 2015; Egbue and Long, 2012; Ferguson et al., 2018; Kormos et al., 2019; Priessner et al., 2018), to vehicle uses and types (Hardman et al., 2016b; Haustein and Jensen, 2018; Nazari et al., 2019; Ščasný et al., 2018), and to socio-demographic characteristics (Andriosopoulos et al., 2018; Hackbarth and Madlener, 2013; Larson et al., 2014; Priessner et al., 2018), and they would lead to consumers having different timings for their purchase of ZEVs.

This heterogeneity can be modelled within the stated-preference discrete-choice approach by interacting the attributes representing the barriers with socio-demographic variables (Hackbarth and Madlener, 2013; Sheldon et al., 2017), either by assuming that the preferences vary in the population according to a particular distribution (Ščasný et al., 2018; Sheldon et al., 2017), or by assuming the existence in the population of different classes (subpopulations) where preferences vary across, but not within, said classes

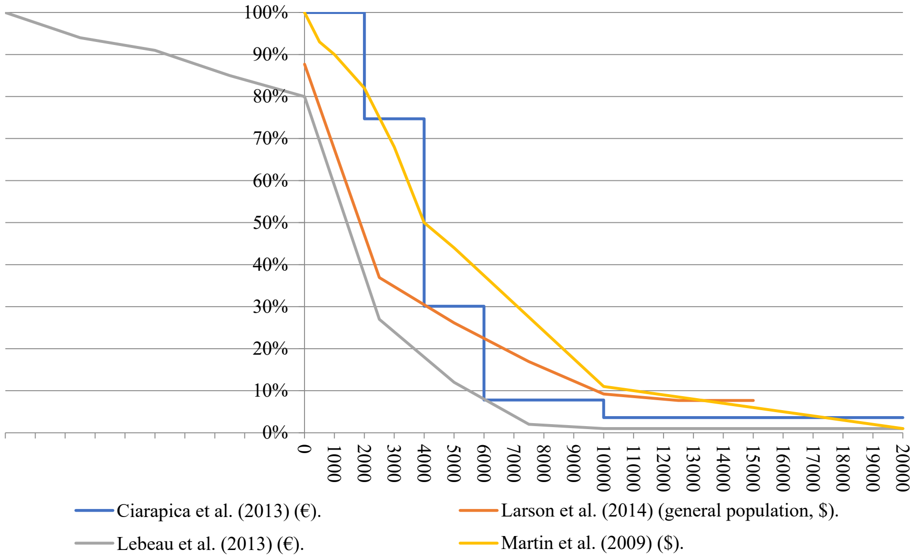

Fig. 8. Cumulative percentage of acceptance of extra purchase price.

(Ferguson et al., 2018; Hackbarth and Madlener, 2016; Hidrue et al., 2011; Kormos et al., 2019; Sheldon et al., 2017).

The aforementioned formulation based on latent classes has been used in the past few years to segment consumers in terms of their preferences for the different car technologies, as well as to characterise these segments. Individuals with similar preferences for the different attributes are grouped together, thereby estimating different preference parameters for each group. As class membership is a latent variable, individuals are assigned to a group with a certain probability, and this probability can be related to certain covariates, which enables the characterisation of each group.

Table 1 shows different consumers' perceptions of the barriers obtained in the literature for different classes (subpopulations) by means of latent class discrete-choice models. For the sake of simplicity, this table only focuses on the four most relevant barriers for BEVs and FCEVs obtained from the previous sections. Hackbarth and Madlener (2016) and Kormos et al. (2019) are shown in both categories since they use specific variables for the two types of technology.

Table 1 reveals the existence of heterogeneity in the population preferences for these four attributes, since there are attributes whose perception differs across classes (and can even be negative for certain classes and positive for others). The only attribute that is consistently perceived is that of purchase price, which is significantly and negatively perceived in all the classes, while significant charging or refuelling infrastructure and range are predominantly positive, and charging time is mostly negative. Up to nine different combinations of preferences (according to the direction of the preferences) have been obtained in the papers that consider said four barriers, with only two combinations repeated in different papers. Several papers in Table 1 obtained the same combinations several times because they differ in the intensity (not the direction) of the preferences for the barriers.

Given the early stage of the introduction of these vehicles in the transport sector in Spain, this paper focuses on the minimum levels of the barriers that Spanish drivers are willing to accept in order to consider the purchase of ZEVs, and accounts for heterogeneity in the stated cutoff levels through the use of latent class models. To the best of our knowledge, this is the first paper modelling these types of responses with this particular approach in this field. The questionnaire is described in Section 3.

3. Survey

This paper is based on a phone survey of drivers (n = 1474) conducted in Spain towards the end of 2017 to study their willingness to purchase ZEVs. This survey method was chosen because it was cheaper than person-to-person interviews and it enabled easy control of the quality of the data-collection process (Bickman and Rog, 2009). Moreover, the questionnaire was short and addressed a familiar commodity, and thus did not require the use of visual aids or photographs.

The sample was stratified by gender and age, following the characterisation of Spanish drivers obtained from the Directorate General for Traffic (2016). The sample was drawn from the 5 most populated cities in Spain (Madrid, Barcelona, Valencia, Seville, and Zaragoza), which accounted for 14.9% of the total population in Spain in 2017 (National Statistics Institute, 2020), since metropolitan areas play a key role in the initial stages of the transition to ZEVs due to the fact that they have the means and resources needed to implement the required actions (International Council on Clean Transportation, 2018). The sample was split up among the cities by ensuring a minimum sample size in each city and, once this criterion was satisfied, proportionally to the population size of each city. Table 2 describes the sample.

The questionnaire was short, comprising 23 questions, and focused on the car usually driven by the respondent and on their next purchase decision for its replacement. The questionnaire included questions on the characteristics of their usual vehicle and on journeys made with said vehicle, the respondent's degree of awareness (measured on a 5-point response scale) of the problems deriving

Table 1
Consumers' perceptions of the barriers by means of latent class models.

Latent Class	Barrier[a]				EV							FCEV		Total
	I	R	RT	PP	Axsen et al. (2015)	Axsen et al. (2016)	Ferguson et al. (2018)	Hackbarth and Madlener (2016)	Hidrue et al. (2011)	Kormos et al. (2019)	Sheldon et al. (2017)	Hackbarth and Madlener (2016)	Kormos et al. (2019)	
1		+		–							3			3
2		+	+	–					2					2
3	+	NS		–	2	2								4
4	NS	NS		–	2	2							4	8
5	NS	+		–	1	1								2
6	+	+		–									1	1
7	NS	+	–	–			1					1		2
8	NS	NS	–	–			1							1
9	+	+	–	–			2	3						5
10	+	+	NS	–				1				4		5
11	NS	+	NS	–				1						1
12	+	NS	NS	–				1				1		2
13	NS	NS	NS	–						3				3
14	NS	–	NS	–						1				1
15	NS	NS	+	–						1				1
Total					5	5	4	6	2	5	3	6	5	41

[a] (I) Infrastructure; (R) Range; (RT) Refuelling time; (PP) Purchase price.

from the use of conventional fuel vehicles (environmental pollution, energy dependency, noise), the respondent's level of knowledge of ZEVs, their willingness to purchase this type of vehicle and pay a premium for said acquisition, and their perception of other market barriers. It also included several socio-economic questions.

Several pre-tests were conducted to develop and validate the final questionnaire (two rounds of focus groups, cognitive interviews, and a small pilot survey). These focused on the understandability (when explained orally) and credibility of the scenario, the incentives for the respondent to provide reliable responses, and the determination of the proper length of the survey.

This paper focuses on the responses provided by drivers in relation to the main barriers faced by ZEVs in achieving significant market penetration: vehicle price, fuel availability, range, and recharging/refuelling time. Obviously, these barriers do not have to influence, in the same way, the decisions to buy either a BEV or a FCEV. BEVs allow home charging and therefore drivers of these vehicles could have a different refuelling paradigm. However, Section 2 shows that potential drivers of these vehicles still demand certain levels of charging time and charging infrastructure. Moreover, only 44.9% of Spanish cars have private parking; a similar percentage is attained in main cities such as Madrid (40.8%) and Barcelona (43.8%) (City Council of Barcelona, 2021; City Council of Madrid, 2021; Directorate General for Traffic, 2019; Ministry of Transport, Mobility and Urban Agenda, 2021; National Statistics Institute, 2011). Hence, this paper considers the general case of a ZEV.

Survey responses were expected to be meaningful because the hypothetical scenario used in the survey was consequential to the respondents (Bishop and Boyle, 2019; Carson and Groves, 2007; Loomis, 2011). For this purpose, first those individuals who were

Table 2
Characteristics of the sample population.

Variable	Sample (%)					
	Madrid	Barcelona	Valencia	Seville	Zaragoza	Total
Sample Size	395	357	273	244	205	1,474
Gender						
Female	43	41.2	41	41.8	37.1	41.2
Male	57	58.8	59	58.2	62.9	58.8
Age						
18–24	0	2.5	2.2	0.4	0.5	1.2
25–34	11.4	7.8	14.7	20.9	14.6	13.2
35–44	36.2	36.1	31.9	26.2	30.7	33
45–54	26.8	27.7	26	25.8	22.9	26.2
55–64	6.1	7.6	17.2	17.2	22.9	12.7
65+	19.5	18.2	8.1	9.4	8.3	13.8
Household size						
1	7.6	7.8	9.2	9.4	8.3	8.3
2	29.1	32.5	27.8	26.6	24.9	28.7
3	26.3	24.9	27.8	27.5	25.9	26.4
4	28.4	25.8	26.7	25.4	32.7	27.5
5+	8.6	9	8.4	11.1	8.3	9
Number of household vehicles						
1	51.1	72.5	69.6	55.3	57.1	61.3
2	40.8	22.1	26	35.7	38	32.3
3+	8.1	5.3	4.4	9	4.9	6.4
Highest level of education completed						
No primary education or only primary education	1	2	3.3	2	0.5	1.8
1st level of Secondary Education	22	22.1	27.5	30.7	29.3	35.5
2nd level of Secondary Education	33.2	34.2	34.1	28.7	33.2	32.8
Higher Education	43.8	41.7	35.2	38.5	37.1	39.9
Household income per month						
Less than €2,000	24.6	24.1	36.6	36.9	29.3	29.4
€2,000-€3,999	49.1	46.5	46.9	41	50.7	46.9
€4,000-€5,999	10.9	13.4	6.6	9.8	5.9	9.8
Over €6,000	5.1	5.6	2.9	5.3	3.9	4.7
Not given	10.4	10.4	7	7	10.2	9.2
Work status						
Hired hand	58	60.5	61.5	52.5	66.8	59.6
Self-employed	13.9	15.1	7.7	14.8	11.7	12.9
Student	0	1.4	1.5	2	1	1.1
Unemployed	7.1	3.6	12.8	14.3	7.8	8.6
Housekeeper	2.3	1.1	2.9	2.5	0.5	1.9
Retired	18.7	18.2	13.6	13.9	12.2	15.9

within the potential market for ZEVs were identified, that is, those individuals who were willing to consider ZEVs in their next purchase option to replace their usual vehicle. To this end, the following question was included in the survey:

> Q12. Would you be willing to consider zero-emission vehicles if they had features (speed, range, etc.), and prices similar to conventional gasoline or diesel vehicles, as an option on your next purchase, **when deciding to replace your current vehicle**?
> ☐ Yes (go to Q13) ☐ No (go to Q12B) ☐ Don't know/No reply (go to Q13)

The individuals who answered negatively to this question were eliminated from the analysis, since it was considered that they were individuals who remained outside the potential ZEV market, since, even within a scenario in which the ZEV was presented as a dominant alternative compared to conventional vehicles (same characteristics in addition to their environmental and energy advantages), these individuals were unwilling to consider such a vehicle.

