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Cognitive consistency and preferences for alternative fuel vehicles: A latent class model

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ABSTRACT

Long-term decisions, such as electric vehicle purchases, typically involve assessing complex interactions among several cognitive components. These psychological constructs are often a source of heterogeneity in the preferences for instrumental attributes. In this paper, we analyse vehicle fuel type choices using a latent class-discrete choice model where attitudinal and emotional appraisals of the electric vehicle purchase decision influence both class membership and preferences within each class. The model is estimated using data from a stated choice experiment and an attitudinal questionnaire. Attitudinal and emotional outputs come from the hot coherence (HOTCO) model, where motivation and behavioural response interact with each other to produce a consistent assessment. Our results reveal three distinct user segments in the sample – potential innovators, laggards, and sceptics, with markedly different purchase motives, preference parameters, and decision-making profiles. The HOTCO attributes help identifying the cognitive aspects that shape decision-making which is beneficial for effective policy design.

1. Introduction

Individual attitudes and emotional appraisals are key determinants of transport choices. Studies addressing the impact of psychological factors on transport preferences tend to rely on attitude-behaviour link theories (such as the Theory of Planned Behaviour – TPB; Ajzen, 1991) that assume linear and unidirectional links between psychological constructs (e.g. attitudes influence intentions, and intentions predict behaviour) and consider independent evaluations of each of their components. However, it is likely that human decision-making is substantially affected by mutual and complex interactions between attitudes, emotions, and other components of the cognitive representation (Simon & Stenstrom, 2015). This is particularly true for long-term transport decisions such as household vehicle purchases and fuel type choices, which typically involve simultaneously assessing several elements, including instrumental variables and cognitive components of the mental representation, before reaching a decision.

Differently from the attitude-behaviour link theory, cognitive consistency theories conceptualise decision-making as a process by which individuals try to minimise inconsistency between given pieces of information to form a consistent mental representation of the decision (Glöckner et al., 2014). The *hot coherence* (HOTCO) model (Thagard, 1989, 2006; Thagard and Millgram, 1997), the most widely used cognitive consistency theory, assumes that individuals make decisions by maximising the coherence of their current beliefs

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and emotions, where coherence is understood in terms of maximal satisfaction of multiple constraints (namely the relation between *needs* to be satisfied and *actions* to be taken) derived from mental representations of the decision-making process (Thagard, 2001).

Cognitive consistency theories, and in particular the HOTCO model, have been used only sparingly to analyse transport decisions. Wolf et al. (2015) and Schröder and Wolf (2017) are the only papers that implement the HOTCO model to analyse attitudes toward electric vehicle adoption and pro-environmental transport behaviour accounting for interaction between agents in an agent-based model simulation. Domarchi et al. (2024) extended these previous works by focusing on the determinants of the decision to purchase alternative fuel vehicles (AFVs),[1] their interactions and interdependencies. They found that electric vehicles (EVs) and hybrid-electric vehicles (HEVs) are perceived in a remarkably similar way from a cognitive consistency perspective, because they produce the same degree of coherence and satisfy the same sets of needs. Environmental awareness and pro-innovative orientation emerge from their analysis as the two differentiating motives, with AFVs perceived as coherent with their satisfaction, and internal combustion engine (ICE) evaluated as strongly incoherent with it. However, Domarchi et al. (2024) focus only on the psychological perspective of the decision-making process, without considering preferences for economic or instrumental attributes such as purchase price, operation cost, driving range, or charging time, or modelling choice behaviour as a function of these attributes and the HOTCO inputs. Other papers report different preferences for these fuel types (e.g. Lane et al., 2018;; Higueras-Castillo et al., 2020), but their emphasis is only on economic preferences for operational and cost-related attributes.

Numerous studies have confirmed that the adoption of AFVs is correlated with latent psychological constructs (including attitudes towards the environment, innovation-oriented beliefs, and social influence), as well as economic and/or instrumental attributes (such as purchase prices and operation costs, driving ranges, motor power and reliability, and the coverage and specific characteristics of the charging network. (reviews can be found in Domarchi & Cherchi, 2023; Liao et al., 2017; Wicki et al., 2023). In addition, it is also likely that psychological constructs are a source of preference heterogeneity, i.e., that economic preferences for instrumental attributes such as purchase prices, driving ranges, or charging times, vary across the population as a result of differences in attitudinal or emotional evaluations of each fuel type. Bansal et al. (2021) and Ghasri et al. (2019) estimate heterogeneity in preferences for EVs by using interaction between latent variables (measured following an attitude-behavioural link theory) and economic/instrumental attributes. In both studies, individual perceptions about EVs interact with preferences for specific attributes, revealing heterogeneity patterns that change linearly with attitudinal evaluations. It is likely however that the latent psychological constructs might rather identify groups of respondents with similar preferences. Latent class choice models (LCCM) have often been applied to measure this effect. Few studies have used LCCM to address preference heterogeneity in AFV choices (Axsen et al., 2015; Hidrue & Parsons, 2015; Ferguson et al., 2018; Abotalebi et al., 2019; Kormos et al., 2019; Gong et al., 2020). These studies incorporate responses to attitudinal questionnaires into the class membership equations as a method to aid the interpretation of the estimated classes. Still, the questionnaires in these studies are based on attitude-behaviour link theories.

In this paper, we aim to assess the role that cognitive consistency plays in shaping users preference for AFVs and their characteristics, i.e. to assess differences in user evaluation between EVs, HEVs, and ICE vehicles, from an attitudinal and emotional perspective. To our knowledge, no previous studies have attempted an integration between HOTCO and the discrete choice modelling paradigm to study psychological effects in individual choices. We therefore model preferences for AFVs using a Hybrid Latent Class Choice Model (HLCCM) that incorporates latent cognitive consistency evaluations based on the HOTCO theory both as alternative-level attributes to address preference heterogeneity among classes and as individual-level attributes that help with the definition of user profiles. Cognitive consistency is measured by the outputs of the HOTCO model, that represents individual decision-making with a "connectionist" network in which motivation and behavioural response interact with each other to produce a consistent assessment.[2]

The outputs of the implementation of the HOTCO network are the cognitive *activation*, that is a measure of the acceptability of *needs* and *actions*, and the *valence*, which measures the respondents' emotional response. Our specification differs from conventional hybrid choice-latent variable models in that it does not assume a linear and unidirectional relationship between attitudinal indicators and latent variables. The emotional coherence perspective requires all the elements of the psychological evaluation to be mutually interdependent, to achieve a more comprehensive representation of the AFV purchase decision. The paper extends the work previously conducted by Domarchi et al. (2024) by modelling EV choice behaviour as a product of the interaction between HOTCO attributes, and other instrumental and economic attributes, in an integrated framework that also considers preference heterogeneity.

Cognitive consistency theories such as HOTCO offer significant advantages compared with other psychological theories more commonly used to address the effects of attitudes on transport behaviour, such as the Theory of Planned Behaviour (TPB, Ajzen, 1991) or the Technology Acceptance Model (TAM; Davis, 1989). From a theoretical perspective, HOTCO is well-suited to address complex decision-making processes involving multiple motivating factors that require simultaneous evaluation. Instead of a linear and unidimensional link between motivating factors and behaviour, HOTCO constructs a mental representation of decision-making by iteratively assessing the bidirectional flow of information between motives and outcomes. Thus, attitudinal and emotional evaluations of available options emerge as a byproduct of a nuanced and multidimensional assessment of the intervening factors – an effect that is often oversimplified in conventional theories. From a practical perspective, the mental representation generated by the HOTCO model reveals the mechanisms of attitude formation, as general evaluations (activations and valences) of available alternatives are modelled as the outcome of the interaction between the assessment of needs to be satisfied, and the perceived effectiveness of those alternatives.

[1] We use the umbrella term AFV to refer to battery electric vehicles (EVs) or plug-in hybrid electric vehicles (HEVs).

[2] In the HOTCO model, the decision-making process is conceptually represented using a "connectionist network" to organise all the elements that produce a cognitive and affective evaluation. In such a network, units (nodes) represent elements (actions and needs) while links between nodes represent positive and negative constraints (Thagard, 2006).

This representation makes possible to test how changes in evaluations of transport needs affect the strength and polarity of attitudinal evaluations towards fuel types, and which motives are more relevant in inducing sustainable attitudinal change, which can in turn strongly influence choice. Conducting this type of analysis with traditional specifications based on TPB or other attitude-behaviour link theories is challenging, as they rely on more complex and less transparent interactions between indicators, latent variables, and socioeconomic attributes.

The data used to estimate the HLCCM come from a SC experiment on electric vehicles (EVs), specifically designed for this study, in which the choice situations still consider hybrid-electric vehicles (HEVs) as an available alternative, in light of their increasing share in the UK market (Department for Transport, 2024). We also validate our model using an independent dataset to test in particular the effect cognitive consistency in predictive accuracy of individual preferences for AFVs.

