

The potential learning effect of a MCDA approach on consumer preferences for Alternative Fuel Vehicles

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Abstract

Despite efforts from governments to increase the diffusion of more sustainable vehicles, such as Alternative Fuel Vehicles (AFV), the market penetration of these vehicles has been difficult. Eliciting consumer preferences may provide valuable information on how to increase AFV diffusion. Since these are unfamiliar and complex products for most consumers, preferences are usually learnt during the process of elicitation. Preference learning is dependent on several factors, which include the type of elicitation task and its complexity. In this work, a stated preference survey was designed to analyze the potential impact of more complex elicitation tasks, Multiattribute Utility Theory approach (MAUT), on the learning of preferences elicited through a traditional approach, Choice-Based Conjoint Analysis (CBC). The survey comprised two CBC sets of questions, one asked before and another asked after the MAUT. As a result three rankings of the vehicles set were obtained for each consumer, one derived from the initial set of CBC answers, a second one derived from the elicited MAUT model, and a third one derived from the second set of CBC answers. According to the results, there are significant differences from the first to the third ranking, possibly due to learning effects. Differences between the CBC-derived rankings were analyzed to assess if they were aligned with the MAUT model.

Keywords: Conjoint analysis; Multicriteria decision analysis; preference learning; elicitation task; alternative fuel vehicles.

Acknowledgments:

The authors thank the editor and the anonymous reviewers for their constructive remarks that contributed to improving this article. This work was developed under the Energy for Sustainability Initiative of the University of Coimbra and supported by the Energy and Mobility for Sustainable Regions – EMSURE – Project (CENTRO-07-0224-FEDER-002004). The support from Portuguese Science and Technology Foundation (FCT) project UID/MULTI/00308/2013 and Grants SFRH/BD/51639/2011 and UIDB/05037/2020 is also acknowledged.

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<https://doi.org/10.1007/s10479-020-03584-x>

1. Introduction

Over the last two decades several Alternative Fuel Vehicles (AFV) have been introduced in the market as a potential answer to the road transportation problems of oil dependency and release of harmful emissions. However, the successful dissemination of these potentially more sustainable technologies in the markets depends on consumers tastes and the characteristics valued by them when choosing a vehicle, i.e., it depends on consumer preferences (Verlegh and Steenkamp, 1999). Knowing these preferences is essential to make choices about the attributes of future vehicles (Hidrué et al., 2011), as well as to forecast AFV penetration in the markets and to forecast the effects of different policies (Oliveira et al., 2019).

Understanding consumer preferences is a difficult process due to their subjective nature (Barzilai, 2005; Eyvindson et al., 2015) and it has become more difficult over the years as consumers face a wider variety of products. For instance, in the past consumers had to decide if they would buy a gasoline, diesel or GPL vehicle, but currently this decision includes a broader group of options such as Battery Electric Vehicles (BEV), Plug-in Hybrid Vehicles (PHEV), Hybrid Electric Vehicles (HEV), hydrogen vehicles, natural gas vehicles, biodiesel, and biofuel. This variety confronts consumers with huge amounts of information about the products, bringing more complexity to the vehicle purchase decision. In this context, preference elicitation methods can play an important role to understand under which conditions a product will succeed (Nikou et al., 2015).

Currently, the most commonly used elicitation tasks to analyze market preferences are designed according to Conjoint Analysis (CA) methodology, where consumers have, for instance, to choose one alternative from a given set. This methodology is frequently used due to its ability to simulate real purchase decisions and, for that reason, it is considered intuitive for respondents (Orme, 2009a). The dominance of CA on assessing consumer preferences led to the development of several comparative studies between this method and other methods, including recently methods from Multicriteria Decision Analysis (MCDA) field, in order to verify which performs better on assessing consumer preferences (e.g. Helm and Steiner, 2004; Meißner et al., 2008; Perini et al., 2009; Kallas et al., 2011; Nikou et al., 2015). Whilst the results have not been consensual so far regarding the assessment of preferences, in general consumers reported that a higher cognitive burden was required to answer to MCDA surveys in comparison to the effort needed for CA surveys (Helm and Steiner, 2004; Moran et al., 2007; Perini et al., 2009; Kallas et al., 2011).

Depending on the assumptions about how preferences are expressed, the process of elicitation is used to uncover stable and well-defined preferences or to construct/learn preferences along the elicitation procedure. Preferences for AFV, as other innovative technologies, tend to not pre-exist because, as several attributes are novelties, consumers did not experience or thought about them before (Axsén et al., 2013). When consumers face a new product category they need to construct their preferences due to the limited knowledge and absence of experience with those products (Hoeffler and Ariely, 1999). Previous studies that used elicitation methods concluded that constructed preferences are dependent on several factors, such as the type of elicitation task (Novemsky et al., 2007), task order (Swait and Adamowicz, 2001; Day and Prades,

2010), task complexity (Swait and Adamowicz, 2001; Deshazo and Fermo, 2002), and cognitive burden (Swait and Adamowicz, 2001), among others. However, to the authors' best knowledge, the question of whether an MCDA analysis can be useful as a preparatory step prior to a CA elicitation has not been addressed in the literature.

The main goal of this work is to analyze the potential impact of using an MCDA preference elicitation method on the learning of preferences elicited through the traditional approach, CA. This research thus contributes to advance knowledge on learning in preference elicitation, by providing a methodological procedure that can leverage the analysis of the learning effect of preferences through the engagement of two preference elicitation methods in a Stated Preference (SP) survey, one from CA and another from MCDA, rather than the traditional analysis of learning effects on preferences that use only one methodology. In this work, the methodological procedure has been designed and tested on a large number of individuals, in the context of a specific application. Concerning the field of MCDA, the contribution of this article is to present a potentially interesting new application for MCDA: to be used as a device to foster learning before other types of elicitation questions (in this case, CA). At the same time, it provides an account of using MCDA to analyze consumer preferences in an application involving over 200 individuals and addressing a type of product not addressed before.