In relation to the purchase price barrier, in order to isolate the existence of premiums for ZEVs, the willingness to pay was raised as an additional cost compared to a conventional vehicle with similar characteristics except for its polluting and noise emissions and for its effects on energy dependence:

> Q13. Suppose you want to replace your current vehicle (*state trademark and model of the car declared in Q3*). You have the option of buying a zero-emission vehicle (that is, without polluting or noise emissions, and whose fuel can be produced in our country). The rest of the characteristics of this vehicle would be the same as those of your current vehicle (speed, time needed to refuel, range, cost of fuel per 100 km, etc.), **BUT** its purchase price would be higher.
> In this case, would you be willing to pay more to purchase such zero-emission vehicle, and if so, **how much would you overpay**?
> ☐ Yes. Q13A. **How much** would you overpay? _ _ _ _ _ _ _ _ _ _ (€) (go to Q14)
> ☐ No (go to Q13B)
> ☐ Don't know/No reply (go to Q13B)

These reported amounts can be interpreted as the maximum premium that drivers are willing to pay for their perceived benefits of driving a ZEV. Deviations from this scenario (by worsening characteristics and/or performance levels of ZEVs) would lead to lower willingness to pay.

Respondents were subsequently told that, despite their advantages, ZEVs do not have the same fuel availability and that they sometimes fail to offer the same performance as gasoline or diesel cars. The respondents were then immediately asked the questions corresponding to fuel availability, range, and refuelling time. Fuel availability was measured as the driving distance to the closest alternative refuelling station instead of as a percentage of alternative refuelling stations over existing conventional stations. The survey pre-tests showed that people found the former measure easier to understand than the latter because this is the kind of information they consider in their refuelling decisions. The pre-tests also suggested describing both fuel availability and refuelling time in terms of time intervals given their small range. These questions were as follows:

> Q14. To consider purchasing a zero-emission vehicle as a **replacement for your current vehicle**, you would want **as a minimum** a network of alternative refuelling stations that guarantees a station within **driving distance** from anywhere in your city of ...

Less than 5 min	Between 5 and 15 min	Between 15 and 30 min	More than 30 min

These measurements of the barriers and attitudes aim to capture their most relevant dimension but they fail to capture their whole complexity. They are based on drivers' perceptions regarding the main barriers that hamper the introduction of ZEVs into the market, because these perceptions guide their decisions. Therefore, they have been chosen after a careful review of the literature based on

Q15. What is the minimum vehicle's range, that is, the **minimum number of kilometres** it would be possible to drive after filling the tank that you would be willing to accept to consider buying a zero-emission vehicle **as a substitute for your current vehicle**?

Q16. What is the **extra** refuelling time (**additional** time in minutes required to fully refuel the vehicle compared to a conventional vehicle) that you would be willing to accept to consider purchasing a zero-emission vehicle **as a substitute for your current vehicle**?

None	Less than 5 min	Between 5 and 15 min	Between 15 and 30 min	More than 30 min

consumers' opinions. This explains why, for example, this paper considers purchase price and not lifetime costs. From our review, we have ascertained that purchase price (and not other costs) is one of the most important barriers, even when cost disaggregation is considered (Adhikari et al., 2020; Chachdi et al., 2017; Hardman et al., 2016a, 2016b; Haustein and Jensen, 2018; Larson et al., 2014). Moreover, several studies on consumers' perceptions of ZEV prices have shown that consumers focus on purchase price rather than on the calculation of the total cost of ownership (Larson et al., 2014; Noel et al., 2020; Turrentine and Kurani, 2007).

4. Methods

This paper aims to study drivers' preferences regarding the levels of range, purchase price, fuel availability, and refuelling time they are willing to accept to consider ZEVs in their next purchase decision. Population heterogeneity in the sample is incorporated into the model by considering the existence in the sample of groups with different preferences for the barriers. These groups are not observable, but since they present differences in perceptions, they can be obtained from individuals' responses to the levels of the barriers they are willing to accept. Therefore, these responses will be taken herein as observed indicators of the latent classes. In this paper, this grouping was made by using a latent class cluster model (Vermunt and Magidson, 2016). Unlike other clustering approaches (such as K-means method or the two-step clustering method), this is a model-based cluster approach that enables observations to be probabilistically grouped with respect to a set of qualitative (nominal and ordinal) and/or quantitative (continuous and discrete) indicators.

This model assumes that there is a nominal latent variable x $(x = 1, 2, ..., K)$ that represents the latent classes, with K being the number of latent classes assumed in the model. This variable is assumed to explain the observed values in T response variables y_t (indicators), where $t = 1, 2, ..., T$ denotes a particular indicator. Given an individual i $(i = 1, ..., n)$, the density function of their values on the set of indicators $y_i = (y_{i1}, ..., y_{iT})$ is written as:

$$f(y_i) = \sum_{x=1}^{K} \pi_x \prod_{t=1}^{T} f(y_{it}|x)$$

where π_x is the prior probability of belonging to class x , and $f(y_{it}|x)$ is the density function of each indicator conditioned on the membership class. This formulation assumes that indicators y_t are conditionally independent of each other within the latent classes, that is, the latent variable explains the relationships between indicators (Cheng, 2012).

The formulations of the density functions depend on the type of indicator. Here we focus on the types used in the survey: continuous (WTP and range) and ordinal (fuel availability and refuelling time) indicators.

Continuous indicators are usually assumed to be normally distributed variables within latent classes with mean μ_{tx} and standard deviation σ_{tx}. In order to make this model more parsimonious, it is assumed that these means depend on only the membership class, that is, $\mu_{tx} = \beta_t + \sum_{j=1}^{K} \sum_{x'=1}^{K} \beta_{tx'} Z_{jx'}(x)$, where β_t is the model intercept for indicator t, β_{tx} is the effect of the latent class x on μ_{tx} for indicator t, and $Z_{jx'}(x)$ is a binary variable that takes a value of 1 if $x' = j = x$. Therefore, in these cases, the density function can be written as:

$$f(y_{it}|x) = \frac{e^{-\frac{1}{2}\left(\frac{y_{it} - \mu_{tx}}{\sigma_{tx}}\right)^2}}{\sqrt{2\pi\sigma_{tx}^2}}$$

Ordinal indicators are modelled in this paper by means of the constant-slope adjacent-category logit models. These models directly consider the ordering of the categories by forming logits of all pairs of adjacent categories. Again, in order to keep the models parsimonious, it is assumed that, for each ordinal indicator, these logits depend on only the membership class. For each category m (with $m = 1, 2, \ldots, M_t$), these logits can be expressed as:

$$log\left(\frac{P(y_{it}=m+1|x)}{P(y_{it}=m|x)}\right)=\beta_{tm}+\sum_{j=1}^{K}\sum_{x`=1}^{K}\beta_{tx`}Z_{jx`}(x).$$

As a consequence of formulation, the probability of choosing a category m can be written as:

$$P(y_{it}=m|x)=\frac{e^{\beta_{tm}+m\sum_{j=1}^{K}\sum_{x`=1}^{K}\beta_{tx`}Z_{jx`}(x)}}{\sum_{m`=1}^{M_t}e^{\beta_{tm`}+m`\sum_{j=1}^{K}\sum_{x`=1}^{K}\beta_{tx`}Z_{jx`}(x)}},$$

This formulation assumes that the effect of the class membership x on the log-odds is independent of m.

As a result of this formulation:

$$\frac{P(y_{it}=m+1|x)}{P(y_{it}=m|x)}=e^{\beta_{tm}}e^{\sum_{j=1}^{K}\sum_{x`=1}^{K}\beta_{tx`}Z_{jx`}(x)}$$

that is, the effect of the class membership x is a proportionate change in the odds of being in category m as opposed to category $m+1$ for all the response categories m. If membership to a cluster x doubles the odds of being in category 1 as opposed to category 2, it also doubles the odds of being in category 2 as opposed to 3, and the same for the odds of any pair of adjacent categories.

This proportional odds assumption can be relaxed by assuming that the effect of the class membership on the log-odds differs depending on m:

$$log\left(\frac{P(y_{it}=m+1|x)}{P(y_{it}=m|x)}\right)=\beta_{tm}+\sum_{j=1}^{K}\sum_{x`=1}^{K}\beta_{tmx`}Z_{jx`}(x).$$

This change in the model leads to the multinomial logit model (Fullerton, 2009).

The probability π_x of an individual belonging to class x is modelled in this paper by a multinomial logit model. In order to reduce the number of parameters to be estimated, no covariates are introduced in this multinomial model to explain class membership. Instead, the ability of different variables to explain class membership is analysed in this paper by applying a variety of non-parametric tests to the latent class assignments based on the maximum-probability assignment rule. Therefore,

$$\pi_x=\frac{e^{\gamma_x}}{\sum_{x`=1}^{K}e^{\gamma_{x`}}}$$

For a sample of n individuals ($i=1,...,n$), the log-likelihood function has the form:

$$logL=\sum_{i=1}^{n}log\left(\sum_{x=1}^{K}\pi_x\prod_{t=1}^{T}f(y_{it}|x)\right).$$

This expression is maximised using the expectation–maximisation algorithm (Leisch, 2004; Skrondal and Rabe-Hesketh, 2004). Once the iterations verify certain convergence conditions, the Newton-Raphson algorithm comes into play to find the solution to the problem (Vermunt and Magidson, 2016).

5. Results

5.1. The individual effect of the barriers

Certain individuals (76 drivers, representing 5.2% of the sample) were reluctant to consider ZEVs in their next purchase decision, although these cars were presented as a dominant alternative (similar to conventional automobiles but with environmental and energy benefits). The main reason given was a lack of confidence in this technology. These individuals were removed from the analysis because they were unwilling to consider ZEVs in their next purchase decision to replace their usual car. This percentage does not differ significantly from the percentage of 5.5% obtained from a similar question in a previous study for Spain (Brey et al., 2017).