The remainder of the paper is organised as follows: Section 2 describes the model structure, the HLCCM, and the utility specification. Section 3 describes the dataset collected to estimate the model. Section 3.1 describes the SC experiment built to collect the choice among AFVs and their characteristics, while Section 3.2 describes the HOTCO questionnaire design (section 3.2.1), and the HOTCO model algorithm implementation (Section 3.2.2). Section 3.3. provides a general overview of the sample collected. Results and discussion are provided in Section 4, while the conclusions, limitations, and recommendations for further research are outlined in Section 5.

2. Modelling framework

The HLCCM model used to estimate the role of cognitive consistency in the preferences for alternative fuel vehicles consists of a Latent Class Choice Model (LCCM) that includes latent variables. The LCCM consists of a Mixed Multinomial Logit (MMNL) model to simulate the probability of choosing a fuel type vehicle and a Multinomial Logit (MNL) model to simulate the probability of belonging to a given behavioural class. The fuel type model considers three purchasing alternatives: electric vehicles (EV), hybrid-electric vehicles (HEV), and internal combustion engine (ICE) cars, as well as an "opt-out" option that was included in the stated choice experiment to increase the realism of the behaviour elicited. The choice probabilities are a function of the classical economic, operational, and instrumental variables, but also a function of the individual cognitive consistency, outputs from the HOTCO model, which are latent variables. Similarly, the class membership models depend on a set of individual-level socioeconomic attributes, as well as on the HOTCO outputs.

Following Walker (2001) and Walker et al. (2007), and extending this framework to consider data collected with a stated choice (SC) experiment, the probability that individual q performs a series of T choices, $P_q(j_1, j, \cdots, j_T)$ is given by:

$$P_q(j_1, j_2, \cdots, j_T) = \sum_{s=1}^{S} P_q(s) \cdot P(j_1, j_2, \cdots, j_T|s) \tag{1}$$

This expression is equal to the sum over all latent classes s of the class-specific choice probability that individual q will make a sequence of choices $j_t = \{j_1, j_2, \cdots, j_T\}$, conditional on belonging to class s, multiplied by the probability of the individual q belonging to class s. Expression (1) represents the contribution by individual q to the likelihood function of the choice model.

The conditional probability of the sequence of choices can, in turn, be expressed as:

$$P_q(j_1, j_2, \cdots, j_T|s) = \int_{\eta} \prod_{t=1}^{T} P_{qt}(j|s, \boldsymbol{\eta}) \cdot f(\boldsymbol{\eta}) \cdot d\boldsymbol{\eta} \tag{2}$$

Where $P_{qt}(j|s, \boldsymbol{\eta})$ are choice probabilities for choice situation t conditional on belonging to class s and on the unknown $\boldsymbol{\eta}$. The product of probabilities is integrated over the distribution of $\boldsymbol{\eta}$, a multivariate Normal vector representing the error components in the model.

Both probabilities in expression (1) can assume any given form and can be estimated assuming any utility specification. In the context of our LCCM, fuel type vehicle choice is modelled using a MMNL with four alternatives (EV, HEV, ICE, and the opt-out option) and class-specific utilities for each alternative with the following specifications:

$$\begin{gathered} U_{EV,qts} = V_{EV,qts} + \theta_{ACT,s} \cdot \left(ACT_{EV,q} + \sigma_{ACT,EV} \cdot \zeta_{ACT,EV,q}\right) + \theta_{VAL,s} \cdot \left(VAL_{EV,q} + \sigma_{VAL,EV} \cdot \zeta_{VAL,EV,q}\right) + \sigma_{EV} \cdot \eta_{EV,q} + \varepsilon_{EV,qts} \\ U_{HEV,qts} = V_{HEV,qts} + \theta_{ACT,s} \cdot \left(ACT_{HEV,q} + \sigma_{ACT,HEV} \cdot \zeta_{ACT,HEV,q}\right) + \theta_{VAL,s} \cdot \left(VAL_{HEV,q} + \sigma_{VAL,HEV} \cdot \zeta_{VAL,HEV,q}\right) + \sigma_{HEV} \cdot \eta_{HEV,q} + \varepsilon_{HEV,qts} \\ U_{ICE,qts} = V_{ICE,qts} + \theta_{ACT,s} \cdot \left(ACT_{ICE,q} + \sigma_{ACT,ICE} \cdot \zeta_{ACT,ICE,q}\right) + \theta_{VAL,s} \cdot \left(VAL_{ICE,q} + \sigma_{VAL,ICE} \cdot \zeta_{VAL,ICE,q}\right) + \sigma_{ICE} \cdot \eta_{ICE,q} + \varepsilon_{ICE,qts} \\ U_{OPT-OUT,qt} = \sigma_{OPT-OUT} \cdot \eta_{OPT-OUT,q} + \varepsilon_{OPT-OUT,qts} \end{gathered} \tag{3}$$

Here,

- $V_{j,qts}$ (with $j = \{EV, HEV, ICE\}$) is the component of the utility that individual q derives from alternative j in choice situation t, conditional on his/her characteristics and the attributes of the alternative j, and conditional of individual q being a member of class s. We use a linear in the parameters specification where parameter θ_{jls} corresponds to the l-th attribute;
- ACT_{jq} and VAL_{jq} are mean values of individual-level activations and valences generated as HOTCO outputs for the alternative j for individual q. In the HOTCO model, these are the outputs associated with the action nodes;

- ε_{jqts} is the random component of the utility function, varying across alternatives *j*, individual *q*, choice situations *t*, and classes *s*, IID EV1 distributed;
- $\sigma_j.\eta_{jq}$ is an error component associated with alternative *j*, which remains constant across choice situations for each individual *q*, but varies across individuals, allowing to account for intra-individual correlation, with η_{jq} distributed Normal (0, σ_j); and
- $\zeta_{ACT,jq}$ and $\zeta_{VAL,jq}$ are also error terms distributed IID Normal (0,1) that vary across alternatives and individuals but are constant across choice situations. These error terms account for the latent nature of valences and activations.

Two comments are relevant at this point. First, since we use a sequential estimation failing to include $\zeta_{ACT,jq}$ and $\zeta_{VAL,jq}$ would result in biased estimators for these parameters. Secondly, cognitive consistency theories posit that "*a sufficient level of consistency is a precondition for terminating the decision process*" (Glöckner & Betsch, 2008, p. 5), which implies that a connectionist network that takes consistency into account (such as the network used in the HOTCO model, which we present in section 3.2.2) should be able to reasonably predict a behavioural intention. According to this, cognitive evaluations and emotional appraisals exist before the behaviour (choice), are available for individual consideration at the moment of performing it and are not modified during it. This assumption aligns with the usual premises of attitudinal-behavioural link theories – that is, attitudes are formed or changed due to several possible factors, including past experiences, learning, and social influence, and they are one of the determinants of behaviour, i.e. they *precede* it (see for example Petty & Wegener, 1998). Under this assumption, activations and valences for EV, HEV, and ICE are treated as latent variables (unobserved initially but measured as a combination of the HOTCO inputs that were collected using the questionnaire). It is important to note that $\zeta_{ACT,jq}$ and $\zeta_{VAL,jq}$ also account for panel effects in the SC data.

In the basic specification of the model, the θ_{jls} parameters of the conditional utility functions V_{jqts} and the activation and valence parameters, $\theta_{ACT,s}$ and $\theta_{VAL,s}$ are assumed to be class-specific, with no restrictions imposed beforehand. The error component parameters ($\sigma_{ACT,j}$, $\sigma_{VAL,j}$, and σ_j for $j =$ EV, HEV, and ICE) are assumed to be invariant across classes. Finally, since the choice set contains four alternatives, all four variances ($\sigma_{EV}, \sigma_{HEV}, \sigma_{ICE}$ and $\sigma_{opt-out}$) are identified and can be estimated (Walker et al., 2007). We tested several specifications for the error terms, including modelling structures that: i) only included activation and valence error components, ii) only included panel effects, or iii) included generic (instead of alternative-specific) error terms. The chosen structure, including both panel effects and alternative-specific error components for activation and valence, was the best-performing specification in terms of AIC and BIC.

We model the class membership probabilities using a MNL structure as follows:

$$P_q(s) = \frac{exp(F_{qs})}{\sum_{s'=1}^{S} exp(F_{qs'})} \tag{4}$$

Here, F_{qs} are class-specific membership functions, defined as:

$$F_{qs} = \gamma_s + \sum_{k=1}^{K} \beta_{ks} \cdot X_{qk} + \sum_{n=1}^{N} \beta_{ACT,ns} \cdot ACT_{qn} + \sum_{n=1}^{N} \beta_{VAL,ns} \cdot VAL_{qn} \tag{5}$$

These functions depend on *K* sociodemographic characteristics X_{qk}, HOTCO outputs for the *N needs* (ACT_{qn} and VAL_{qn}), individual-specific but invariant across alternatives, and a corresponding set of parameters $(\gamma_s, \beta_{ks}, \beta_{ACT,ns}, \beta_{VAL,ns})$ to be estimated. While the role of alternative-specific variables is clearly limited to the class-specific choice components, individual (e.g., socioeconomic, or psychological/attitudinal) attributes could, in principle, play roles in either the choice model, the class membership model, or in both. As Kim and Mokhtarian (2023) point out, if a variable is conceived as directly influencing the outcome, it should belong to the choice component. Conversely, if a variable is seen as influencing the weight an individual places on other variables that affect the outcome, it should be seen as affecting the class the individual belongs to, and in that case, the class membership function should include it. In our case, HOTCO activations and valences associated with *needs* or motives are individual-level attributes not associated with any alternative and thus we use them as part the class membership functions.