The application of this study to innovative and environmental friendlier vehicle technologies is particularly relevant for two reasons. First, because AFV are rather complex, and often unfamiliar, products for consumers. Second, as AFV have a public good character due to their potential environmental benefits, the preference assessment of AFV is more prone to anomalies, i.e. to differences between stated and actual preferences (Carlsson, 2010). Therefore, collection of preference data through two methods may allow obtaining less biased SP data from the potential "revealed" future preferences.

This paper is organized as follows. Section 2 presents a brief literature review covering the application of MCDA for consumer preferences assessment and studies focused on analyzing the learning effects that elicitation techniques may have on preferences. Section 3 describes the selected methods for preference elicitation. Section 4 presents the survey design in detail and the results are depicted on Section 5. The last section presents the main conclusions of this work.

2. Literature review

Considering the scope of this study, this section reviews two main topics: studies where MCDA approaches are applied to assess consumer preferences (§2.1) and studies that assess the existence of learning effects on preferences that may occur when consumers are surveyed (§2.2).

2.1. Applications of MCDA methods for consumer preference assessment

MCDA methods have different applications in the preference analysis field. These applications depend on their aggregation paradigm, i.e. if the MCDA method is a disaggregation or aggregation method.

MCDA disaggregation methods (Jacquet-Lagrèze and Siskos, 2001) involve the inference of preference models from knowledge about holistic preferences of decision makers. Two popular disaggregation methods are UTA (Utility Theory Additive) and MUSA (Multicriteria Satisfaction

Analysis), where an ordinal regression formulation is used to measure consumer preferences and satisfaction, respectively (Siskos et al., 1998; Jacquet-Lagrèze and Siskos, 2001; Grigoroudis and Siskos, 2002; Greco et al., 2008).

UTA has been applied to identify the most determinant attributes that could explain consumers' choices about several agricultural products (Baourakis et al., 1996; Matsatsinis et al., 1999; Siskos et al., 2001) and to understand the impact of some attributes on brand preferences (Ghaderi et al., 2015). MUSA has assessed the consumer satisfaction mainly in the services sector, such as banking (Mihelis, 2001; Grigoroudis et al., 2002), transportation-communication (Grigoroudis and Siskos, 2004), internet services (Kyriazopoulos and Spyridakos, 2007), tourism (Arabatzis and Grigoroudis, 2010) and public services (Manolitzas et al., 2013). Afterwards, MUSA-INT was introduced in the literature where the interaction among attributes is taken into account (Angilella et al., 2014)

MCDAs aggregation approaches start with a separate assessment of preferences for each product attribute in order to achieve a global preference relation (a global utility value or, in some methods, a system of relations accepting incomparability) through an aggregation rule (Jain et al., 1979; Belton and Stewart, 2002). There are two aggregation methods that are used more often in the consumer preference analysis field, namely Analytic Hierarchical Process (AHP) and Multiattribute Utility/Value Theory (MAUT/MAVT). AHP involves an importance-ratio assessment procedure based on hierarchies of attributes (Saaty, 2008). This method has been used with different purposes within the preferences field, such as to incorporate preferences into regional forest planning (Ananda and Herath, 2003), to prioritize mission simulators for space travels based on preferences (Tavana, 2006), to analyze preference shifting applied to wooden furniture (Scholz and Decker, 2007), to elicit preferences for health technologies (Danner et al., 2011), or to test if AHP was a good representation of preferences for chocolate boxes (Ishizaka et al., 2011). AHP has been also applied in studies where its ability to represent consumer preferences is compared with the traditional approach to assess preferences in the marketing field, Conjoint Analysis (CA). These studies addressed several topics, such as textile products (Mulye, 1998), education (Helm and Steiner, 2004; Scholl et al., 2005), tourism packages (Meißner et al., 2008), environment policies (Moran et al., 2007), health disorders (Ijzerman et al., 2008, 2012), household small appliances (Meißner and Decker, 2009), food (Kallas et al., 2011), or mobile service platforms (Nikou et al., 2015).

MAUT/MAVT allows consumers to define their preferences in the form of multiattribute utility functions (Keeney and Raiffa, 1993) in MAUT or value functions (Dyer and Sarin, 1979) in MAVT. The difference between MAUT and MAVT is that the former defines functions that can be used in lotteries (i.e., in decisions involving uncertainty), whereas the latter does not involve uncertainty. Although such a distinction is important in theory, von Winterfeldt and Edwards argue that in practice the distinction often does not matter (von Winterfeldt and Edwards, 1986). For simplicity, and also to match the use of the word "utility" in CA, in this work we use the term MAUT even though we do not use lotteries in the elicitation. Thus, in our context "utility" refers to the value or worth of an alternative to a consumer, as in CA, UTA, and MUSA methods which also do not involve von Neumann-Morgenstern lotteries. Nevertheless, our context does not involve

uncertainty and we are in fact using multiattribute value functions, which require less stringent independence conditions than MAUT for using an additive model (Keeney and Raiffa, 1993).

MAUT has been applied very often in environmental-related fields. A review of MAUT applications in energy and environmental modeling shows that, in these application areas, MAUT was applied more often to assess preferences about energy utility operations and management, and energy-related environmental control (Zhou et al., 2006). MAUT has been also applied to analyze preferences regarding natural resource management problems (Bell, 1975; Teeter and Dyer, 1986; Pukkala, 1998; Prato, 1999; Ananda and Herath, 2005).

2.2. Analysis of preference learning effects in surveys

The data collection of consumer preferences is commonly done through SP surveys which comprise a set of choice tasks (rating or ranking tasks are also possible, but are currently less used). A sequence of choice-based tasks has a high potential for providing rich data about consumer preferences. However, it also raises concerns about the stability of preferences, as the accuracy of choices and the underlying decision strategies may change during the survey answering process (Czajkowski et al., 2014). These phenomena are known as ordering effects and they have several possible explanations. One explanation is institutional learning: since most consumers never answered to SP surveys before, it is expected an increase of accuracy of responses as they become more familiar with the mental mechanism to answer the choice questions. A second explanation is preference learning or value learning: as the consumer becomes more familiar with its own preferences and with the decision environment, the decisions become more coherent. A third explanation is fatigue or boredom: as consumers can get tired by answering to several choice tasks, after some time their responses may exhibit high levels of randomness. Lastly, there is the starting point effect: as consumers anchor their preferences to features included in the initial SP question (Day et al., 2012). The literature focused on analyzing ordering effects is extensive (see Czajkowski et al., 2014). However, as in this study we are particularly interested in the potential effect of value or preference learning on preferences we centered the review on studies focused on analyzing this effect (Table 1).