This section individually analyses the responses provided by the remaining sample to the various questions regarding the barriers. This information is useful in the very early stages of the transition in order to determine the minimum requirements that consumers demand to consider the purchase of ZEVs, as well as the percentages of acceptance for different levels of each barrier.

Fig. 9a presents the stated maximum driving times to a service station that drivers in the sample are willing to accept to consider the purchase of a ZEV. As can be observed, 77.83% of the sample would be willing to travel up to 15 min by car to reach a service station that could supply them with alternative fuel. The percentage of the sample willing to accept a greater distance (up to 30 min), drops to a mere 29.18%.

Fig. 9b shows what percentage of acceptance is presented by a given range for a ZEV. As can be observed, a range of 250 km is accepted by only 28.47% of the sample. To achieve an acceptance of at least 50%, the car must have a minimum range of 400 km, which satisfies 61.59% of the sample. A range of 600 km satisfies the needs of more than 90% of the sample (90.92%).

Fig. 9c represents the predisposition of the interviewees to tolerate the need for extra refuelling time with a ZEV, compared to a conventional vehicle. One can see that 97.85% would accept that they need up to 5 min more to refuel a ZEV (over what is required for a conventional vehicle). However, this percentage falls rapidly when the time gap increases: only 23.39% of the sample would be

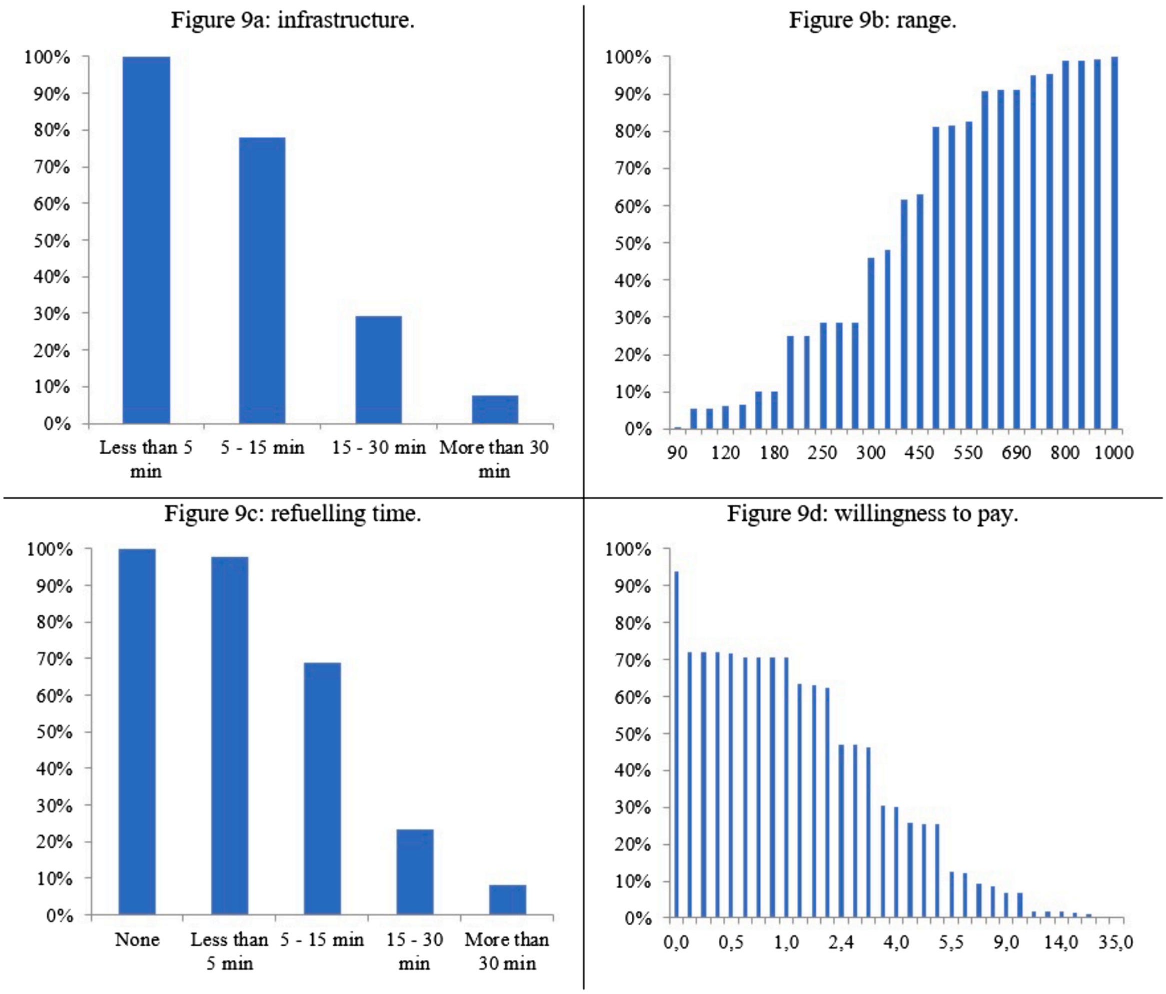

Fig. 9. Cumulative percentage of acceptance for the barriers.

willing to wait between an extra 15 to 30 min, and this percentage drops to 8.01% for more than an extra 30 min.

Fig. 9d shows that 21.64% of the sample is unwilling to pay premiums for ZEVs, and 46.2% would accept having to pay a surcharge of €3000 over the cost of a conventional vehicle to buy a ZEV; however, this willingness to buy ZEVs falls rapidly to only 12.28% for a premium of €6000, and to a mere 6.78% for a premium of €9000. Purchase price is revealed as a major obstacle to the penetration of clean cars into the market.

5.2. Joint effect of the barriers

The previous figures show the minimum levels of the barriers that consumers demand to consider the purchase of ZEVs. However,

Table 3
Summary of model fit.

	Goodness of Fit				Classification Statistics			
Number of clusters	**LL**	**BIC(LL)**	**AIC(LL)**	**CAIC(LL)**	**Reduction of errors (Lambda)**	**Entropy R-squared**	**Standard R-squared**	**Npar**
2	−15993.6	32117.4	32023.22	32135.4	0.5984	0.5448	0.6004	18
3	−14353.6	28880.73	28755.17	28904.73	0.8764	0.8353	0.8526	24
4	−14308.1	28840.42	28678.22	28871.42	0.7525	0.734	0.712	31
5	−13339.5	26946.62	26753.04	26983.62	0.8496	0.8419	0.8161	37
6	−12910.9	26132.71	25907.73	26175.71	0.8765	0.8724	0.8417	43
7	−12855.9	26073.31	25811.7	26123.31	0.8876	0.8946	0.8633	50
8	−12111.3	24627.55	24334.55	24683.55	0.9492	0.9517	0.9383	56

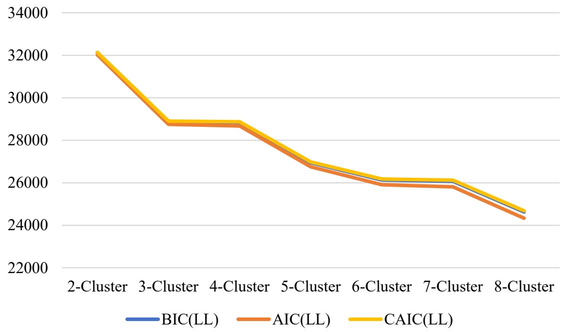

Fig. 10. Model fit graph.

these figures could hide groups of individuals with other requests. The elicitation of these groups is relevant because it would provide information on the penetration rates that could be reached with different levels of the barriers. This information, together with the monetary and technological difficulties in attaining those levels, would be very useful in planning the roll-out of the market transition to the use of ZEVs in Spain.

For this multivariate analysis, redundancy between the chosen indicators was tested by means of Pearson's and Spearman's correlation tests. Half of these correlations were not significant, and when they were significant, they reached only low values, which implies that these indicators capture different information and are therefore suitable for this analysis.

5.2.1. *Choosing the number of groups*

The number of underlying groups (or clusters) is identified by running the latent class cluster model with continuous and ordinal indicators for different values of K and comparing and interpreting their output in terms of different criteria. This paper considers goodness of fit, parsimony, entropy, meaningfulness and interpretability. These models were run in Latent Gold 4.5.

Table 3 shows the values obtained for the various measures of fit and entropy from $K = 2$ to $K = 8$. Higher values of K were not considered, since $K = 7$ and $K = 8$ provided clusters with low meaningfulness (group sizes of approximately 1.74% and 1.95%, respectively). Regarding goodness of fit, higher values of the log-likelihood function indicates a better fit, whereas the lower the value of BIC, AIC, or CAIC, which consider parsimony, the better the model fit. Table 3 shows that the model fit improved when the number of groups increased, with it being possible to identify two "elbows" or ranges with comparatively smaller improvements: 3–4 groups and 6–7 groups (see Fig. 10).

Higher values of the classification statistics indicate a higher precision of classification (Tein et al., 2013; Vermunt and Magidson, 2005). The reduction of errors, entropy R-squared, and standard R-squared reached their lowest values for the cases with 2 and 4 groups, remained higher than 0.8 for all the other cases, and increased with K for $K > 4$ (see Table 3).

As a result, these criteria suggest a range of 5–6 groups. These two groupings were compared by using the Adjusted Rand Index (Everitt et al., 2011; Rand, 1971), which measures the level of agreement between two groupings of the same individuals with not necessarily the same number of groups. When comparing partitions with 5 and 6 groups, the value of this index is 0.83, which indicates good agreement (>0.8) between the two groupings (Steinley, 2004). The 6-class model separates out relatively minor gradations of preferences. Considering this agreement, and the simplicity and interpretability of the 5-class model as compared with that of the 6-class model, the 5-class solution is analysed here.

At this point, correlations between indicators were also evaluated for each class (local independence assumption) (Fop et al., 2017; Lee et al., 2020; Vermunt and Magidson, 2002). Hardly any of these correlations were significant, and when they were significant, they presented only low values.

5.2.2. *Analysing the clusters*

The proportionality odds assumption for the ordinal indicators is tested by also running the 5-class models treating ordinal indicators as nominal indicators, and comparing the two outputs. The p-value corresponding to the likelihood ratio test is 0.43, which supports the proportionality assumption. A similar conclusion is obtained when comparing both partitions by employing the Rand Index. The value of this index is 0.95, which is very close to 1, and indicates a very high agreement.