The likelihood function in equation (1) depends on $\boldsymbol{\eta}$, a 10-dimensional vector of multivariate Normal variables, i.e. the 4 alternative-specific error components plus the 6 error components associated with activations and valences described in expression (3). The 10-dimensional integral in equation (2) must be evaluated using numerical integration. The models were estimated using Pandas Biogeme (Bierlaire, 2023).

3. Data collection and Methodology

To estimate the model presented in the previous section, a survey was specifically built to collect the data needed. The survey includes two main components: first, a stated choice (SC) experiment to elicit preference towards vehicle segments and fuel types; and second, a HOTCO questionnaire to measure attitudinal and emotional appraisal of the car purchasing decision and its motivating factors. The survey also included a set of questions to collect socioeconomic information and data about vehicles features in each household.

3.1. Stated choice experiment design

The SC experiment was designed to study the impact of specific attributes on vehicle choice. The experiment was customised to present the respondents with alternatives and attributes that would appear realistic. We used two screening questions to create customised designs, as described in Section 3.1.1. The experimental design, attributes, and levels are discussed in Section 3.1.2. Fig. 1 presents a general flowchart of the choice experiment. The first screening question (Q1) concerns the type of car that respondents would likely purchase. The figure assumes the respondent chose vehicle type 3 (large). The second screening question (Q2) asks about the preferred purchase option, and the figure illustrates the three design scenarios generated for large cars, depending on whether the respondent prefers new cars (7), second-hand cars (8), or both purchase options (9). We built three scenarios for each of the other car types (not shown here). The total number of scenarios is $5 \times 3 = 15$.

3.1.1. Screening questions and scenario definition

Previous research has shown that fuel type and vehicle segment choices are highly correlated, and that the chosen purchase option (i.e., whether the vehicle is bought new or second hand) also plays a relevant role (e.g. Domarchi & Cherchi, 2024). To include these effects in the experiment and customise the choice tasks, the experiment was preceded by two screening questions in which respondents were asked to think about their next car purchase:

- *Which of these car types would you most likely buy?* (Five options: Small, Medium, Large, SUV/MPV, Sports/Luxury). We defined these groups considering aggregations of the nine vehicle segments defined in the European classification scheme (Commission of the European Communities, 1999; Thiel et al., 2014). The survey included a list of illustrative models, as well as a small non-labelled drawing of each vehicle type (see Table 1 and Fig. 2).
- *Which of these purchase options would you consider?* (Three options: I would only consider new cars, I would only consider second-hand cars, I would consider both new and second-hand cars).

The combination of responses to these screening questions generated 15 possible scenarios (5 vehicle groups × 3 purchase options), and a customised SC design was built for each. First, 10 different designs were built for respondents who stated they consider only one purchasing option (i.e. new OR second hand) – one for each segment (5 vehicle groups × 2 purchase options). Each choice task in these designs included four alternatives: EV, HEV, ICE, and opt-out. The choice tasks for each of these scenarios were built using efficient

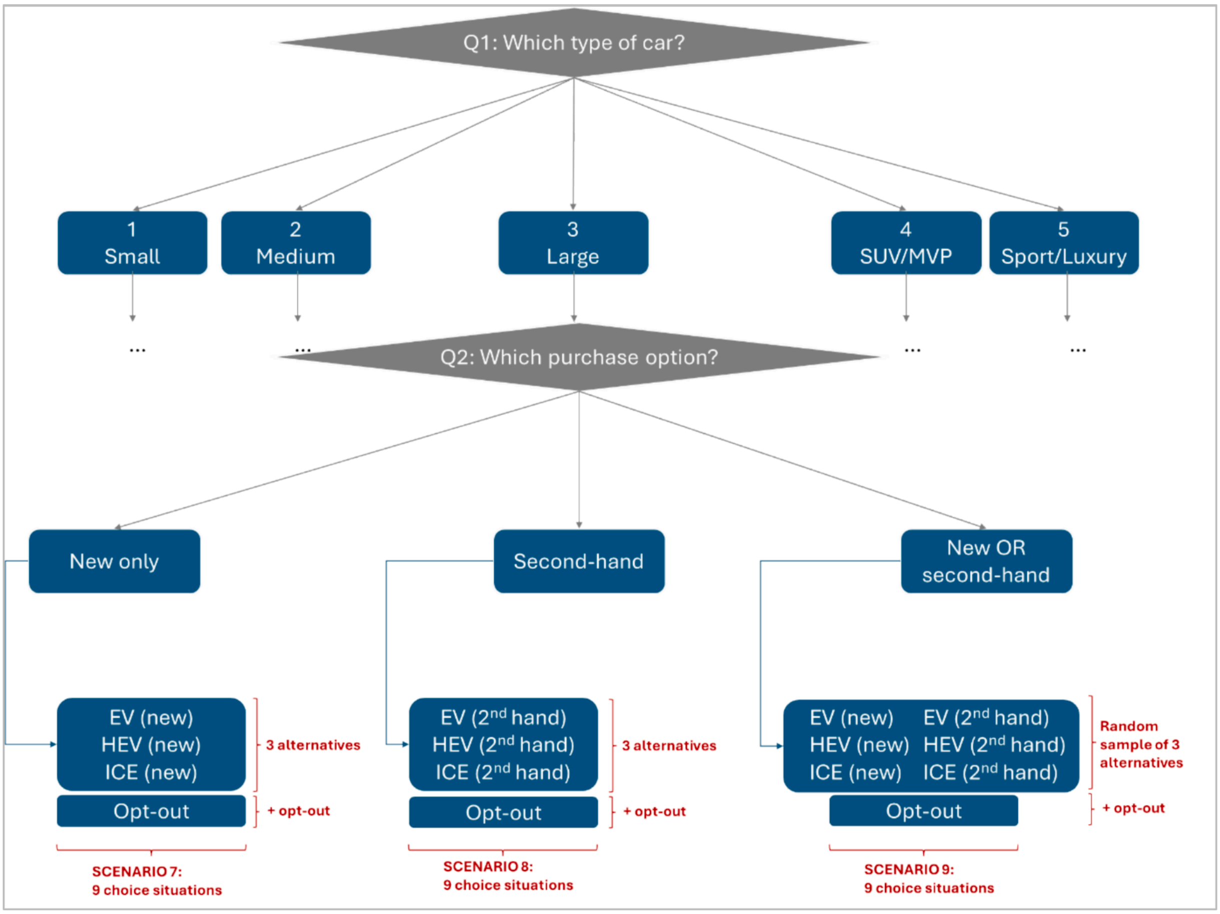

Fig. 1. Flowchart of the stated choice experiment.

Table 1
Summary of vehicle groups and segments.

Group	Segment	NTS share (%)	Example models (for Survey)
1 / Small car	A and B	36.5	Fiat 500, Hyundai i10, Renault Clyo, Vauxhall Corsa, Ford Fiesta, Volkswagen Polo
2 / Medium car	C	20.7	Ford Focus, Volkswagen Golf, Vauxhall Astra, Peugeot 306
3 / Large car	D	10.8	BMW 3 Series, Peugeot 406, Mazda 6, Volkswagen Passat
4 / SUV and multi-purpose	J and M	25.2	Hyundai Tucson, Toyota RAV-4, Honda CRV, Nissan Qashqai, Citroën C4 Picasso, Ford Galaxy
5 / Sport and luxury	E, F, and S	6.8	BMW 7-Series, Jaguar XF, Audi TT, Porsche 911

Vehicle shares are adapted from the National Travel Survey (Department for Transport, 2021)