Study	Goal	Subject	SP survey design	Results
Morrison (2000)	To examine willingness to pay and willingness to accept responses while controlling for substitutability, learning, and imprecise preferences	Mugs and chocolates	Five repeated trials of the same group of questions	Consumers learned their preferences over the trials
Shiell et al. (2000)	To test whether people have complete preferences over health states or whether the process of eliciting values forces influences preferences	Health services	Interviews in three time periods	Respondents constructed their preferences during the elicitation tasks
Carlsson and Martinsson (2001)	To analyze the existence of differences between a hypothetical choice and an actual choice experiments	Donations for environmental projects	Answer to 16 different choice sets (two sequences of 8 choices)	The elicitation task influences the construction of consumer preferences
Johnson and Bingham (2001)	To evaluate how consistency and rationality can provide tests of the validity of SPs estimates for health valuation research	Health state	Repeated questions from the beginning and end of the SP question sequence	Preferences were almost consistent across the questions
Swait and Adamowicz (2001)	To test if preferences change with choice complexity and task order	Food choice (Frozen concentrate orange juice)	Answer to 16 different choice sets	Aggregate preferences change as choice complexity changes and as the task progresses
Desarbo et al. (2004)	To capture structural changes that may affect the elicitation of consumer preferences	Student apartment	30 rating profiles	The structure of preferences changes significantly over the sequence of profile responses
Holmes and Boyle (2005)	To test whether preferences are stable across a sequence of policy packages	Forest management	4 profiles to vote	People learn about their preferences for attribute based environmental goods by comparing attribute levels across choice sets
Savage and Waldman (2008)	To investigate the survey mode on respondent learning and fatigue	High speed internet service	8 questions of paired comparisons	Respondents answer questions consistently throughout a series of choice experiments
Brouwer et al. (2010)	To examine how repeated choice affects preference learning in SP experiments	Water scarcity	Five choice cards with repetition of the first card in the end	Results indicate that learning occurs
Carlsson et al. (2012)	To understand how learning processes potentially affect respondents' SP in a sequence of choice sets	Food choice (chicken breast filets)	two trials of eight choice sets	Preference learning can be of significant structural importance when conducting choice experiment surveys
Hess et al. (2012)	To investigate evidence of respondent fatigue across a larger number of different surveys	Transport (route choice)	8 choice tasks	Possibility of learning of true preferences as a respondent proceeds through the survey
Czajkowski et al. (2014)	To analyse the presence or fatigue on preferences taking into account unobservable preference and scale heterogeneity	Environmental protection)	26 choice sets (order randomized for each respondent)	Evidence of learning on consumer preferences

Table 1 Studies focused on learning effects on preferences.

Studies focused on the existence of a learning effect usually have SP surveys with specific design characteristics in order to identify such effect. There are three main survey designs reported in the literature. One corresponds to the traditional SP survey where data is collected through a set of different questions (Desarbo et al., 2004; Holmes and Boyle, 2005; Savage and Waldman, 2008; Hess et al., 2012; Czajkowski et al., 2014) and the other two involve the repetition of questions. In some studies the repetition of questions is done through repeated trials of questions in different time periods (Morrison, 2000; Shiell et al., 2000; Carlsson et al., 2012) or at the same time (Carlsson and Martinsson, 2001). Other studies repeat at least one question in the beginning and in the end of a sequence of questions (Johnson and Bingham, 2001; Brouwer et al., 2010). A common characteristic to all the surveys is the use of only one type of elicitation method along the survey and the type of questions used more often is choice (Carlsson and Martinsson, 2001; Swait and Adamowicz, 2001; Brouwer et al., 2010; Carlsson et al., 2012; Hess et al., 2012; Czajkowski et al., 2014).

Regarding the results, with the exception of Johnson and Bingham (2001) and Savage and Waldman (2008) that verified almost consistent preferences across the questions, all the studies found learning effects on preferences.

3. Methodology

In this study two elicitation methods were applied in order to analyze if a learning effect about consumer preferences for AFV could be obtained through performing an MCDA task prior to answering CBC questions. These methods are described next.

3.1. Choice-Based Conjoint Analysis (CBC)

CBC, a method from CA, was chosen for two main reasons. First, CBC, by consisting in simulated purchase decisions, is considered to be a more realistic and simple method than CA methods that ask for product ratings (Jaeger et al., 2001; Borghi, 2009). Second, CBC has become the most commonly used method in the literature to analyze consumer preferences in the context of purchasing a vehicle (e.g. Ewing and Sarigöllü, 2000; Potoglou and Kanaroglou, 2007; Ahn et al., 2008; Mau et al., 2008; Axsen et al., 2009; Caulfield et al., 2010; Hidrue et al., 2011; Glerum et al., 2014) and in studies focused on analyzing learning effects on preferences (subsection 2.2).

Choice-Based Conjoint/Hierarchical Bayes (CBC/HB) was selected to analyze SP data from CBC as it allows analyzing data at the individual level. CBC/HB models preference data through an iterative process as a function of an upper-level model (pooled across consumers) and a lower-level model, at the individual level (pooled within-consumer) (Orme and Howell, 2009). The upper-level model gives the variation of consumer's preferences and the variation in their part-worths over the population (Lenk et al., 1996):

$$Y_c = X_c \beta_c + \epsilon_c \quad (1)$$

$$\beta_c = \Theta z_c + \omega_c \quad (2)$$

In equation (4.1), Y_c represents a vector of m_c metric responses for consumer c ($c = 1, 2, \dots, l$) to the profiles described by a given design matrix X_c . β_c is the p -dimensional vector of regression

part-worths for consumer c . Equation (2) represents the heterogeneity of each consumer by giving individual-level part-worths via a multivariate regression model with q -dimensional covariates, z_c , and Θ , a p by q matrix of regression coefficients. The error terms ϵ_c and ω_c are assumed to be mutually independent (Lenk et al., 1996).