Table 4 shows the mean values of the indicators for each cluster in the 5-class model, and Table 5 reports the significance tests of these values while taking Cluster 1 as a reference. Cluster 1 is the biggest group, representing approximately 32% of the sample. This is the most demanding group as regards fuel availability, range, and refuelling time, and its mean willingness to pay is the second smallest amount (around €2,300). Cluster 2 is the second-biggest group (about 23% of the sample). These individuals have requirements similar to those in Cluster 1 in terms of infrastructure and refuelling time, but they demand a significantly lower range, and they are unwilling to pay a premium for ZEVs. Cluster 4 (15% of the sample) is very similar to Cluster 1, except this group is willing to accept a significantly lower range. Clusters 3 and 5 (approximately 16% and 14% of the sample, respectively) are entirely different to Cluster 1. They are less demanding in terms of refuelling infrastructure and refuelling time (especially Cluster 3 in refuelling time), and both have significantly higher willingness to pay a premium for ZEVs (around €8,600 and €5,000, respectively), but lower range requirements. There is a significant difference between Clusters 3 and 5 in terms of all the indicators except for refuelling

Table 4
Probabilities or means associated with each indicator.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster size	0.3181	0.2305	0.1605	0.1514	0.1394
N	481	319	187	203	193
Infrastructure (4-point scale)					
Less than 5 min.	0.254	0.2316	0.1686	0.243	0.1718
Between 5 and 15 min.	0.4963	0.4928	0.4666	0.4949	0.4686
Between 15 and 30 min.	0.1914	0.2069	0.2547	0.1989	0.2522
More than 30 min.	0.0584	0.0687	0.1101	0.0632	0.1074
Mean	2.0542	2.1128	2.3062	2.0823	2.2954
Range (km)					
Mean	460.2885	396.028	412.3603	215.7619	380.2969
Refuelling Time (5-point scale)					
None	0.0258	0.0241	0.0109	0.0255	0.0166
Less than 5 min.	0.3179	0.3079	0.2041	0.3166	0.256
Between 5 and 15 min.	0.4555	0.457	0.4427	0.4558	0.4571
Between 15 and 30 min.	0.1388	0.1442	0.2041	0.1394	0.1735
More than 30 min.	0.062	0.0668	0.1381	0.0626	0.0967
Mean	2.8935	2.9216	3.2544	2.8969	3.0777
WTP (thousand euros)					
Mean	2.2855	0	8.6189	2.3723	5

infrastructure.

These groups can be characterised in terms of different variables capturing socio-economic and mobility characteristics of drivers, drivers' attitudes, and their knowledge (see Tables 6 and 7). Differences across these groups are tested by applying the Kruskal-Wallis test to continuous indicators and the chi-square test of homogeneity to ordinal indicators. When the null hypothesis of equality is rejected, pairwise tests with Bonferroni corrections are employed to explain the differences. Table 8 contains these results.

Compared to the other groups, individuals in Cluster 1 are younger, with a lower level of income, and are at an intermediate level in terms of knowledge of ZEVs. However, the individuals in Cluster 2 are more likely to be individuals with a lower awareness of the implications of the use of fossil fuels in terms of energy dependence and environmental pollution and a lower knowledge of ZEVs. Individuals belonging to the cluster with the highest willingness to pay (Cluster 3) are more likely to be men characterised by a higher knowledge of ZEVs, who aim to replace a high-end car, and enjoy a higher level of income. Individuals in Cluster 4 are more likely to be women, using their car for trips shorter than 200 km and with a low knowledge of ZEVs. Finally, individuals in Cluster 5 also have a high knowledge of ZEVs but they seem to have higher awareness than individuals in Cluster 3 of the negative consequences of the use of fossil fuels in transportation in terms of environmental pollution and economic dependence (Cluster 5 has the highest mean ratings among all the groups for environmental pollution and economic dependence with 4.25 and 4.19, respectively).

6. Discussion

This paper clearly shows the existence in the population of groups with different perceptions regarding the main barriers hampering the introduction of ZEVs. These groups also differ in terms of certain socio-economic and mobility characteristics, attitudes, and knowledge of ZEVs.

Fig. 11 plots the average requirements of each group with respect to each of the four barriers. Movements away from the origin imply less exacting demands. Therefore, Group 1 (the largest group containing 34.8% of the final sample) is more demanding than are Groups 3, 4, and 5. From this graph, the description given in the previous section can be clearly observed: there are substantial differences between the groups in terms of their perceptions of the barriers. This is significant because reductions in these gaps will affect each group differently and lead to different ZEV market penetrations. This information can be very useful in planning optimal medium- and long-term ZEV-promoting policies.

These differences can also be associated with certain characteristics of the groups' members. Groups 3 and 5 have higher knowledge of ZEVs and they are the most tolerant regarding all the attributes, except for range as compared with Group 4, although this more flexible behaviour in this last group may be due to their different driving needs, as they are more likely to use their vehicle for trips shorter than 200 km. There appear to be different motivations for this flexibility: Group 3 is more prone to demand high-end ZEVs and pay more for them (this group has the highest percentage of people aiming to replace high-end cars, with 26.7%, followed by Group 5 with 17.6%), and therefore these individuals could be looking for new, cutting-edge technology, whereas Group 5 is more aware of the environmental benefits (this group has the highest mean ratings for environmental pollution and economic dependence), which in turn could lead it to be more flexible regarding the barriers.

The results also enable us to approximate the size of the gap for each group with respect to each barrier by comparing these requirements with the current status of the barriers. For this purpose, the Tesla Model 3 and the Nissan Leaf are taken as the BEV models, since they were the most frequently sold BEV models in Spain in 2019 (European Alternative Fuels Observatory, 2021) and they represent different segments, while for the case of the FCEVs, the Hyundai Nexo is chosen, since it was the only fuel cell car model sold in Spain in 2018 and has a clear conventional counterpart. Fig. 12 replicates Fig. 11 and adds approximations of the current levels of the barriers for the aforementioned models. It should be borne in mind that, in Fig. 12, the axes are not to scale so that the values of the

Table 5
Models for indicators.

	Cluster1	Cluster2	s.e.	Cluster3	s.e.	Cluster4	s.e.	Cluster5	s.e.	Wald	p-value
Infrastructure	[Base]	0.0852	0.0957	0.3478***	0.1135	0.0412	0.1411	0.3336***	0.1076	17.3532	0.0017
Range	[Base]	−64.2604****	18.9743	−47.9282**	20.8253	−244.5266****	14.0133	−79.9915****	20.284	461.8637	1.20e-98
Refuelling time	[Base]	0.035	0.0889	0.4144****	0.1052	0.0043	0.1306	0.2201**	0.1001	22.4491	0.00016
WTP	[Base]	−2.2855****	0.0539	6.3334****	0.4191	0.0868	0.1127	2.7145****	0.0539	236,842,530	1.2e-51

Significance levels: * 10%; ** 5%; *** 1%; **** 0.1% or less.

Table 6
Variables used in the profiling of the Latent Class Cluster Model.

Variable	Explanation	Levels
Socio-economic		
Age	Respondent's age.	Continuous.
Gender	Respondent's gender.	1 (female), 0 (male).
Higher education	The respondent's highest level of education is tertiary.	1 (yes), 0 (no).
Income over €4,000/ month	The monthly overall net income in the respondent's home exceeds €4,000.	1 (yes), 0 (no).
Remunerated employment	The respondent currently has remunerated employment.	1 (yes), 0 (no).
Mobility		
Annual use higher than 200 km	The car is sometimes used during the year to do trips of more than 200 km.	1 (yes), 0 (no).
Daily use higher than 1 h	The average daily use of the car is over one hour.	1 (yes), 0 (no).
Daily use higher than 2 h	The average daily use of the car is over two hours.	1 (yes), 0 (no).
High-end car	The car that the respondent usually uses is a high-end car.	1 (yes), 0 (no).
Private parking	The respondent has private parking at home.	1 (yes), 0 (no).
Two or more cars at home	The respondent has two or more cars at home.	1 (yes), 0 (no).
Attitudes		
Importance of engine noise	Importance the respondent gives to the noise caused by the engine of their current car.	Scale: 1 (not important) – 5 (very important).
Importance of pollution	Importance the respondent gives to the pollution generated by the use of their current car.	Scale: 1 (not important) – 5 (very important).
Importance of imports	Importance the respondent gives to dependence on other countries for oil imports to produce the fuel of their current car.	Scale: 1 (not important) – 5 (very important).
Knowledge		
Knowledge of ZEV	The respondent has heard about ZEVs and is able to specify a correct ZEV model.	1 (yes), 0 (no).

Table 7
Proportions and means of variables used in the profiling of the Latent Class Cluster Model.

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Socio-economic					
Age (years)	46.24	48.45	47.7	47.51	48.31
Gender (female)	42.4%	40.4%	27.8%	57.1%	38.3%
Higher education	39.3%	37%	45.5%	39.4%	46.1%
Income over €4,000/month	11.1%	14.3%	24.3%	18.1%	20.8%
Remunerated employment	73.6%	71.2%	73.8%	71.9%	76.7%
Mobility					
Annual use higher than 200 km	86.1%	82.1%	84%	71.9%	83.9%
Daily use higher than 1 h	31.2%	37.3%	33.2%	35.5%	29.5%
Daily use higher than 2 h	13.1%	16%	15%	10.8%	11.4%
High-end car	15.5%	17.4%	26.7%	11.3%	17.6%
Private parking	64%	64.9%	65.2%	70.4%	66.8%
Two or more cars at home	36.6%	41.4%	38%	37.4%	38.9%
Attitudes					
Importance of engine noise (1–5)	3.75	3.55	3.63	3.7	3.66
Importance of pollution (1–5)	4.17	3.86	4.11	4.09	4.25
Importance of imports (1–5)	4.11	3.89	4.04	4.08	4.19
Knowledge					
Knowledge of ZEVs	44.1%	32.9%	61%	32.5%	49.7%

different models can also be included. However, the interpretability of this figure remains unaffected: values for the models further from the origin than group values imply that group requirements are not met.

For these models, purchase prices, refuelling times on the road, and ranges were obtained from the official webpages of the car companies (Hyundai Motor Company, 2021; Nissan Motor Company, 2021; Tesla Incorporated, 2021). For Nissan Leaf, we assumed a purchase price of €35,620 and one-hour fast charging with a 32 kW charger, which implies 80% of capacity, although this is not the best charging option to extend the life of the battery. This implies a range of 216 km (80% of 270 km). For Tesla Model 3, we considered a purchase price of €54,420 and a refuelling time of 29 min, which is the time needed to refuel 80% of capacity with a 150 kW charger, obtaining a range of 464 km (80% of 580 km). Full charge of these vehicles was not considered due to the long time needed to refuel the final 20% of capacity. For the Hyundai Nexo, we used a price of €72,250 and a refuelling time of 5 min to attain 100% of the range (666 km). In order to compare these figures with the values reported in the survey, these purchase prices and refuelling times were expressed with respect to the values of their conventional counterparts: Nissan Micra (€19,528), Audi A4 (€41,020), and Hyundai Santa Fe (€50,324), respectively. For all these models, a refuelling time of 3 min was assumed (Audi, 2021; Hyundai Motor Company, 2021; Nissan Motor Company, 2021).