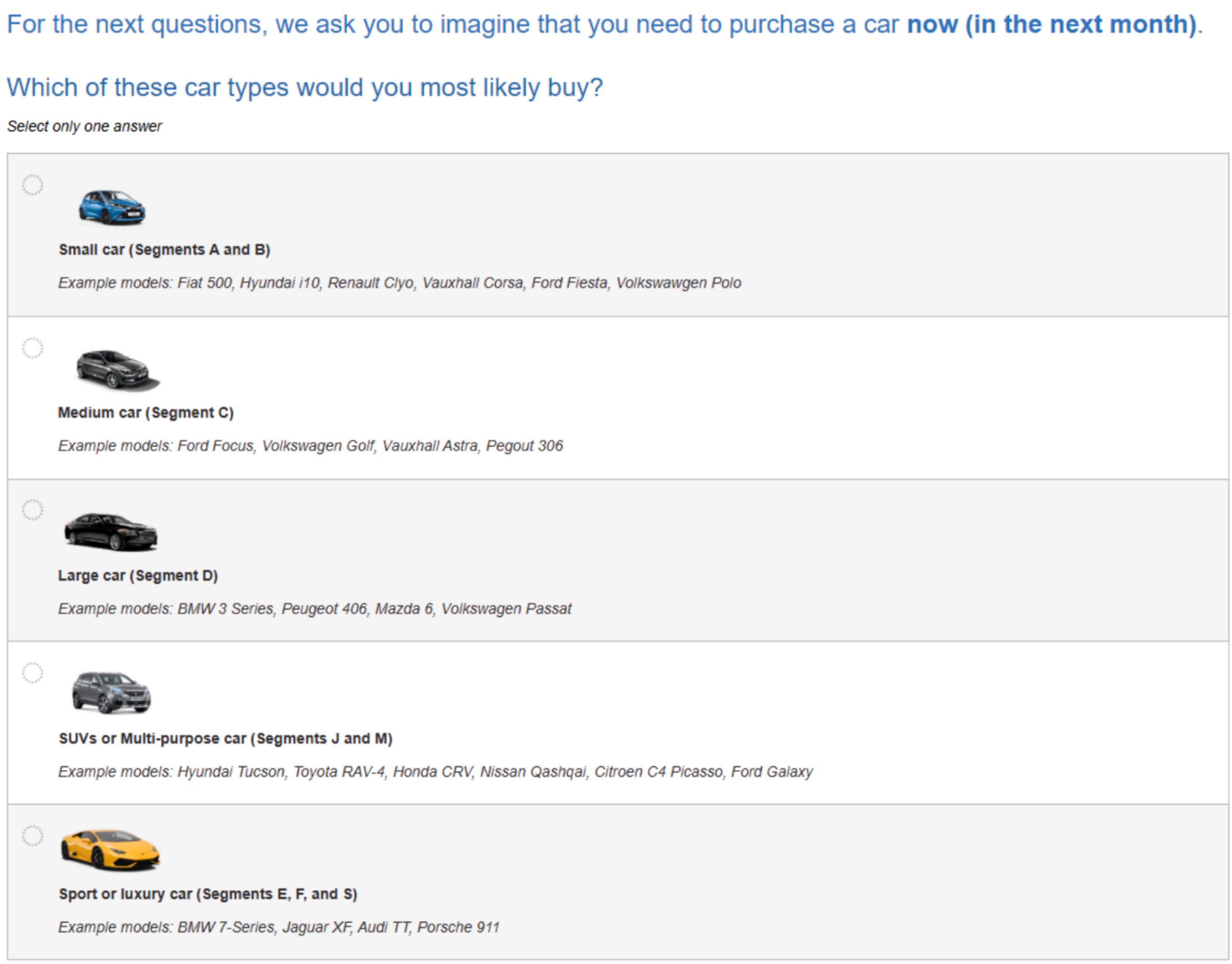

Fig. 2. Screenshot from screening question #1 (on car types).

designs (Rose & Blimier, 2009). Five additional designs were then built for respondents who declared considering *both* purchase options (i.e. new AND second hand). While these respondents should theoretically face seven alternatives (3 fuel types × 2 purchase options + 1 opt-out) in each choice task, such a detailed scenario might be too cognitively demanding (Caussade et al., 2005). To avoid this, five partial choice set designs (or *availability designs*) were built where a subset of four alternatives (rather than seven) is selected for display in each choice task using a modified Federov algorithm (Cook & Nachtrheim, 1980) along with an efficient design. This algorithm creates a series of designs by randomly selecting four alternatives to display among the seven available, and then chooses the combination with the lowest efficiency error. Each of the 15 scenarios contains nine choice situations with three purchasing alternatives plus the opt-out option.

3.1.2. Experimental design, attributes, and levels

We defined the attributes for the experiment based on the specialised literature, mostly focusing on recent SC experiments applied in the European context to model EV choice. We imposed a maximum of five attributes to reduce the risk of mistakes or biases by respondents (Caussade et al., 2005). We obtained the status-quo (*SQ*) levels for each attribute from Teoalida (2021), a privately sourced dataset assembling detailed information about vehicle makes and models available in the UK market. We defined variations around the *SQ* values to reflect the expected market trends in the attributes, and to generate choice situations that elicit meaningful preferences, while retaining the realism of the experiment. The attributes considered and the criteria used to define their levels in the experiment are as follows:

- *Purchase cost* was defined as the upfront cost of purchasing a vehicle, including any applicable taxes, rebates, or subsidies. This attribute was defined separately for new and second-hand purchases. In both cases, three levels were used. For ICE cars, we used the mean *SQ* value for each segment and purchase option, as well as variations of −10 % and + 25 % to reflect the varying shifts in the price trends. For EVs and HEVs, the *SQ* and variations of −10 % and −25 % were used to reflect the expected decreasing trend over time.
- *Operation cost* was defined as the mean cost per distance unit (in this case, 100 miles), considering fuel or energy expenditures. As petrol costs are expected to rise in the long-term (Department for Transport,2022a), the *SQ* plus variations of + 20 % and + 40 % were considered. The cost of electricity is harder to forecast, and subsequently the *SQ* and variations of −20 % and + 20 % were assumed for EVs and HEVs.
- *Driving range* was specified as the maximum number of miles a car can travel before recharge or refuel. The average driving range for EVs during 2022 was about 200 miles or 350 km (International Energy Agency, 2022). While an increase in this figure would be expected over time, some car models still have significantly lower ranges. Three levels were considered for EV range: the *SQ* plus variations of + 20 % and + 40 %. For ICE and HEVs (where the range is a much less significant concern) the three levels are the mean *SQ* plus variations of –20 % and + 20 %.
- *Distance to recharge/refuel* was defined as the average distance (in miles) from home to the nearest charging station. As we could not find any consistent statistics about average distance to petrol stations in the UK, we carried out a set of measurements on Google Maps, which yielded a mean of about 0.5 miles in urban environments. For EV charging stations, it was assumed that they would have a *SQ* value of 0.75 miles in an urban environment to reflect the current upward trend in the total number of stations across the country ZapMap.Com (2024). Variations of + 50 % and + 100 % were also considered to account for their uneven distribution both in urban and rural settings.
- *Charging time* was specified as the time (in minutes) to get the vehicle charged up to 80 % of its capacity (tank or battery). The design assumed that an EV adoption might stimulate the development in rapid and ultra-rapid charging stations in the upcoming years, as predicted by the EV infrastructure strategy (HM Government, 2021). Three levels were then used: fast charge (60 min to 80 % charge), rapid charge (20 min to 80 % charge), and ultra-rapid charge (5 min to 80 % charge). For ICE and HEV, a charging time of 3 min was used as a reference value.

A summary of the attribute levels and values is provided in Table 2. In the table, the SQ value is the mean value for 2020 – 2021 as reported in the Teoalida (2021) dataset. SQ values are **bolded** in the table.

The NGene software (ChoiceMetrics, 2018) was used to generate the designs. Efficient designs require priors for the coefficients, which are typically derived from existing literature. In our case, the most appropriate source of priors for building the SC experiment is the model estimated in our previous work (Domarchi & Cherchi, 2024), where we obtained purchase price and operating cost coefficients for the UK using a revealed preference dataset. In the case of driving range, charging time, and distance to charging points, we reviewed the preference parameters estimated in several studies that modelled preferences for EVs in the European context (Valeri and Cherchi, 2016; Liu and Cirillo, 2018; Kormos et al., 2019; Giansoldati et al., 2020; Manca et al., 2020; Aravena & Denny, 2021; Jensen et al., 2021; Rotaris et al., 2021), and chose the inter-study mean values as priors for our design. The priors used are listed in Table 3, which also summarises the wide range of variation of estimatest in the literature:

We then adjusted considering the results of two pilot surveys (further details are provided in Domarchi, 2023). The nine choice situations were randomised, and each situation was presented consecutively one after the other. Fig. 3 illustrates the layout of one of the nine choice situations for a respondent who chose new medium-sized cars in the screening questions. The survey was hosted by the Survey Engine platform (SurveyEngine, 2022).

3.2. HOTCO outputs: Valence and activations

3.2.1. HOTCO questionnaire design

The HOTCO questionnaire was designed to measure attitudinal and emotional appraisal of the car purchasing decision and its motivating factors. The questionnaire consists of a list of motives of vehicle purchases that respondents are asked to rate using a Likert scale. Table 4 lists the ten most relevant motives for car purchases, identified as those having a statistically significant influence in either short- or long-term EV purchase intentions in a preliminary survey of households in England. The table also lists the sentences

Table 2
Summary of attribute values by vehicle group and fuel type.