The output of the CBC/HB methodology is a set of utilities for each attribute for each consumer, attributes part-worth utilities, that are assumed to have a multivariate normal distribution (Allenby and Ginter, 1995; Orme, 2009b). The consumer is assumed to choose the alternative that yields the maximum overall utility, U . The overall utility of an alternative for the consumer c , $U_c(a)$, is obtained by adding up the part-worths for the attribute levels that describe that alternative according to the following equation (Malhotra, 2008):

$$U_c(a) = \sum_{k=1}^m \sum_{j=1}^p \beta_{kjc} x_{kj} \quad (3)$$

Where,

β_{kji} is the part-worth utility of level j ($j = 1, 2, \dots, p$) of attribute k ($k = 1, 2, \dots, m$) for consumer c ($c = 1, 2, \dots, l$);

x_{kj} is a dummy variable, equal to 1 if the level j of the attribute k is present in alternative a , and 0 otherwise.

3.2. Multiattribute Utility Theory-based method (MAUT)

Among the MCDA methodologies, the additive MAUT was selected as it is one of the most widely used multicriteria methodologies (Belton and Stewart, 2002), namely in preference assessment in the environmental-related field (see subsection 2.1). This method rests on the assumption that there is an intuitive attempt to maximize the function that aggregates all the attribute utilities of each alternative into a global evaluation (Bous et al., 2010). Similarly to the model in Equation (3), MAUT assumes the existence of a utility function (formally, in our case, a value function) that represents the consumer preferences. The overall utility of each alternative for each consumer c , $U_c(a)$ is a weighted sum of the attribute utilities and their weights through the following equation (Keeney and Raiffa, 1993):

$$U_c(a) = \sum_{k=1}^m w_{kc} u_{kc}(a) \quad (4)$$

Where,

w_{kc} is the weight (scaling constant) of attribute k ($k = 1, 2, \dots, m$) for consumer c ($c = 1, 2, \dots, l$);

$u_{kc}(a)$ is the marginal utility of alternative a in the attribute k for consumer c .

4. Stated Preference survey

The SP survey elicited preferences through CBC and MAUT, but each consumer had to perform three tasks. Similarly to previous studies (Morrison, 2000; Shiell et al., 2000; Carlsson and Martinsson, 2001; Carlsson et al., 2012) our analysis comprised the repetition of the same group

of choice sets, the CBC task in this case. Therefore, the structure of the survey was the following (Figure 1):

- Task 1 (CBC Initial): CBC group of questions where consumers had to choose the best and worst option among three vehicles (9 questions);
- Task 2 (MAUT): consumers underwent a MCDA elicitation process to derive their individual utility functions for each attribute separately and to determine their weights;
- Task 3 (CBC Final): Repetition of task 1.

The main novelty of our methodological approach is the “elicitation chain” above specified, where three elicitations were performed for each consumer through two elicitation methods. This allows comparing the results of Task 1 and Task 3, aiming at assessing the potential role of MAUT to stimulate introspection and learning. In Task 3 the consumer answers the same questions already answered in Task 1. This has the advantage of allowing to compare not only the resulting CA models, but also to compare the individual answers, thereby allowing a richer analysis. On the contrary, it has the disadvantage that the consumer might remember the original answers given in Task 1. To mitigate this risk, the consumers were not given a record of questions and answers, and Tasks 1- 3 were carried out on different days.

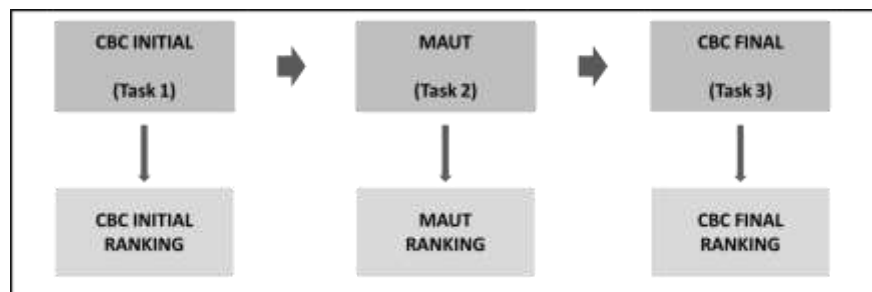


Figure 1 Flow chart of the survey tasks and main output.

The survey design is detailed in the next subsections with the description of the attributes and alternatives (§4.1) and the specifications of each task, CBC (§4.2) and MAUT (§4.3)

4.1. Attribute and alternatives selection

The selection of attributes that allow characterizing and distinguishing the alternatives set is an important feature in studies that assess preferences. When the focus is on innovative products such selection becomes more relevant because consumers are not familiar with the products that are going to be assessed. According to a previous study, purchase price, fuel consumption, range and CO2 emissions, in this order, are the most relevant characteristics for consumers when differentiating similar vehicles with different powertrains (Oliveira and Dias, 2015). The type of engine was added to this list of attributes in order to distinguish the vehicle technology of each alternative. The attributes are described as follows:

- Type of engine: vehicle technology;
- Purchase price: cost to acquire a vehicle, measured in €;

- Range: distance that can be driven without fueling/charging the vehicle, measured in km;
- Fuel consumption: cost to drive 100 km, measured in €/100km;
- CO₂ emissions: quantity of CO₂ emissions released to the environment during the usage phase of the vehicle, measured in g/km.

The selection of these attributes was corroborated by the sets of attributes most commonly used in consumer preferences studies applied to the purchase of AFV. In order to approximate the vehicle purchase scenario of this study with the real market context of Portugal, five existing vehicle technologies were considered, BEV, PHEV, HEV, Diesel and Gasoline. The attribute values of each vehicle followed existing models in the Portuguese market (Table 2). Consumers were instructed to consider the vehicles equal on all the attributes not listed.