For BEVs, rough estimates of the maximum driving time to the closest charging station were obtained by considering surface and

Table 8
Profiling of the Latent Class Cluster Model.

Multiple Proportions Test/Kruskal-Wallis Test			Pairwise comparisons between classes[a] (p-values[b] with Bonferroni correction)									
			Cluster 1 vs.				Cluster 2 vs.			Cluster 3 vs.		Cluster 4 vs.
Variables	Chi-squared	p-value[b]	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 3	Cluster 4	Cluster 5	Cluster 4	Cluster 5	Cluster 5
Socio-economic												
Age	8.602	*	− (*)									
Gender (female)	35.985	****		+ (***)	− (***)		+ (*)	− (***)		− (****)		+ (***)
Higher education	6.445											
Income over €4,000/month	21.316	****		− (****)		− (**)	− (*)					
Remunerated employment	2.113											
Mobility												
Annual use higher than 200 km	20.566	****			+ (****)			+ (*)		+ (*)		− (*)
Daily use higher than 1 h	4.937											
Daily use higher than 2 h	4.076											
High-end car	17.932	***		− (**)						+ (***)		
Private parking	2.842											
Two or more cars at home	1.972											
Attitudes												
Importance of engine noise	4.139											
Importance of pollution	17.429	***	+ (***)				− (*)	− (*)	− (***)			
Importance of imports	7.932	*							− (**)			
Knowledge												
Knowledge of ZEVs	50.795	****	+ (**)	− (***)	+ (*)		− (****)		− (***)	+ (****)		− (***)

[a] A plus (minus) sign denotes that the value of the class in the second row is significantly higher (lower) than the value of the class in the third row.
[b] Significance levels: * 10%; ** 5%; *** 1%; **** 0.1% or less.

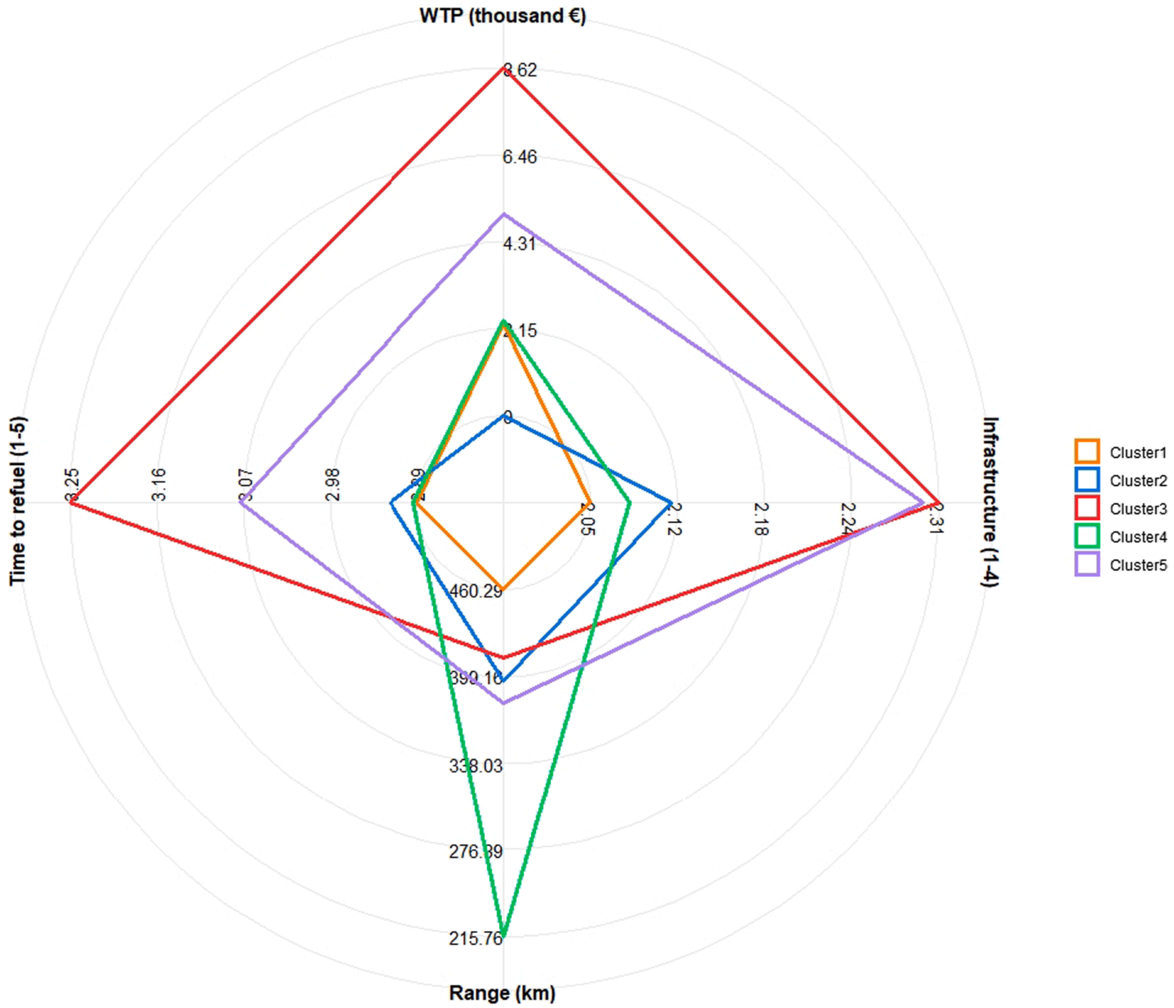

Fig. 11. Average requirements of each barrier by groups.

number of charging stations with the required charging capacity in regions of Madrid, Barcelona, Valencia, Seville, and Zaragoza (Electromaps, 2021; National Statistics Institute, 1996), and by assuming that these points are equidistantly located throughout the regions and that the area of influence of each station is a square. The area of the squares for each region is obtained by dividing the area of the region by the number of charging stations in that region. Under this framework, Manhattan distance was used to compute the distance from each corner of the square to its centre, where the station is assumed to be located, and this distance converted to travelling time by using a 20 km/h average speed in city traffic in Spain (Directorate General for Traffic (DGT) and Spanish Federation of Municipalities and Provinces, 2021). The average of these travelling times for each alternative model is plotted in Fig. 12. In the case of the FCEVs, this procedure was applied to the 5 Spanish regions that featured hydrogen stations, which incidentally contained only one station each.

As previously expected, from Fig. 12, it can be concluded that none of the models verify all the requirements of each consumer group. The Tesla Model 3 satisfies only the requirement of range for all the groups, whereas Hyundai Nexo only satisfies refuelling time and range. However, it is worth mentioning that the hydrogen model is able to meet the technological barriers. The other two barriers that Hyundai Nexo fail to meet belong to the economic field and could be overcome through infrastructure investments, subsidies, and incentives. This fact suggests that the transition to these vehicles could indeed be sooner than expected.

To explore this idea, Fig. 13 plots the five groups in terms of these two attributes: extra WTP and fuel availability. In this figure, the points represent observed values, their sizes indicate the absolute frequency of each particular observation, and their colour represents their group membership. The coloured areas show the dispersion of the members of each group and the black dashed vertical line indicates the extra purchase price of a Hyundai Nexo. This figure provides an insight into the effects, in terms of market penetration, of different subsidies and hydrogen refuelling infrastructure investments. For example, incentives for the purchase of ZEVs of approximately €10,000 (which would be graphically equivalent to a shift of the black line to the left by that amount) combined with

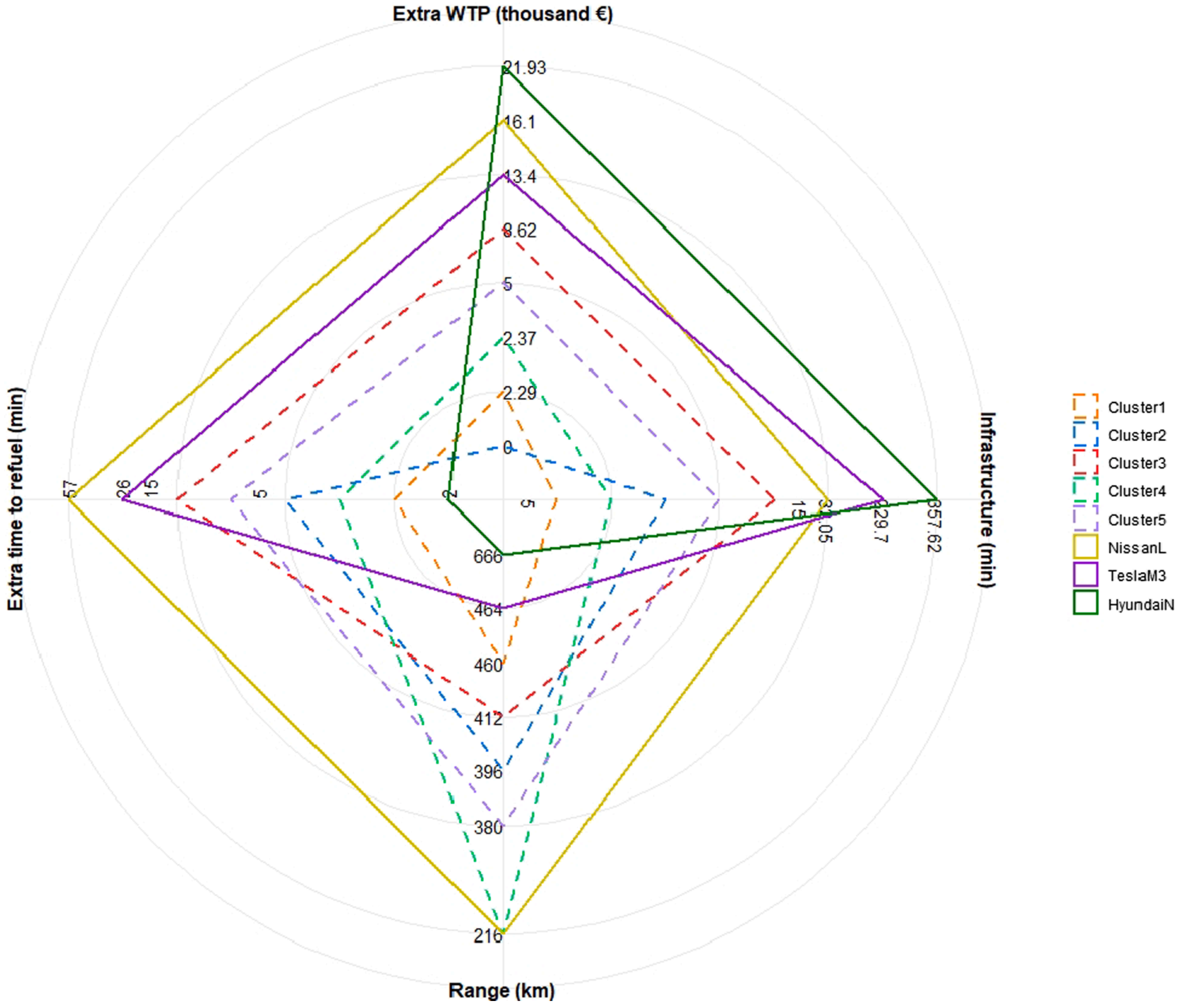

Fig. 12. Average requirements of each barrier by groups and current levels.

development in the hydrogen infrastructure leading to hydrogen stations being 15 min apart from anywhere in the city could jointly lead to penetration rates of 0.94%, due mainly to a shift in the drivers of Group 3. The same percentage could be reached with an incentive of €5,000 but higher fuel availability (stations no more than 5 min apart). A higher incentive (of around €12,000) with fuel availability no more than 15 min apart could increase the penetration rate to around 2.75%. This information could help decision-makers to study the suitability of these policies in advance, and to formulate public–private partnerships.