Group	Fuel type	New Price (£1,000)	2nd hand Price (£1,000)	Operation cost (£/100 miles)	Driving range (miles)	Distance to Recharge/Refuel (miles)	Charging Time (min)
1 /	ICE	[15, **17**, 20]	[7, **8**, 10]	[**11.4**, 13.6, 15.8]	[420, **520**, 625]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
Small	EV	[16, 18, **20**]	[8, 9, **10**]	[4.8, **6.1**, 7.4]	[**350**, 420, 490]	[**0.75**, 1.1, 1.5]	[3, 20, **60**]
	HEV	[14, 16, **18**]	[7, 8, **9**]	[7.7, **9.6**, 11.5]	[480, **600**, 720]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
2 /	ICE	[23, **26**, 31]	[14, **15**, 18]	[**12.3**, 14.7, 17.3]	[475, **590**, 710]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
Medium	EV	[24, 27, **30**]	[14, 15, **17**]	[4.5, **5.6**, 6.7]	[**400**, 480, 560]	[**0.75**, 1.1, 1.5]	[3, 20, **60**]
	HEV	[22, 25, **28**]	[13, 14, **16**]	[7.7, **9.6**, 11.5]	[570, **710**, 855]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
3 /	ICE	[24, **27**, 32]	[14, **15**, 18]	[**13.0**, 16.0, 18.6]	[490, **610**, 735]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
Large	EV	[27, 31, **34**]	[17, 19, **21**]	[9.1, **11.4**, 13.6]	[**500**, 600, 700]	[**0.75**, 1.1, 1.5]	[3, 20, **60**]
	HEV	[24, 27, **30**]	[15, 17, **19**]	[8.6, **10.9**, 13.1]	[685, **855**, 1030]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
4 /	ICE	[29, **32**, 38]	[17, **19**, 23]	[**13.8**, 16.5, 19.2]	[480, **595**, 715]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
SUV/	EV	[29, 32, **36**]	[20, 23, **25**]	[5.3, **6.6**, 7.8]	[**500**, 600, 700]	[**0.75**, 1.1, 1.5]	[3, 20, **60**]
MPV	HEV	[27, 31, **34**]	[18, 20, **22**]	[4.2, **5.1**, 6.1]	[590, **735**, 885]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
5 /	ICE	[54, **60**, 72]	[41, **45**, 54]	[**17.6**, 21.1, 24.6]	[430, **535**, 645]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**
Sport/	EV	[56, 63, **70**]	[38, 42, **47**]	[4.5, **5.6**, 6.7]	[**400**, 480, 560]	[**0.75**, 1.1, 1.5]	[3, 20, **60**]
Luxury	HEV	[52, 59, **65**]	[34, 38, **42**]	[8.0, **10.1**, 12.2]	[540, **675**, 810]	[**0.5**, 0.8, 1.0]	**[3, 3, 3]**

Table 3
Summary of priors for the experimental design.

Attribute	Alternative	Value	Range of variation
Purchase price (£1,000)	All	−0.02	–
Cost per 100 miles (£1,000)	ICE, HEV	−0.23	–
Distance to charging point (miles)	All	−0.032	[-0.006, −0.773]
Driving range (100 miles)	All	0.725	[0.346, 2.000]
Charging time (hour)	All	−0.067	[-0.025, 0.120]

Fig. 3. SC experiment – General layout (Screenshot).

used to present them in the survey. Full details about this survey and the work done to select the motives are provided in Domarchi et al. (2024).

Respondents were asked to rate these ten motives in three types of scale:

Table 4
List of car purchasing motives for the HOTCO model.

ID	Motive	Sentence
1	Environmental awareness	*A car that is environmentally friendly*
2	Purchase cost	*A car with a low purchase cost*
3	Performance	*A car that offers a good performance, in terms of speed, acceleration, handling, and brakes*
4	Pleasure/Enjoyment	*A car that makes you enjoy the driving experience*
5	Pro-technological orientation	*A car with advanced technological features and gadgets*
6	Flexibility	*A car that provides flexibility for your daily activities*
7	Self-identification	*A car that distinguishes you from others*
8	Pro-innovative orientation	*A car that satisfies your curiosity for innovation*
9	Comfort	*A car that makes you feel comfortable when driving*
10	Convenience	*A car that provides a convenient mean to carry out your daily activities*

- *Priority* that refers to the desirability that each motive has to the participant "*for intrinsic or other non-coherence reasons*", and was measured using an importance rating question, i.e. "*Please rate the following elements according to their importance to you when you decide which type of car to buy*", with a 5-point Likert scale ranging from "Not important at all" to "Very important".
- *Emotional* that is a composite score of two emotional scales – one measuring *pleasure* (happy/unhappy) and another one measuring *arousal* (calm/excited). Both were measured asking respondents to rate "*To what extent do these concepts make you feel happy (instead or sad)*" or "*excited (instead of calm)*". The 5-point Likert scale here ranged between "To no extent" and "To a very large extent", and the emotional score is the arithmetic mean of these two dimensions.
- *Facilitation* links were measured using questions worded as follows: "*To what extent do you think these needs or requirements would be satisfied by choosing a* [petrol car, electric vehicle or hybrid-electric vehicle]". The Likert scale here is the same used for the emotional scores, ranging from "to no extent" to "to a very large extent". Three facilitation scales were used, one for each fuel type available (ICE, EV, HEV).

Six scales in total were used – one priority scale, two emotional scales, and three facilitation scales. The complete list of ten motives for each scale was placed in a single screen (six successive screens in total), using a randomised order for the motives to avoid any biases derived from question ordering.

3.2.2. HOTCO algorithm

The HOTCO model assumes that individuals will aim to satisfy a set of *needs* represented as a set of nodes in the connectionist network) by purchasing (which is the *action,* represented as another set of nodes in the connectionist network) one of the available options (EV, ICE, HEV). *Needs* and *actions* are joined by facilitation links, which represent the perceived coherence (or the positive and negative constraints) between each need-action pair. For example, a person with strong pro-environmental attitudes might feel that their need of engaging in a "green" behaviour might be satisfied by purchasing an EV, in which case the facilitation weight is defined as positive, and the need is "coherent" with the action. Conversely, if the action is deemed as detrimental to the satisfaction of the need, it is said to be "incoherent" with it. In our example, buying an EV might be perceived as incoherent with a strong need of reliability in transport if the person is too concerned about battery range or charging times. In this case, the facilitation link is negative.

The HOTCO algorithm involves an iterative process of coherence maximisation. During this process, *activation* and *valence* in each node are updated in parallel with all other units on every cycle, as a function of their previous value on the cycle as well as the combined stimulus (activations and valences) received from all the connected nodes (Thibault, 2013), including the action nodes. These stimuli depend on the activations and valences on all these nodes, and the value of the weight that connects them. On each cycle, all the activations and valences are updated in parallel considering the values of the stimuli from the previous cycle. The process is repeated until no significant change is observed between two iterations. At the end of this process, each node will have a certain degree of activation and valence, and the resulting network will involve the best possible satisfaction of all the given constraints in parallel (Thagard, 2001). The final output for individual q in the sample is a set of real numbers in the $[-1, 1]$ range that represent activations (ACT_{nq}) and valences (VAL_{nq}) associated with the *needs* nodes *n*, and activations ($ACT_{EV,q}$, $ACT_{HEV,q}$, $ACT_{ICE,q}$) and valences ($VAL_{EV,q}$, $VAL_{HEV,q}$, $VAL_{ICE,q}$) associated with each *action* node (EV, HEV, ICE). Further details about the algorithm can be found in Thagard (2006) and Thibault (2013), with its adaptation to this this study described in detail in Domarchi et al. (2024).

As an illustration, Fig. 4 depicts an example of the activations in the settled HOTCO connectionist network for one respondent in our dataset. Here, the nodes between 1 and 10 represent the needs, the nodes ICE, EV, and HEV represent the actions, and the nodes *SpA* and *SpV* are special units, built for computational purposes, that allow for the spread of activation and valence across the network. Green nodes represent positive activations, while yellow nodes negative activations. The diameter of each node is proportional to the absolute value of the activation score (bigger green nodes have activations closer to $+1$ while bigger yellow nodes have activations closer to -1). The green and yellow coding also applies to the weights of the links. It should be noted that the coherence maximisation process involves needs 4 and 8, plus the HEV action node, in a final state of indifference (activation equal to zero, hence no colour in the figure).

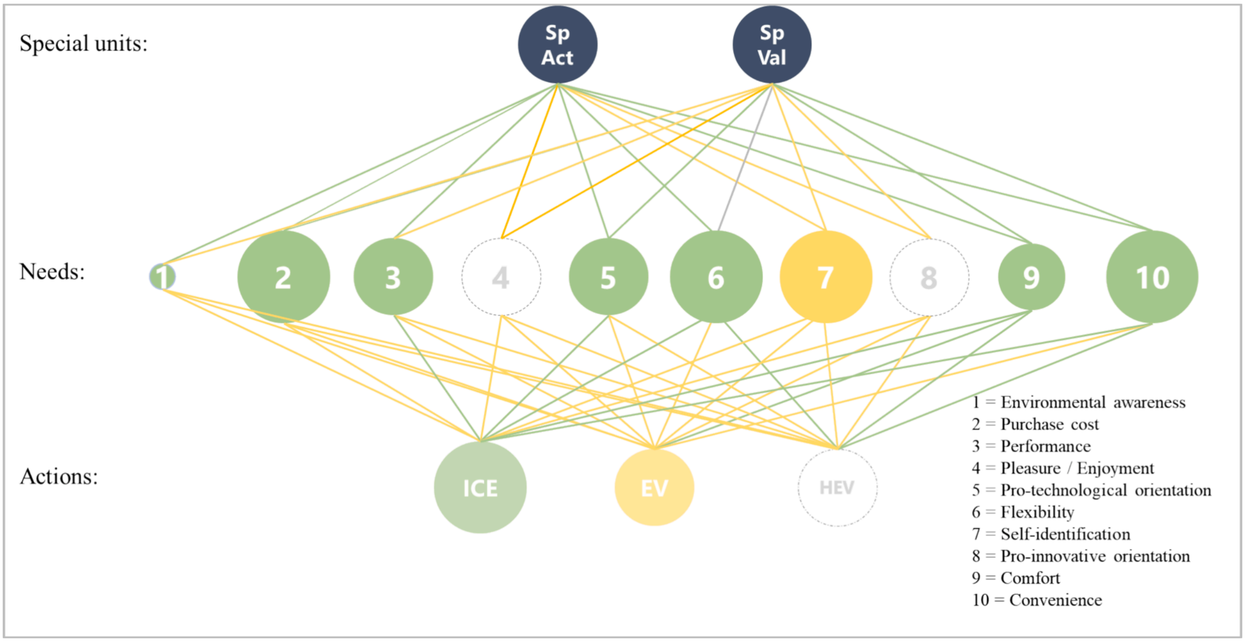

Fig. 4. Example of activations in a settled HOTCO network.