Type of engine	Price (€)	Range (km)	Fuel consumption (€/100km)	CO ₂ Emissions (g/km)
BEV1	29,000	180	2	50
BEV2	31,000	250	2	50
HEV	27,000	1100	5	110
Gasoline	24,000	800	9	150
Diesel	27,000	1200	6	120
PHEV	34,000	1200	3	90

Table 2 Characteristics of the alternatives set.

4.2. CBC task

As a specific alternative set was considered (Table 2) the attribute levels were defined in order to be as similar as possible to the alternatives' attributes values. This procedure ensured an approximation of the experience with a real purchase context in the Portuguese market (Kotri, 2006). The attribute levels are depicted in Table 3. The CBC task was determined by a fractional factorial design that combined all these attribute levels. This allowed obtaining a comfortable number of questions for each consumer once a full factorial design would comprise $3125=5^5$ product profiles (different combinations of attribute levels). As possible unrealistic combinations might occur, some prohibitions were defined in order to make this task as realistic as possible. These prohibitions were made carefully in order to minimize the impact on the design efficiency that they might have. Examples of those prohibitions were the combination of BEV with ranges of 900km or higher, and the combination of Gasoline or Diesel vehicles with fuel consumption of 2€/100km or with CO₂ emissions of 50g/km.

The CBC task was designed using Sawtooth® software, which obtained 8 versions of 9 questions each that were randomly assigned to each consumer. Each question comprised a choice set of three vehicles to order (rank-order questions), i.e., to choose which one was the most and least preferred alternative in each triplet according to his or her preferences. A careful check was made through each choice set in order to avoid and, if necessary, eliminate the existence of

dominated alternatives that would provide redundant information for the analysis, without compromising the efficiency of the survey design.

The full set of CBC questions (9) was revealed at the same time to mitigate the existence of order effects, namely the starting point effect (Day et al., 2012). Figure 2 shows an example of such questions that include three choices that vary on the five attributes selected.

<i>Attribute</i>	<i>Levels</i>
Type of engine	BEV / PHEV / HEV / Diesel / Gasoline
Price	24,000€ / 27,000€ / 30,000€ / 32,000€ / 34,000€
Range	150 km / 250 km / 350 km / 900 km / 1200 km
Fuel consumption (per 100 km)	2€ / 4€ / 6€ / 8€ / 10€
CO ₂ emissions (per km)	50 g / 90 g / 110 g / 130 g / 150 g

Table 3 Attribute levels for experimental design.

Choose the best and worst option according to your preferences:

	Option A	Option B	Option C
Type of engine	Diesel	BEV	PHEV
Purchase price	27000 €	30000 €	34000 €
Range	1200 Km	150 Km	1200 Km
Fuel consumption	6€/100Km	2€/100Km	4€/100km
CO ₂ Emissions	130g/Km	50g/Km	90g/Km
BEST OPTION	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
WORST OPTION	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 2 Example of a CBC question.

4.3. MAUT task

The MAUT-based approach was defined in order to require a higher cognitive effort during the preferences elicitation from consumers and, therefore, allowing to fulfil the outlined goal for this study. In this context the MAUT-based approach comprised the bisection method to elicit utility functions and the trade-offs method to elicit attributes' weights (Morton, 2018) as described next.

The bisection method was selected to compute attribute utilities because it is a common approach for continuous attributes. This method is an indirect assessment of the attributes' utility functions. It assumes that these functions are monotonically increasing or decreasing, if the attribute is to maximize or minimize respectively, along the attribute range of values (Belton and Stewart, 2002). In order to assess the utility functions, the maximum and minimum performance utilities of each attribute were defined, so that all attributes have performance utilities within the same interval. Next, consumers had to define which performance value would split the full range

interval in two, in terms of utility (Table 4), such that when the performance value changes from the minimum performance (utility=0) to the midpoint performance the added utility is the same as when changing from that midpoint performance value to upper performance (utility=10). This performance corresponds to the utility of 5. Then, the same process was repeated to bisect the interval values [0, 5] and [5, 10], or if more precision was needed the bisection of subintervals could be continued (Belton and Stewart, 2002; Morton, 2018). Consumers could visualize the graphs of the utility functions that were constructed for the different attributes, giving them the opportunity to revise the assigned values in case of disagreement with the shape of a function.

Regarding the computation of the attribute weights the trade-off method was used. Given a pair of alternatives that differ in only two attributes (and such that one does not dominate the other), consumers were asked to perform a matching task consisting in the adjustment of one attribute level of one of the alternatives such that the alternative became as attractive as the other one (Keeney and Raiffa, 1993). The purpose of this approach was to find pairs of values of two attributes such that these outcomes were indifferent for the consumer, i.e., these outcomes were equal in utility, from which the attribute weights trade-off rate was derived. The attribute weights task consisted in the adjustment of pairwise comparisons in order to obtain the mentioned equalities between attribute values. For the example in Figure 3 the following question would be asked: “Would you prefer a vehicle costing 30,000€ with a range of 1000km or a vehicle costing 25,000€ but with a lower range of 800km”. If the consumer preferred the alternative on the left, then the question would be repeated considering a lower price for the alternative on the right. Otherwise, the price of the alternative on the right would increase. The process continues by trial-and-error until the consumer is indifferent between the two alternatives.

As the consumer is questioned separately on each attribute, the MAUT based approach minimizes the information overload problem that is common on CA methods (Srinivasan and Park, 1997) but it demands more cognitive effort from consumers by requiring a more detailed analysis of each attribute.

Level	Range
10	1300 Km
7.5	?
5	?
2.5	?
0	150 Km

Table 4 Bisection method for range attribute.

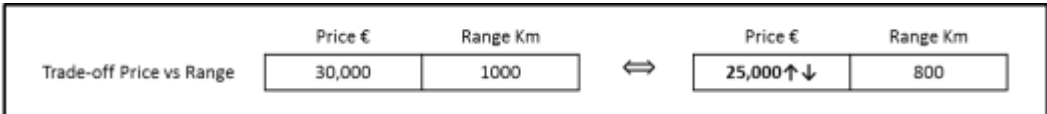


Figure 3 Example of trade-off task between attributes price and range.

5. Analysis of results

Data was collected through face-to-face interviews. After excluding incomplete surveys 219 consumers were considered for this analysis.