7. Conclusion

This paper studies Spanish drivers' perceptions regarding the main barriers that hamper the introduction of ZEVs in the Spanish car market. A thorough review of the existing literature based on consumers' surveys has allowed us to identify the most important obstacles stated by consumers to consider the purchase of a ZEV. These barriers could affect both the consideration of ZEVs in consumers' car-purchase decisions and their final choice. Given the low penetration of these vehicles into the Spanish car market, this paper focuses on the consideration stage.

The requirements of the Spanish drivers for each barrier to consider ZEVs in their next car-purchase decision were elicited by means of a stated-preference survey of Spanish drivers that directly asked them to provide point values or to select the interval containing such a value. This information is crucial for policy-makers and car manufacturers to ascertain how to entice consumers into considering ZEVs in their car-purchase decisions. Given the very high number of car alternatives in the car market, the inclusion of ZEVs in the consideration set considerably increases the probability of their sale (Hauser et al., 2009). This formulation also implies that consumers will never experience improved ZEVs (changes in certain attributes) if they never consider such vehicles because these cars fail to meet their requirements for the barriers (Hauser, 2014).

The survey was very carefully designed to avoid potential biases. The responses were analysed with a model-based cluster approach to group drivers according to their perception of the barriers. This approach clearly shows the gaps with respect to each barrier for each

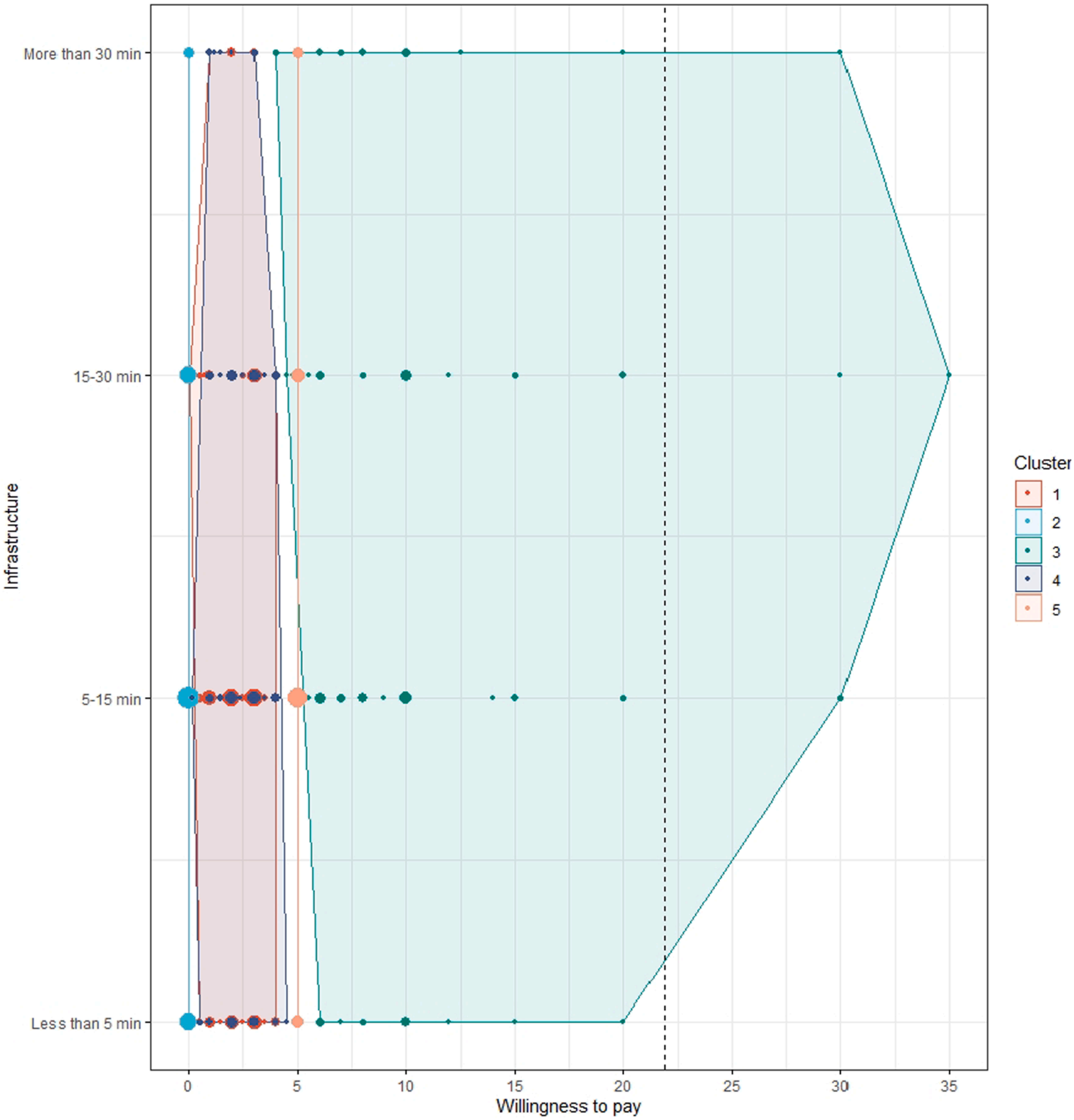

Fig. 13. Group distributions in terms of fuel availability and extra WTP.

group. This information is highly useful in designing optimal ZEV-promoting policies because each policy will not have the same impact in each group. To the best of our knowledge, this is the first paper using this approach in this particular context. These groups were characterised in terms of socio-economic and mobility characteristics, their attitudes, and their knowledge of ZEVs.

Most of the sample belongs to the most demanding group in terms of the levels of the barriers. Knowledge of ZEVs is a common feature of the least demanding groups, although they do appear to have different motivations: one group aims to replace high-end models and presents a high WTP, which suggests these individuals could be looking for new, cutting-edge technology; however, another group is more aware of the environmental benefits of the use of ZEVs, which could be its main motivation.

The results also show that the switch to FCEVs is more attainable than previously expected. The main barriers that hamper the introduction of these vehicles into the market are largely economic, affordable with the help of governments if they deem it appropriate. However, in the case of BEVs, there are also certain technological barriers. Therefore, for FCEVs, the focus needs to be on fuel availability and purchase price. According to our results, purchase incentives of approximately €12,000, together with refuelling infrastructure investment policies leading to hydrogen stations no more than 15 min apart from anywhere in the city, could lead to penetration rates of approximately 2.75%.

This information could prove highly useful in planning optimal medium- and long-term ZEV-promoting policies. Educational and environmental awareness policies, together with purchase incentives and infrastructure investment policies can be decisive in attaining a significant transition to ZEVs in Spain in both the medium and long term

CRediT authorship contribution statement

Abel Rosales-Tristancho: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Raúl Brey:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Ana F. Carazo:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **J. Javier Brey:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This project has been partially funded by FEDER/Ministerio de Ciencia, Innovación y Universidades – Agencia Estatal de Investigación/ Proyecto ECO2017-89452-R. Funding for open access publishing: Universidad de Sevilla/CBUA.

References

Achtnicht, M., Bühler, G., Hermeling, C., 2012. The impact of fuel availability on demand for alternative-fuel vehicles. Transp. Res. Transp. Environ. 17 (3), 262–269. https://doi.org/10.1016/j.trd.2011.12.005.

Adhikari, M., Ghimire, L.P., Kim, Y., Aryal, P., Khadka, S.B., 2020. Identification and analysis of barriers against electric vehicle use. Sustainability 12 (12), 1–20. https://doi.org/10.3390/SU12124850.

Andriosopoulos, K., Bigerna, S., Bollino, C.A., Micheli, S., 2018. The impact of age on Italian consumers' attitude toward alternative fuel vehicles. Renew. Energy 119, 299–308. https://doi.org/10.1016/j.renene.2017.11.056.

Audi, 2021. Available at: https://www.audi.es/es/web/es.html (Last accessed: March 2021).

Axsen, J., Bailey, J., Castro, M.A., 2015. Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers. Energy Econ. 50, 190–201. https://doi.org/10.1016/j.eneco.2015.05.003.

Axsen, J., Goldberg, S., Bailey, J., 2016. How might potential future plug-in electric vehicle buyers differ from current "Pioneer" owners? Transp. Res. Transp. Environ. 47, 357–370. https://doi.org/10.1016/j.trd.2016.05.015.

Bakken, D.G., 2006. Agent-based simulation for improved decision-making. 2006 Sawtooth Software Conference Proceedings: Sequim, WA (Delray Beach, Florida, March 29-31).

Barisa, A., Rosa, M., Kisele, A., 2016. Introducing electric mobility in Latvian municipalities: results of a survey. Energy Procedia 95, 50–57. https://doi.org/10.1016/j.egypro.2016.09.015.

Berkeley, N., Jarvis, D., Jones, A., 2018. Analysing the take up of battery electric vehicles: An investigation of barriers amongst drivers in the UK. Transp. Res. Transp. Environ. 63, 466–481. https://doi.org/10.1016/j.trd.2018.06.016.

Bickman, L., Rog, D., 2009. The Sage Handbook of Applied Social Research Methods, 2nd ed. Sage Publications, Thousand Oaks, CA.