3.3. Data collection

The survey was collected between November and December 2022. The questionnaire was responded by 620 individuals, with an average completion time of 14 min. After discarding incomplete or inconsistent responses (for example, individuals who responded too fast,[3] or who provided invariant responses to the HOTCO questionnaires), 555 individuals (90 % of the initial sample) remained in the sample. Table 5 presents a descriptive summary. For reference, the survey is compared with the 2021 subset of the National Travel Survey (NTS; Department for Transport, 2021) sample – albeit excluding car-less households, to make it comparable with the target population of the present study.

The 555 respondents owned a total of 889 cars in their households, with EVs representing 2.5 % of the sample, and HEVs (either plug-in hybrid or hybrid cars) accounting for 3.5 % (6.0 % of alternative fuels in total). These figures are similar to the shares of licenced vehicles for the same period in England (Department for Transport, 2022b), which are equal to 2.1 % of EVs and 4.3 % of HEVs (6.4 % of alternative fuels) and indicate that the sample appropriately represents the target population in this dimension. Further details about the sample are reported in Domarchi et al. (2024).

One month after this data collection stage was finalised, we conducted a follow-up survey using an identical questionnaire, and only recruiting individuals who had previously responded to the main survey. We obtained 91 valid responses in this follow-up and used them to validate the results of the estimated model.

4. Results and discussion

4.1. Latent class choice model specification

The HLCCM introduced in Section 2 is illustrated in Fig. 5. In the class membership model, socioeconomic variables and HOTCO outputs (activations and valences, depicted as grey arrows) for need nodes (representing motives to be satisfied by the car purchase) are used to estimate class membership probabilities. In the class-specific choice model, utilities depend on latent class membership, but also on socioeconomic variables, alternative attributes, and HOTCO outputs for action nodes (representing the available fuel types). The HOTCO model links activations and valences for needs and actions.

To estimate the LCCM, the class-specific direct utility functions (equation (2) was specified including the following attributes:

[3] The threshold was set at 6 min after analysing the results of two pilot surveys. Details are reported in Domarchi (2023).

Table 5
Descriptive stats of the sample.

Dimension	Variable	Level	Survey	Reference (NTS 2021-R)	Comparison
Sample size	Total respondents	–	620	–	–
	Number of complete responses	–	555	–	–
	Mean response time (minutes)	–	14.6	–	–
	(Complete responses only)		(*SD* = 6.1)		
Vehicles	% of households by number of vehicles	0	–	–	–
		1	52.3	56.3	
		2	37.8	35.9	
		3 or more	9.9	7.8	
	Mean vehicles per household	–	*1.60*	*1.53*	$t(df = 4478) = 1.98 p < 0.024$
	% of vehicles by fuel type	Petrol	65.4	60.2	–
		Diesel	28.6	35.8	–
		Electric	2.5	0.8	–
		Hybrid-electric	3.5	3.2	–
	% of households by number of driving licences	1	26.7	38.8	–
		2	58.7	53.4	
		3	9.9	5.9	
		4 or more	4.7	1.8	
	Mean licences per household	–	*1.94*	*1.70*	$t(df = 4478) = 6.78, p < 0.001$
Households	% of households by annual income (Thousands of £)	<15	5.8	11.9	–
		15 – 29	19.5	23.4	
		30 – 44	24.6	24.7	
		45 – 60	20.1	9.2	
		60 – 150	28.6	26.8	
		>150	1.3	4.1	
	Mean annual income (Thousands of £)	–	*56.6*	*52.2*	$t(df = 4478) = 0.08, p = 0.46$
	% of households by size (persons)	1	13.0	*22.2*	–
		2	35.3	*41.3*	
		3	19.3	*16.2*	
		4 or more	32.4	*20.2*	
	Mean household size (persons)	–	*2.82*	*2.42*	$t(df = 4478) = 4.88, p < 0.001$
	% of urban households	–	69.0	74.0	–

- All the five attributes from the SC experimental design (Table 2), with all attributes customised according to the response to the screening question.[4]
- Both HOTCO attributes (activations and valences) for each fuel type (ICE, HEV, EV). The HOTCO decision is assumed conditional to the decision of purchasing a vehicle, and therefore the opt-out option does not appear in the coherence network, and the opt-out alternative in the choice model does not depend on any HOTCO attribute.
- An inertia variable that takes the value 1 if the respondent chooses a vehicle purchased new in the experiment, *and* they currently own a new vehicle. Inertia is usually incorporated into discrete choice models to reflect the tendency to stick with the past choice even when another alternative becomes more appealing (e.g. Cherchi & Manca, 2011; González et al., 2017).
- An annual mileage variable added to the ICE utility function, to test whether respondents with higher distances travelled were more or less likely to choose AFVs.

To determine the number of classes required, we estimated first a model that did not consider user heterogeneity (1 class model). Then we estimated several models with 2-, 3- and 4-classes, and compared their results in terms of level-of-fit indicators (AIC and BIC, with lower values preferred in both cases), but also considering the microeconomic plausibility and statistical significance of their coefficients. Table 6 summarises these results, with the lowest AIC and BIC values bolded. All the models were estimated with 4,725 responses coming from 525 respondents.

All the statistics in the table suggest that any model with latent class segmentation is superior to the model without segments. The minimum AIC value is given by the 4-class model (7165.2. about 0.4 % lower than the AIC value associated with the 3-class model), this comes at the cost of a significant increase in the number of estimated parameters and only a slight increase in the adjusted ρ^2 index. Importantly, the 4-class model yields several parameters with non-intuitive signs (according to the behavioural theory) and non-significant parameters. The classes were also difficult to interpret. The chosen specification is the 3-class model, as it provides the

[4] The experiment was designed considering operation costs per unit distance (100 miles). However, we found a better level of fit when including annual operation costs, defined as the mean operation cost per distance unit, multiplied by the distance driven by each vehicle, as reported by respondents.

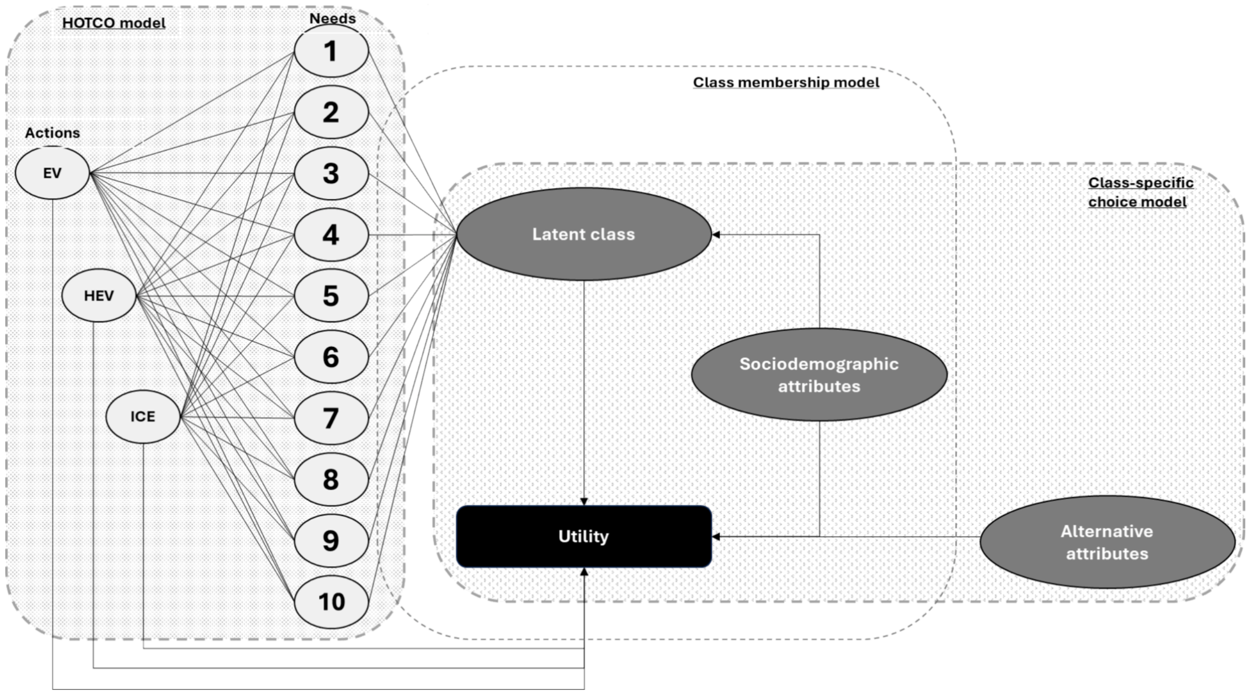

Fig. 5. Graphic illustration of the estimated model.