The analysis of learning effects on preference data was done through ranking analysis techniques in order to answering to the outlined research questions:

- RQ1: Are the CBC answers different from Task 1 to Task 3?
- RQ2: Are the rankings derived from CBC answers different from Task 1 to Task 3 and, if so, are differences aligned with the performed MAUT analysis?

First, we analyzed the differences between CBC tasks to verify if the preference data collected in the two CBC trials was significantly different. Then, we analyzed the reversals alignment between CBC-derived rankings and MAUT ranking.

The analysis of differences between the CBC Initial and CBC Final tasks was based on the Kemeny distance, which measures the number of permutations (pairwise disagreements) between linear rankings (Kemeny, 1959). As each choice task consisted in three alternatives to rank, the Kemeny distance between the CBC Initial and the CBC Final answers was computed. The results showed that only 8% of consumers gave exactly the same answers to the nine CBC Initial and Final questions (figure 4). The average distance between the two sets of answers was found to be statistically different from 0 (at a significance level of 0.05).

The Sawtooth® software was used to run the CBC-HB model, where a goodness of fit (“percent certainty” measure) of 0.68 and 0.70 for CBC Initial and CBC final, respectively, was obtained. The best-fit parameters for the CBC-HB model (β of equation 3) were used to rank the alternatives on Table 2. We refer to the ranking thus obtained after Task 1 as the CBC Initial ranking and we refer to the ranking obtained from the answers in Task 3 as the CBC Final ranking (Figure 1). The differences between these two rankings were also assessed using the Kemeny distance. Results showed that 15% of consumers had the same derived rankings (CBC Initial ranking=CBC Final ranking) (Figure 5) and that the average distance between the rankings was found to be statistically different from 0 (at a significance level of 0.05).

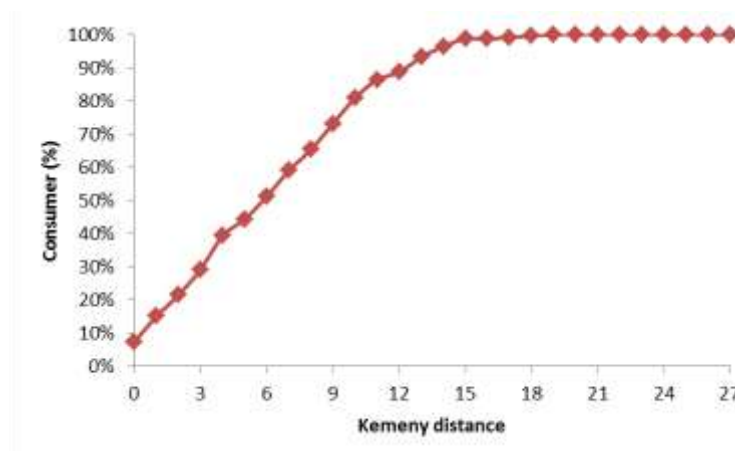


Figure 4 Kemeny distance between CBC Initial and Final answers (cumulative frequency).

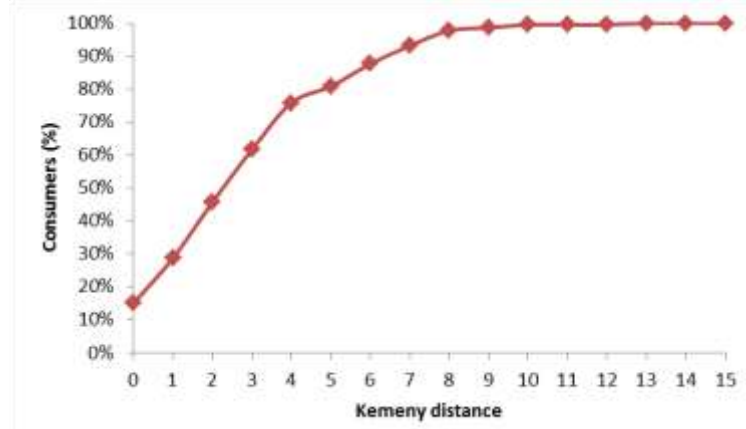


Figure 5 Kemeny distance between CBC Initial and Final rankings (cumulative frequency).

An analysis of ranking reversals was also made, based on the 85% of consumers that had different CBC Initial and Final rankings, aiming to assess how much were these reversals of preferences aligned with the MAUT task. This analysis was made in three steps, considering each consumer c . First, we built a matrix that indicated the ranking reversals between pairs of alternatives, i and j , from CBC Initial ranking to CBC Final ranking, $HD_c(i, j)$ (equation 5). The second step consisted in building a second matrix that indicated the preference relation between pairs of alternatives, i and j , according to the MAUT ranking, $AD_c(i, j)$ (equation 6). The third and final step consisted in the combination of the two matrixes (from step 1 and 2) according to the equation 7 and 8. SA_c represent the sum of all the reversals for each consumer c ($c = 1, 2, \dots, l$) that agree with MAUT preference relations, i.e. SA_c counts the reversals from CBC initial to CBC final ranking that were aligned with the preference relations in the MAUT ranking. SD_c counts the reversals from CBC Initial to CBC Final ranking that disagree with the MAUT preference relations, for each consumer c .

$$HD_c(i, j) = \begin{cases} 1, & \text{if } i >_c j \text{ in CBC Initial ranking} \wedge j <_c i \text{ in CBC Final ranking} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$$AD_c(i, j) = \begin{cases} 1, & \text{if } j <_c i \text{ in MAUT ranking} \\ -1, & \text{otherwise} \end{cases} \quad (6)$$

$$SA_c = \sum_{i \neq j: AD_c(i, j) = 1} HD_c(i, j) = \#\{(i, j): HD_c(i, j) = 1 \wedge AD_c(i, j) = 1\} \quad (7)$$

$$SD_c = \sum_{i \neq j: AD_c(i, j) = -1} HD_c(i, j) = \#\{(i, j): HD_c(i, j) = 1 \wedge AD_c(i, j) = -1\} \quad (8)$$

In this step, the percentage of aligned reversals, $A_c = SA_c / (SA_c + SD_c)$, was computed. The results are depicted on Figure 6, where the following observations can be made:

- Approximately 50% of the consumers have more than 60% of their reversals aligned with MAUT rankings.
- For 25% of the consumers the reversals between the CBC rankings were totally aligned with their MAUT rankings.