Bishop, R.C., Boyle, K.J., 2019. Reliability and validity in nonmarket valuation. Environ. Resour. Econ. 72 (2), 559–582. https://doi.org/10.1007/s10640-017-0215-7.

Brey, J.J., Brey, R., Carazo, A.F., 2017. Eliciting preferences on the design of hydrogen refueling infrastructure. Int. J. Hydrogen Energy 42, 13382–13388. https://doi.org/10.1016/j.ijhydene.2017.02.135.

Bühler, F., Cocron, P., Neumann, I., Franke, T., Krems, J.F., 2014. Is EV experience related to EV acceptance? Results from a German field study. Transp. Res. Traffic Psychol. Behav. 25, 34–49. https://doi.org/10.1016/j.trf.2014.05.002.

Byun, H., Shin, J., Lee, C.Y., 2018. Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. Energy 144, 312–321. https://doi.org/10.1016/j.energy.2017.12.035.

Carson, R.T., Groves, T., 2007. Incentive and informational properties of preference questions. Environ. Resour. Econ. 37 (1), 181–210. https://doi.org/10.1007/s10640-007-9124-5.

Cellina, F., Cavadini, P., Soldini, E., Bettini, A., Rudel, R., 2016. Sustainable mobility scenarios in Southern Switzerland: insights from early adopters of electric vehicles and mainstream consumers. Transp. Res. Procedia 14, 2584–2593. https://doi.org/10.1016/j.trpro.2016.05.406.

Chachdi, A., Rahmouni, B., Aniba, G., 2017. Socio-economic analysis of electric vehicles in Morocco. Energy Procedia 141, 644–653. https://doi.org/10.1016/j.egypro.2017.11.087.

Cheng, Z., 2012. The relation between uncertainty in latent class membership and outcomes in a latent class signal detection model. Columbia University.

Chen, S.-J., Hwang, C.-L., 1992. Fuzzy Multiple Attribute Decision Making. Methods. https://doi.org/10.1007/978-3-642-46768-4_5.

Choi, H., Shin, J., Woo, J.R., 2018. Effect of electricity generation mix on battery electric vehicle adoption and its environmental impact. Energy Policy 121, 13–24. https://doi.org/10.1016/j.enpol.2018.06.013.

Ciarapica, F.E., Matt, D.T., Rossini, M., Spena, P.R., 2013. Quality, environmental and economic factors influencing electric vehicles penetration in the Italian market. In: Proceedings of the Summer School Francesco Turco, 11-13-September-2013, pp. 358–363.

Cirillo, C., Liu, Y., Maness, M., 2017. A time-dependent stated preference approach to measuring vehicle type preferences and market elasticity of conventional and green vehicles. Transp. Res. Policy Pract. 100, 294–310. https://doi.org/10.1016/j.tra.2017.04.028.

City Council of Barcelona, 2021. Major Works Licenses. Number of parking lots foreseen annually. Territorial Coordination Management. Statistics and Data Diffusion Department. Available at: https://www.bcn.cat/estadistica/castella/dades/timm/llic/evo/t3.htm (Last accessed: April 2021).

City Council of Madrid, 2021. Construction of Homes. Characteristics of newly constructed homes. Government Office for Urban and Sustainable Development, General Coordination of Urban Development. Available at: http://www-2.munimadrid.es/CSE6/control/seleccionDatos?numSerie=05040101070 (Last accessed: April 2021).

Directorate General for Traffic (DGT), 2016. General Statistics Yearbook. Available at: http://www.dgt.es/Galerias/seguridad-vial/estadisticas-e-indicadores/publicaciones/anuario-estadistico-de-general/Anuario-estadistico-general-2016.pdf (Last accessed: April 2020).

Directorate General for Traffic (DGT), 2019. Vehicle fleet – Ancillary Tables Yearbook – 2019. Available at: https://www.dgt.es/es/seguridad-vial/estadisticas-e-indicadores/parque-vehiculos/tablas-estadisticas/2019/ (Last accessed: April 2021).

Directorate General for Traffic (DGT), Spanish Federation of Municipalities and Provinces, 2021. Implementation manual for new speed limits on urban roads. Available at: https://www.dgt.es/Galerias/prensa/2021/04/Manual_reduccion_30_urbano.pdf (Last accessed: April 2021).

Dzyabura, D., Hauser, J., 2011. Active Machine Learning for Consideration Heuristics. Market. Sci. 30 (5), 801–819. https://doi.org/10.1287/mksc.1110.0660.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. Energy Policy 48, 717–729. https://doi.org/10.1016/j.enpol.2012.06.009.

Electromaps, 2021. Available at: https://www.electromaps.com/ (Last accessed: March 2021).

European Alternative Fuels Observatory, 2021. Available at: https://www.eafo.eu/ (Last accessed: March 2021).

European Commission, (CE), 2011. Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system. COM/2011/144 final. Available at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0144:FIN:EN:PDF (Last accessed: April 2020).

European Commission, (CE), 2014. European Energy Security Strategy. COM/2014/0330. Available at: https://www.eesc.europa.eu/resources/docs/european-energy-security-strategy.pdf (Last accessed: April 2020).

Everitt, B.S., Landau, S., Leese, M., Stahl, D., 2011. Cluster Analysis, 5th ed. John Wiley & Sons Ltd.

Ferguson, M., Mohamed, M., Higgins, C.D., Abotalebi, E., Kanaroglou, P., 2018. How open are Canadian households to electric vehicles? A national latent class choice analysis with willingness-to-pay and metropolitan characterization. Transp. Res. Transp. Environ. 58, 208–224. https://doi.org/10.1016/j.trd.2017.12.006.

Fop, B.M., Smart, K.M., Murphy, T.B., 2017. Variable Selection for Latent Class Analysis with Application to Low Back Pain Diagnosis. Ann. Appl. Stat. 11 (4), 2080–2110. https://doi.oig/10.1214/17-AOAS1061.

Fu, J.S., Sha, Z., Huang, Y., Wang, M., Fu, Y., Chen, W., 2017. Two-Stage Modeling of Customer Choice Preferences in Engineering Design Using Bipartite Network Analysis. In: Proceedings of the ASME 2017 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 2A: 43rd Design Automation Conference. Cleveland, Ohio, USA. August 6–9, 2017. V02AT03A039. ASME. https://doi.org/10.1115/DETC2017-68099.

Fullerton, A.S., 2009. A conceptual framework for ordered logistic regression models. Sociolog. Methods Res. 38 (2), 306–347. https://doi.org/10.1177/0049124109346162.

Gensch, D.H., 1987. A Two-Stage Disaggregate Attribute Choice Model. Market. Sci. 6 (3), 223–239. https://doi.org/10.1287/mksc.6.3.223.

Giansoldati, M., Danielis, R., Rotaris, L., Scorrano, M., 2018. The role of driving range in consumers' purchasing decision for electric cars in Italy. Energy 165, 267–274. https://doi.org/10.1016/j.energy.2018.09.095.

Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. Transp. Res. Transp. Environ. 25, 5–17. https://doi.org/10.1016/j.trd.2013.07.002.

Hackbarth, A., Madlener, R., 2016. Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. Transp. Res. Poicy Pract. 85, 89–111. https://doi.org/10.1016/j.tra.2015.12.005.

Han, W., Zhang, G., Xiao, J., Bénard, P., Chahine, R., 2014. Demonstrations and marketing strategies of hydrogen fuel cell vehicles in China. Int. J. Hydrogen Energy 39 (25), 13859–13872. https://doi.org/10.1016/j.ijhydene.2014.04.138.

Hardman, S., Chandan, A., Shiu, E., Steinberger-Wilckens, R., 2016a. Consumer attitudes to fuel cell vehicles post trial in the United Kingdom. Int. J. Hydrogen Energy 41 (15), 6171–6179. https://doi.org/10.1016/j.ijhydene.2016.02.067.

Hardman, S., Shiu, E., Steinberger-Wilckens, R., 2016b. Comparing high-end and low-end early adopters of battery electric vehicles. Transp. Res. Policy Pract. 88, 40–57. https://doi.org/10.1016/j.tra.2016.03.010.

Hardman, S., Shiu, E., Steinberger-Wilckens, R., Turrentine, T., 2017. Barriers to the adoption of fuel cell vehicles: A qualitative investigation into early adopters' attitudes. Transp. Res. Policy Pract. 95, 166–182. https://doi.org/10.1016/j.tra.2016.11.012.

Hauser, J.R., Ding, M., Gaskin, S.P., 2009. Non-Compensatory (and Compensatory) Models of Consideration-Set Decisions. Sawtooth Softw. Conf. 1–2.

Hauser, J.R., 2014. Consideration-set heuristics. J. Bus. Res. 67 (8), 1688–1699. https://doi.org/10.1016/j.jbusres.2014.02.015.

Hauser, J.R., Dong, S., Ding, M., 2014. Self-reflection and articulated consumer preferences. J. Prod. Innov. Manag. 31 (1), 17–32. https://doi.org/10.1111/jpim.12077.

Haustein, S., Jensen, A.F., 2018. Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior. Int. J. Sustain. Transp. 12 (7), 484–496. https://doi.org/10.1080/15568318.2017.1398790.

Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33 (3), 686–705. https://doi.org/10.1016/j.reseneeco.2011.02.002.

Horowitz, J.L., Louviere, J.J., 1995. What is the role of consideration sets in choice modeling? Int. J. Res. Mark. 12 (1), 39–54. https://doi.org/10.1016/0167-8116(95)00004-L.

Huang, Y., Qian, L., 2018. Consumer preferences for electric vehicles in lower tier cities of China: Evidences from south Jiangsu region. Transp. Res. Transp. Environ. 63, 482–497. https://doi.org/10.1016/j.trd.2018.06.017.

Huber, J., Klein, N.M., 1991. Adapting Cutoffs to the Choice Environment: The Effects of Attribute Correlation and Reliability. J. Consum. Res. 18 (3), 346–357. https://doi.org/10.1086/209264.

Hyundai Motor Company, 2021. Available at: https://www.hyundai.com/es.html (Last accessed: March 2021).

International Council on Clean Transportation, 2018. Electric vehicle capitals: Accelerating the global transition to electric drive. Available at: https://theicct.org/sites/default/files/publications/EV_Capitals_2018_final_20181029.pdf (Last accessed: July 2020).

Iribarren, D., Martín-Gamboa, M., Manzano, J., Dufour, J., 2016. Assessing the social acceptance of hydrogen for transportation in Spain: An unintentional focus on target population for a potential hydrogen economy. Int. J. Hydrogen Energy 41 (10), 5203–5208. https://doi.org/10.1016/j.ijhydene.2016.01.139.

Ito, N., Takeuchi, K., Managi, S., 2019. Do battery-switching systems accelerate the adoption of electric vehicles? A stated preference study. Econ. Anal. Pol. 61, 85–92. https://doi.org/10.1016/j.eap.2017.02.004.