Table 6
Overview of the results of the latent class choice models.

Indicator	Number of classes			
	1	2	3	4
Log-likelihood (*)	−3810.7	−3598.9	−3535.7	−3507.6
ρ^2 indicator (market shares)	0.246	0.296	0.308	0.314
Akaike Information Criterion (AIC)	7669.5	7295.9	7195.4	**7165.2**
Bayesian Information Criterion (BIC)	7824.5	7612.5	**7595.9**	7649.7
Number of parameters	24	49	62	75

minimum BIC value (7595.9, about 0.7 % lower than the BIC value associated with the 4-class model), a richer interpretation for the class profiles, and more significant and consistent parameters.

4.2. Estimation results and class profiling

This section contains the estimation results of the 3-class LCCM, alongside the class profiling, and some post-estimation analyses. Table 7 includes the general results of the 3-class model, as well as the general level-of-fit indicators. For comparison purposes, the table includes a hybrid mixed logit model estimated without considering class heterogeneity (baseline model). Table 8 reports the coefficients estimated for the class membership functions in the 3-class specification of the LCCM.

We estimate several versions of our chosen specification, removing non-significant coefficients at the 95 % confidence level. However, following the recommendations in Ortuzar and Willumsen (2024, p. 288), we retain all "*relevant (*i.e. *Policy type) variable[s] with a correct sign even if it fails any significance tests. The reason is that the estimated coefficient is the best approximation available for its real value; the lack of significance may just be caused by lack of enough data*". We apply this criterion for the purchase price, operation cost and driving range parameters, as well as the HOTCO coefficients, the alternative-specific constants, and the variances of random terms. For the remaining variables (including all the individual-level attributes in the class membership equations), we only retain them when the *t*-test comparing the coefficients with zero is significant at the 90 % confidence level (i.e., *t*-test > 1.282 using a one tail distribution). It must be noted that we chose the opt-out alternative as the reference, and therefore all three alternative-specific constants associated with fuel type (EV, HEV, and ICE) were estimated.

As expected, the level-of-fit results reveal that the latent class specification performs significantly better than the baseline model, indicating that there is significant heterogeneity in the preferences. However, in the hybrid mixed logit specification, each respondent is deterministically associated to a certain level of preference. In the HLCCM, individuals have a probability of belonging to each class,

Table 7
Latent class choice model estimation results – I: Class-specific choice model and general model indicators[(*)].

Attribute	Alternative	*Baseline*	*Latent class choice model*			
			Attributes generic among classes	**Attributes specific among classes**		
				Class 1 (47.5 %)	**Class 2 (14.9 %)**	**Class 3 (37.6 %)**
		Coef. (*t*-test)	**Coef. (*t*-test)**	**Coef. (*t*-test)**	**Coef. (*t*-test)**	**Coef. (*t*-test)**
A) Class specific choice model						
Alternative specific constants						
	EV	9.349 (10.81)	–	10.694 (6.47)$^{\{2,3\}}$	1.995 (1.17)$^{\{1,3\}}$	19.454 (9.07)$^{\{1,2\}}$
	HEV	10.068 (12.56)	–	11.797 (9.09)$^{\{2,3\}}$	4.197 (3.41)$^{\{1,3\}}$	18.201 (10.51)$^{\{1,2\}}$
	ICE	8.135 (9.99)	–	9.341 (5.99)$^{\{2,3\}}$	1.557 (1.05)$^{\{1,3\}}$	16.047 (8.84)$^{\{1,2\}}$
Vehicle parameters						
Purchase price	EV; HEV; ICE	−0.167 (−14.21)	–	−0.138 (−10.32)$^{\{2,3\}}$	−0.001 (−0.03)$^{\{1,3\}}$	−0.589 (−8.54)$^{\{1,2\}}$
Annual operation cost	EV; HEV; ICE	−2.272 (−9.58)	–	−3.261 (−6.23)$^{\{2\}}$	−0.567 (−1.13)$^{\{1,3\}}$	−2.602 (−6.00)$^{\{2\}}$
Charging distance	EV; HEV; ICE	−0.408 (−3.98)	–	–	–	−1.199 (−4.14)$^{\{1,2\}}$
Charging distance × Charger awareness	EV	0.383 (2.53)	–	–	–	0.848 (1.97)$^{\{1,2\}}$
Driving range	EV	0.302 (10.22)	–	0.281 (4.79)	0.181 (1.75)	0.435 (5.96)
	HEV; ICE	0.422 (7.73)	–	0.506 (4.83)	0.406 (2.27)$^{\{3\}}$	0.234 (1.41)$^{\{2\}}$
Charging time	EV; HEV; ICE	−0.791 (−8.71)	–	−1.197 (−6.40)$^{\{2\}}$	−0.57 (−2.07)$^{\{1\}}$	−0.818 (−2.43)
Annual mileage	ICE	0.054 (6.10)	–	0.082 (3.67)$^{\{2\}}$	–	0.075 (4.43)$^{\{2\}}$
Inertia parameters						
New vehicles	EV; HEV; ICE	0.599 (3.40)	–	–	–	1.426 (1.55)$^{\{1,2\}}$
HOTCO outputs						
Activation	EV; HEV; ICE	0.549 (3.34)	–	0.44 (1.78)$^{\{2\}}$	4.395 (1.90)$^{\{1,3\}}$	0.317 (0.62)$^{\{2\}}$
Valence	EV; HEV; ICE	1.111 (4.39)	–	–	2.834 (0.95)	1.746 (2.71)$^{\{1\}}$
Error components						
Panel effect	Opt-out	4.652 (11.25)	5.248 (10.35)	–	–	–
	EV	−0.5 (−0.79)	1.693 (8.14)	–	–	–
	HEV	−0.157 (−0.96)	0.435 (0.82)	–	–	–
	ICE	−1.225 (−5.54)	−1.359 (−3.80)	–	–	–
Activation error component	EV	0.806 (0.96)	0.211 (1.93)	–	–	–
	HEV	−0.216 (−0.57)	0.642 (2.25)	–	–	–
	ICE	−1.89 (−2.49)	−0.087 (−0.49)	–	–	–
Valence error component	EV	−1.36 (−4.56)	−0.472 (−0.7)	–	–	–
	HEV	−0.522 (−2.37)	0.135 (0.79)	–	–	–
	ICE	−0.049 (−0.21)	−0.714 (−1.34)	–	–	–
B) General model indicators and level-of-fit						
Log-likelihood (*)		−3810.7	−3535.7			
Number of individuals		525	525			
Number of observations		4,725	4,725			
Number of parameters		24	62			
ρ^2 (market share)		0.414	0.451			
Akaike Information Criterion (AIC)		7669.5	7195.4			
Bayesian Information Criterion (BIC)		7824.5	7595.9			

(*) Values below each class denomination in the top row indicate the mean membership probability. Values in parenthesis next to each coefficient are *t*-test values testing the null hypotheses that the coefficient is equal to zero. For the latent class model parameters, superscripts in each line indicate that the coefficient is statistically different from the corresponding class-specific coefficients in the other classes. The comparisons were assessed with pairwise t-tests of equality between coefficients and considering a 95% confidence level.

and class-specific parameters that characterise their preferences. In addition, the HLCCM yields class membership probabilities that depend on individual attributes, and facilitate respondent profiling. Both models contain alternative-specific error components to account for the panel effect, as well as additional components to account for the effect of the random distribution of the activation and valence scores in the sequential estimation. The random components of activation and valence appear to be playing a role in accounting for this effect in the baseline specification, so that the measurement error in the HOTCO outputs might be correlated with the

Table 8
Latent class choice model estimation results – II: Class membership functions(*).

C) Class membership functions			
Attribute	**Class 1 (47.5 %)**	**Class 2 (14.9 %)**	**Class 3 (37.6 %)**
	Coef. (*t*-test)	**Coef. (*t*-test)**	**Coef. (*t*-test)**
Class-specific constant	–	−8.443 (−3.24)	–
Gender (Male = 1)	–	1.801 (2.67)	–
Number of driving licences	–	1.020 (2.42)	–
Number of employed people	–	−1.551 (−3.58)	−0.351 (−2.26)
Household has bought a car new	–	–	−0.892 (−2.45)
Household owns a medium car	–	1.305 (1.82)	–
Household owns a large car	–	2.155 (2.12)	–
Household owns a SUV/MPV	–	1.835 (2.16)	–
Activation 2: *Purchase price*	–	–	1.245 (3.21)
Activation 3: *Driving performance*	–	1.905 (1.56)	–
Activation 4: *Technological features*	–	2.889 (2.66)	–
Activation 5: *Driving enjoyment*	–	−2.262 (−2.86)	–
Activation 8: *Curiosity for innovation*	–	1.423 (2.46)	–
Activation 10: *Convenience*	–	3.21 (2.47)	–
Valence 5: *Driving enjoyment*	–	–	−1.009 (−2.34)
Valence 6: *Flexibility*	–	–	1.368 (1.72)
Valence 10: *Convenience*	–	–	−1.378 (−1.99)

(*) Class 1 is treated as the reference. Values below each class indicate the mean membership probability. Values in parenthesis next to each coefficient are *t*-test values testing the null hypotheses that the coefficient is equal to zero with 90% confidence.

panel effect.