- For 23% of consumers all the reversals between the CBC rankings occurred in the opposite direction of the MAUT ranking.

The analysis of the structure of preferences of the consumers that had a complete alignment with MAUT ranking allowed us to observe that for 11% of the consumers the ranking reversals led to a perfect match between CBC Final ranking and MAUT ranking. Additionally, we observed that the three main ranking reversals of these consumers led to an AFV being preferred to fossil vehicles, namely, HEV>Diesel; PHEV>Diesel; and BEV1>Gasoline.

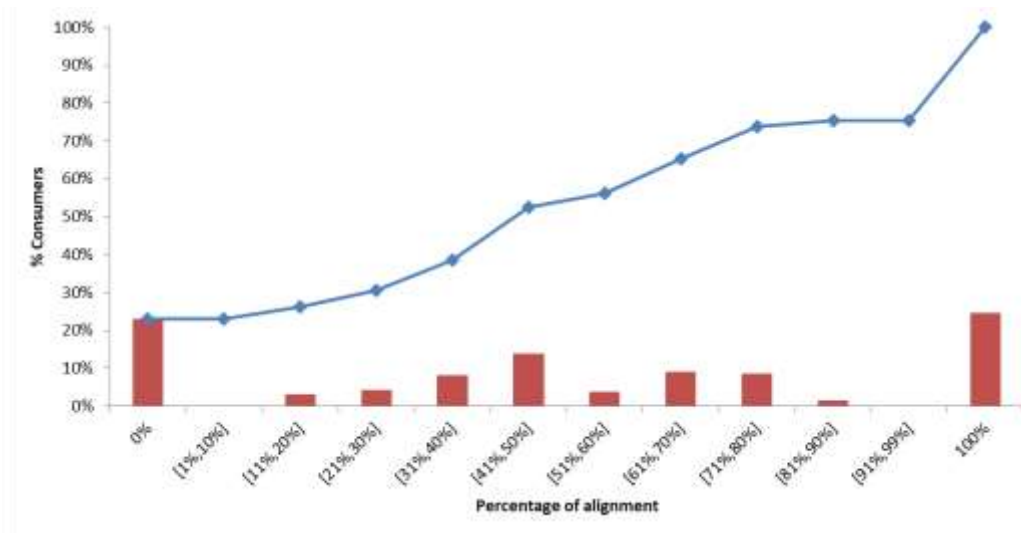


Figure 6 Percentage of reversals aligned between CBC-derived rankings and MAUT ranking (bars represent the relative frequency and the line the cumulative frequency of the alignment).

Finally we analyzed the most frequent reversals between the CBC elicited rankings and the MAUT ranking, independently of the reversal direction (Figure 7). This analysis allowed identifying that consumers reversed the position of three pairs of vehicles more often, namely Diesel-HEV, BEV1-BEV2 and HEV-BEV1, which represent 10.2%, 9.2% and 8.6% of the total reversals, respectively. On the opposite, the three most stable preferences between two pairs of vehicles were Gasoline-PHEV, Gasoline-HEV and Diesel-Gasoline, accounting for 4.2%, 4% and 3.3% of total reversals, respectively.

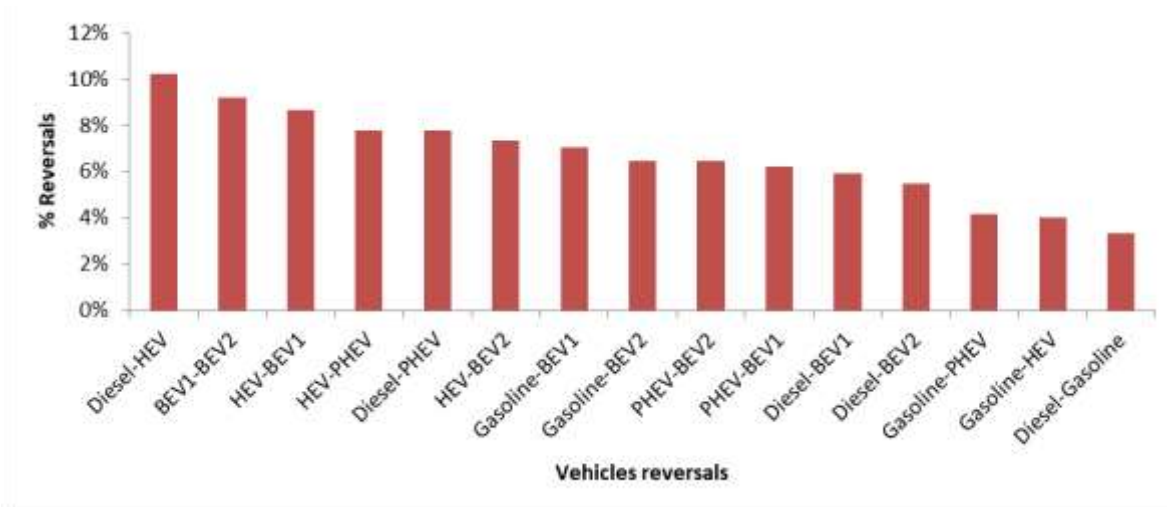


Figure 7 Percentage of total reversals, by decreasing order.

Looking at the reversal direction between AFV and fossil vehicles (Figure 8), one can observe a general trend where the reversals favoring an AFV over a fully fossil fuel vehicle (Diesel or Gasoline) tend to be aligned with the MAUT ranking, mainly regarding to the preferences of HEV and PHEV over Diesel vehicles and BEV over Gasoline vehicles. The reversals aligned between CBC and MAUT rankings that favor AFV reach 85% of the total aligned reversals (Figure 9).

Concerning the least stable pair, there was a potential preference construction between HEV and Diesel vehicles as the reversal from Diesel to HEV, aligned with MAUT, occurred for a majority of the consumers (Table 5).