Kaplan, S., Bekhor, S., Shiftan, Y., 2009. Two-stage model for jointly revealing determinants of noncompensatory conjunctive choice set formation and compensatory choice. Transp. Res. Rec. 2134 (1), 153–163. https://doi.org/10.3141/2134-18.

Kim, J.S., Ratchford, B.T., 2012. Consideration set of automobiles: Purchase feedback and exclusivity in formation. J. Manag. Mark. Res. 9, 1–12.

Kim, M.K., Park, J.H., Kim, K., Park, B., 2020. Identifying factors influencing the slow market diffusion of electric vehicles in Korea. Transp. 47 (2), 663–688. https://doi.org/10.1007/s11116-018-9908-1.

Kormos, C., Axsen, J., Long, Z., Goldberg, S., 2019. Latent demand for zero-emissions vehicles in Canada (Part 2): Insights from a stated choice experiment. Transp. Res. Transp. Environ. 67, 685–702. https://doi.org/10.1016/j.trd.2018.10.010.

Larson, P.D., Viáfara, J., Parsons, R.V., Elias, A., 2014. Consumer attitudes about electric cars: Pricing analysis and policy implications. Transp. Res. Part A: Policy Pract. 69, 299–314. https://doi.org/10.1016/j.tra.2014.09.002.

Lebeau, K., Van Mierlo, J., Lebeau, P., Mairesse, O., Macharis, C., 2013. Consumer attitudes towards battery electric vehicles: A large-scale survey. Int. J. Electr. Hybrid Vehicles 5 (1), 28–41. https://doi.org/10.1504/IJEHV.2013.053466.

Lee, J., Jung, K., Park, J., 2020. Detecting Conditional Dependence Using Flexible Bayesian Latent Class Analysis. Front. Psychol. 11, 1–10. https://doi.org/10.3389/fpsyg.2020.01987.

Leisch, F., 2004. FlexMix: A General Framework for Finite Mixture Models and Latent Class Regression in R. J. Stat. Softw. 11 (8).

Lipman, T.E., Elke, M., Lidicker, J., 2018. Hydrogen fuel cell electric vehicle performance and user-response assessment: Results of an extended driver study. Int. J. Hydrogen Energy 43 (27), 12442–12454. https://doi.org/10.1016/j.ijhydene.2018.04.172.

Loomis, J., 2011. What's to know about hypothetical bias in stated preference valuation studies? J. Econ. Surv. 25 (2), 363–370. https://doi.org/10.1111/j.1467-6419.2010.00675.x.

Manski, C.F., 1977. The Structure of Random Utility Models. Theory Decision 8 (3), 229–254.

Martin, E., Shaheen, S.A., Lipman, T.E., Lidicker, J.R., 2009. Behavioral response to hydrogen fuel cell vehicles and refueling: Results of California drive clinics. Int. J. Hydrogen Energy 34 (20), 8670–8680. https://doi.org/10.1016/j.ijhydene.2009.07.098.

Ministry of Transport, Mobility and Urban Agenda, 2021. Construction of buildings (municipal work licenses). Characteristics of residential buildings to be built. Available at: https://apps.fomento.gob.es/BoletinOnline/?nivel=2&orden=10000000 (Last accessed: April 2021).
Moe, W.W., 2006. An empirical two-stage choice model with varying decision rules applied to Internet clickstream data. J. Mark. Res. 43 (4), 680–692. https://doi.org/10.1509/jmkr.43.4.680.
National Statistics Institute. Spain, 1996. Yearbook 1996. Documentary Collection of the National Statistics Institute. Available at: https://www.ine.es/inebaseweb/pdfDispacher.do?td=145938 (Last accessed: March 2021).
National Statistics Institute. Spain, 2011. Population and Dwellings Censuses 2011. Buildings. Available at: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176992&menu=resultados&idp=1254735572981 (Last accessed: April 2021).
National Statistics Institute. Spain, 2020. Available at: https://www.ine.es/ (Last accessed: July 2020).
Nazari, F., Mohammadian, A. (Kouros), Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transp. Res. Part D Transp. Environ. 72, 65–82 https://doi.org/10.1016/j.trd.2019.04.010.
Nissan Motor Company, 2021. Available at: https://www.nissan.es/ (Last accessed: March 2021).
Noel, L., Zarazua de Rubens, G., Kester, J., Sovacool, B.K., 2020. Understanding the socio-technical nexus of Nordic electric vehicle (EV) barriers: A qualitative discussion of range, price, charging and knowledge. Energy Policy 138, 111292. https://doi.org/10.1016/j.enpol.2020.111292.
Ou, S., Lin, Z., He, X., Przesmitzki, S., 2018. Estimation of vehicle home parking availability in China and quantification of its potential impacts on plug-in electric vehicle ownership cost. Transp. Policy 68, 107–117. https://doi.org/10.1016/j.tranpol.2018.04.014.
Paleti, R., 2015. Implicit choice set generation in discrete choice models: Application to household auto ownership decisions. Transp. Res. Methodol. 80, 132–149. https://doi.org/10.1016/j.trb.2015.06.015.
Paulssen, M., Bagozzi, R.P., 2005. A self-regulatory model of consideration set formation. Psychol. Mark. 22 (10), 785–812. https://doi.org/10.1002/mar.20085.
Pernollet, F., Crocombette, C., Cayla, J. M., 2019. Who is willing to buy an electric vehicle in France? Electric vehicle penetration split by household segments. In: ECEEE Summer Study Proceedings, 2019-June, 1035–1045.
Pham, M., Higgins, E., 2004. Promotion and Prevention in Consumer Decision Making: State of the Art and Theoretical Propositions. Inside Consumption: Consumer Motives, Goals, and Desires. https://doi.org/10.4324/9780203481295.
Priessner, A., Sposato, R., Hampl, N., 2018. Predictors of electric vehicle adoption: An analysis of potential electric vehicle drivers in Austria. Energy Policy 122, 701–714. https://doi.org/10.1016/j.enpol.2018.07.058.
Punj, G., Brookes, R., 2002. The influence of pre-decisional constraints on information search and consideration set formation in new automobile purchases. Int. J. Res. Mark. 19 (4), 383–400. https://doi.org/10.1016/S0167-8116(02)00100-3.
Rand, W.M., 1971. Objective criteria for the evaluation of clustering methods. J. Am. Stat. Assoc. 66 (336), 846–850. https://doi.org/10.1080/01621459.1971.10482356.
Ščasný, M., Zvěřinová, I., Czajkowski, M., 2018. Electric, plug-in hybrid, hybrid, or conventional? Polish consumers' preferences for electric vehicles. Energy Effic. 11 (8), 2181–2201. https://doi.org/10.1007/s12053-018-9754-1.
Shaheen, S., Martin, E., Totte, H., 2020. Zero-emission vehicle exposure within U.S. carsharing fleets and impacts on sentiment toward electric-drive vehicles. Transp. Policy 85, A23–A32. https://doi.org/10.1016/j.tranpol.2019.09.008.
She, Z.Y., Sun, Q., Ma, J.J., Xie, B.C., 2017. What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. Transp. Policy 56, 29–40. https://doi.org/10.1016/j.tranpol.2017.03.001.
Sheldon, T.L., DeShazo, J.R., Carson, R.T., 2017. Electric and Plug-in Hybrid Vehicle Demand: Lessons for an Emerging Market. Econ. Inq. 55 (2), 695–713. https://doi.org/10.1111/ecin.12416.
Simon, H.A., 1955. A Behavioral Model of Rational Choice. Q. J. of Econ. 69 (1), 99–118.
Skrondal, A., Rabe-Hesketh, S., 2004. Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models. Chapman & Hall/CRC, Boca Raton, Fla.; London.
Steinley, D., 2004. Properties of the Hubert-Arabie adjusted Rand index. Psychol. Methods 9 (3), 386–396. https://doi.org/10.1037/1082-989X.9.3.386.
Suzuki, Y., 2007. Modeling and testing the "two-step" decision process of travelers in airport and airline choices. Transp. Res. Logist. Transp. Rev. 43 (1), 1–20. https://doi.org/10.1016/j.tre.2005.05.005.
Swait, J., Ben-Akiva, M., 1987. Incorporating random constraints in discrete models of choice set generation. Transp. Res. Methodol. 21 (2), 91–102. https://doi.org/10.1016/0191-2615(87)90009-9.
Tein, J.Y., Coxe, S., Cham, H., 2013. Statistical power to detect the correct number of classes in latent profile analysis. Struct. Equ. Model. 20 (4), 640–657. https://doi.org/10.1080/10705511.2013.824781.
Tesla Incorporated, 2021. Available at: https://www.tesla.com/es_es/ (Last accessed: March 2021).
Truong, T.D., Adamowicz, W.L. (Vic), Boxall, P.C., 2015. Modeling non-compensatory preferences in environmental valuation. Resour. Energy Econ. 39, 89–107. https://doi.org/10.1016/j.reseneeco.2014.12.001.
Turrentine, T.S., Kurani, K.S., 2007. Car buyers and fuel economy? Energy Policy 35 (2), 1213–1223. https://doi.org/10.1016/j.enpol.2006.03.005.
Vermunt, J., Magidson, J., 2002. Latent Class Cluster Analysis.
Vermunt, J.K., Magidson, J., 2005. Latent GOLD 4.0 User's Guide. Statistican Innovations Inc., Belmont, MA.
Vermunt, J.K., Magidson, J., 2016. Technical Guide for Latent GOLD 5.1: Basic, Advanced, and Syntax. Statistical Innovations Inc., Belmont, MA.
Wesseling, J.H., Farla, J.C.M., Sperling, D., Hekkert, M.P., 2014. Car manufacturers' changing political strategies on the ZEV mandate. Transp. Res. Transp. Environ. 33, 196–209. https://doi.org/10.1016/j.trd.2014.06.006.
Xu, G., Miwa, T., Morikawa, T., Yamamoto, T., 2015. Vehicle purchasing behaviors comparison in two-stage choice perspective before and after eco-car promotion policy in Japan. Transp. Res. Transp. Environ. 34, 195–207. https://doi.org/10.1016/j.trd.2014.11.001.
Zhang, F., Cooke, P., 2010. Hydrogen and fuel cell development in China: A review. Eur. Plan. Stud. 18 (7), 1153–1168. https://doi.org/10.1080/09654311003791366.
Zhang, H., Song, X., Xia, T., Yuan, M., Fan, Z., Shibasaki, R., Liang, Y., 2018. Battery electric vehicles in Japan: Human mobile behavior based adoption potential analysis and policy target response. Appl. Energy 220, 527–535. https://doi.org/10.1016/j.apenergy.2018.03.105.