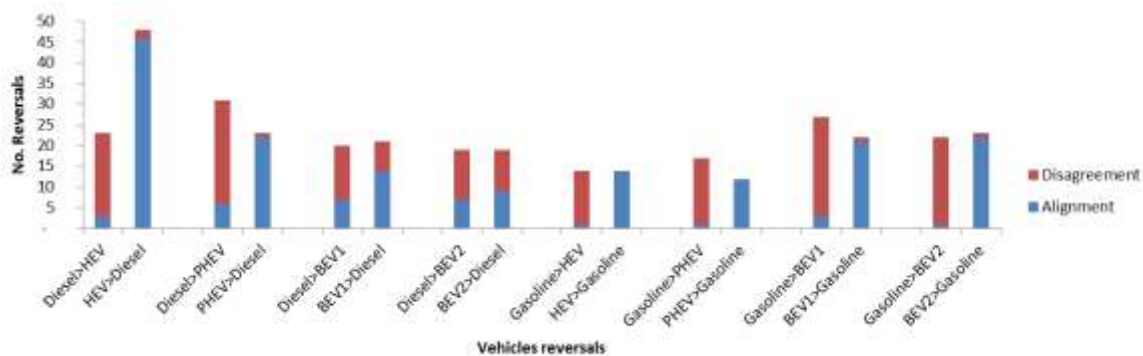


Figure 8 Number of aligned and disagreed reversals between AFV and fossil fuel vehicles according to the preference direction in the MAUT model.

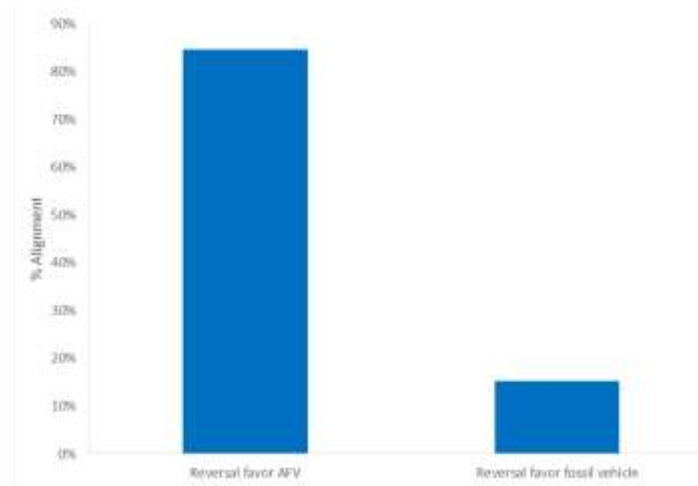


Figure 9 Percentage of alignment of reversals between CBC and MAUT favoring AFV and fossil vehicles.

	Alignment	Disagreement	
Diesel>HEV	3 (4%)	20 (28%)	23 (32%)
HEV>Diesel	46 (65%)	2 (3%)	48 (68%)
	49 (69%)	22 (31%)	

Table 5 Potential preference construction for the least stable pair.

6. Conclusions

The problematic of market penetration of AFV has led to several studies aiming to understand how to increase the demand for these vehicles. Understanding consumer preferences and the process of construction of such preferences is a valuable knowledge that can help identifying strategies to overcome the low diffusion of AFV.

This study suggests the use of another elicitation method that demands a higher cognitive effort in comparison with CBC, namely a MAUT-based approach. The purpose was to analyze its potential to leverage the learning of preferences elicited through CBC, i.e. to understand if consumers learned/constructed their preferences through the MAUT task and reflect that learning in the CBC answers.

In line with previous findings, significant differences were found between the two CBC elicited rankings. As mentioned earlier, these results may have several explanations, such as institutional learning, preference learning, fatigue or starting point effect. As the number of CBC questions was small (fatigue usually appears in surveys with more than 10 questions (Caussade et al., 2005)) and the set of CBC questions was displayed at the same time (to mitigate the starting point effect), we excluded these two possible causes for the differences found between the two preference elicitation trials. Therefore, we can assign the potential differences in elicited preferences to institutional learning and preference learning. It is unclear how to separate the effects of these two types of learning and it is usually expected that institutional learning takes place in the initial questions and preference learning emerges later (Bateman et al., 2008;

Czajkowski et al., 2014). Therefore, learning effects occurred but it was not possible to specify which one. Consumers may have constructed/learned their preferences at the time of preference elicitation, possibly due to two interrelated reasons. First, consumers may not have well-formed preferences at the time they stated their preferences as the vehicles set included three innovative technologies were unfamiliar for most of them. And second, the inclusion of the MAUT procedure in the preferences elicitation process may have supported the preference formation/learning process by demanding more cognitive effort and time to elicit preferences.

In order to understand the potential effect of the MAUT task on the preference learning process we analyzed the alignment between the preference reversals from the CBC Initial to the CBC Final ranking, and the elicited MAUT preference model. The outcome of this analysis revealed a strong influence of the MAUT task on CBC Final results for one quarter of consumers (100% of preferences alignment) and a relative influence for another quarter of consumers (>60% of preferences alignment).

Rather than seeing MCDA and CBC as competing approaches, our study suggests using these approaches complementarily. Instead of asking CBC questions to obtain immediate responses, an MCDA task can be used as a “warming up” device to encourage the consumer to think and learn (construct) about his or her preferences. Our results suggest that the ensuing CBC answers, informed by such learning, are different from the ones the consumer gave if the MCDA task was not carried out. Nevertheless, it should be noted that this study focused on a specific type of products. We conjecture that the effect of performing an MCDA before answering CBC questions will be more pronounced when products are complex and when the consumer’s immediate self-interest conflicts with long term or public good rewards. Further studies considering different types of products are needed to confirm (or not) this conjecture.

This work highlights the relevance of collecting preferences through different elicitation procedures as it provides a deeper understanding about consumer preferences construction and also richer data about the preferences structure. Therefore, for future research we suggest that more studies should be carried out in preference learning for AFV because a deeper knowledge about consumer preferences would allow identifying and suggesting more efficient diffusion strategies for more sustainable types of vehicles.

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