In the baseline model, all panel effects are significant, as are the variances of the random terms of the valence for two of three alternatives (EV and ICE). However, all three activation random components are non-significant.

Conversely, the panel effect for the HEV alternative is non-significant in the LCCM specification; however, two of the tree error components for activation (EV and HEV) become significant in this structure, and there are no changes in the significance for the error components of valence. These results seem to indicate that consideration of user heterogeneity helps to correctly identify the measurement error in the HOTCO components (activation and valence).

Preference parameters for purchase price, annual operation cost, charging distance, and driving range, fall generally within the range of estimators previously available in the literature, whose ranges of variation were reported in Table 4 (considering changes in measurement units). Our estimated parameters for charging time are higher than the ones previously obtained in the literature for all three classes. Familiarity with the EV charging process might play a role in this result. With adoption increasing in the UK in recent years, respondents might be more familiar with charging points and consequently might value the process more negatively. In addition, the studies used for obtaining priors were from 2021 or before (when adoption was significantly lower) and still showed a high degree of variability in the parameter estimates, as reported in Domarchi & Cherchi (2023).

Table 9
Weighted mean values of attributes by latent class(*).

Attribute	**Units**	**Class 1 (47.5 %)**	**Class 2 (14.9 %)**	**Class 3 (37.6 %)**
Mean predicted choice probabilities				
ICE	–	$0.104^{\{2,3\}}$	$0.195^{\{1\}}$	$0.165^{\{1\}}$
EV	–	$0.435^{\{2,3\}}$	$0.351^{\{1\}}$	$0.346^{\{1\}}$
HEV	–	0.430	0.414	0.436
Opt-out	–	$0.040^{\{2,3\}}$	$0.077^{\{1,3\}}$	$0.075^{\{1,2\}}$
Sociodemographic attributes				
Population density	Persons/hectare	22.6	21.8	22.1
Household size	Persons	$3.1^{\{2\}}$	$2.6^{\{1\}}$	2.9
% of children	%	24.7	18.0	26.9
% of women	%	$75.6^{\{2\}}$	$33.9^{\{1,3\}}$	$75.2^{\{2\}}$
Annual income	Thousands of GBP	58.8	50.1	52.5
Car attributes				
Number of driving licences	–	2.1	2.1	1.9
Number of cars	–	1.8	1.8	1.6
% of households owning an EV/HEV	%	$6.7^{\{2\}}$	$29.8^{\{1,3\}}$	$4.7^{\{2\}}$
% of cars bought as new	%	$38.3^{\{3\}}$	$47.5^{\{3\}}$	$16.3^{\{1,2\}}$
Annual mileage driving (by car)	Thousands of miles	17.3	18.1	18.2

(*) Superscripts indicate that the class-specific weighted mean differs across classes. The comparisons were assessed with t-tests for the equality of means and considering a 95% confidence level.

Classes can be identified by analysing the class membership equations as well as some post-estimation indicators. First, as can be noted from Table 8 among the several socioeconomic explanatory variables tested in the class membership equations, respondent gender, the number of driving licences, and the number of employed people were significant. Moreover, four attributes related to previous cars bought by the household were also significant in explaining class membership, as were seven of the ten car purchasing motives modelled with HOTCO.

Table 9 shows the average values of some attributes for individuals within each of the three classes. These values were calculated as the weighted average of each variable, where the weight is the probability of belonging to a particular class. The same calculation was performed with the mean values of HOTCO activations and valences, and illustrated visually in Fig. 6 and Fig. 7 with error bars representing the standard error of the mean. These weighted means are helpful for interpretation of user profiling and class identification. For example, Table 9 reveals that respondents in class 2 live in significantly smaller households than those in class 1, and that these households have a lower proportion of women compared with households in classes 2 and 3. Similarly, respondents in class 2 have a significantly higher proportion of EVs and of vehicles bought as new. Figs. 6 and 7 illustrate inter-class differences in terms of HOTCO outputs. Fig. 6 reveals that, in contrast to classes 1 and 3, respondents in class 2 have a positive activation (associated with a positive attitude) in their pro-innovation character. They also assign a significantly higher activation score to attributes like driving performance, pleasure and enjoyment, flexibility, comfort and convenience, compared with the other two classes. They also have significantly higher activation scores for EVs and HEVs than the other two classes. Similarly, respondents in class 3 have a significantly higher activation score for purchase cost, and a strong and negative activation value for pro-innovative character. Similar effects, albeit with lower differentiation, appears in valence scores (Fig. 7), which reveal a significantly higher emotional appraisal for pro-innovation character and for EVs in general in class 2 (compared to classes 1 and 3), and lower valence scores for pro-technology and pro-innovation needs in class 3 (compared to classes 1 and 2).

Using all these results, we can identify the profiles of three user classes as follows:

- **Class 1 (“Potential innovators” – mean class membership probability = 47.5 %).** Respondents belonging to this class appear to have a higher income level than the other two classes, as well as the highest predicted probabilities of EV purchase. While this class appears inclined to adopt EVs, translating these intentions into actual behaviour might not be as straightforward for them. Their activation and valence scores in key motives including environmental awareness, pro-technology, and pro-innovation, are relatively weak, as are their mean activations and valences towards purchasing EVs and HEVs. The class-specific parameters for purchase price, operation cost, driving range, and charging time, are all significant for this class, revealing a concern for instrumental and economic attributes that might impede adoption. This rational approach to purchases is reinforced by the fact that HOTCO activations and valences do not play a significant role in their choices, with activation only significant at 90 % confidence. In fact, only 7.9 % of individuals in this class currently own an EV or an HEV.
- **Class 2 (“Innovators” – 14.9 %).** Respondents in this class do not appear majorly concerned for any economic attribute in the model, as their cost parameters are all non-significant. They have the second-highest income level in the sample, live in less densely populated areas, and typically buy their cars as new. Crucially, this class has the highest activation and valence scores for EV and

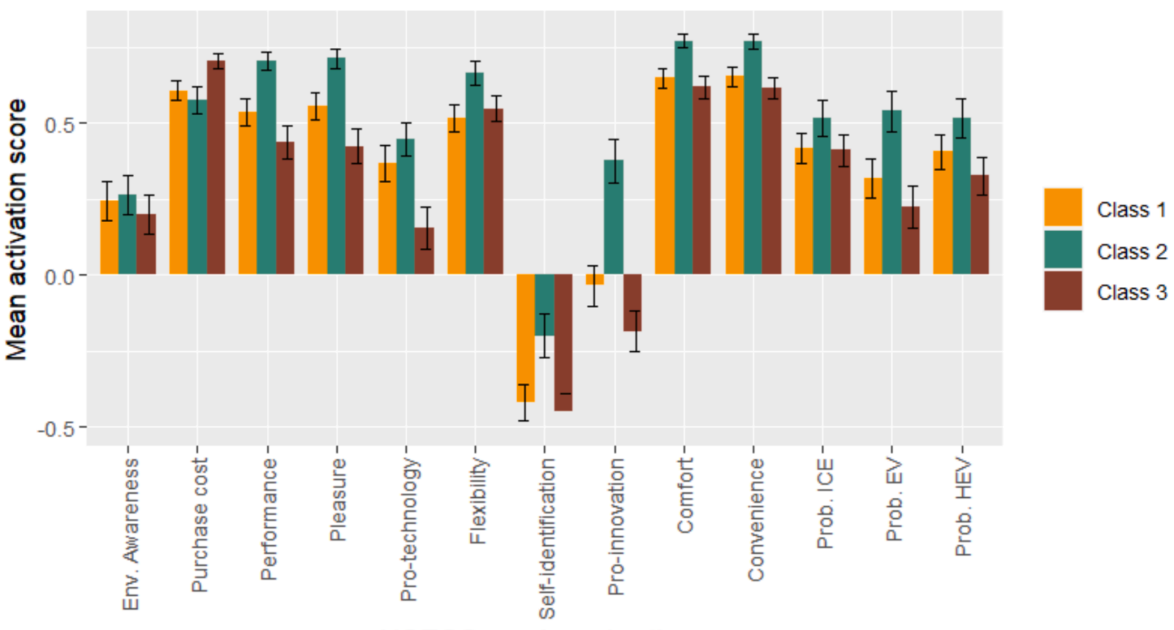

Fig. 6. Latent class choice model – Weighted mean activation scores by class.

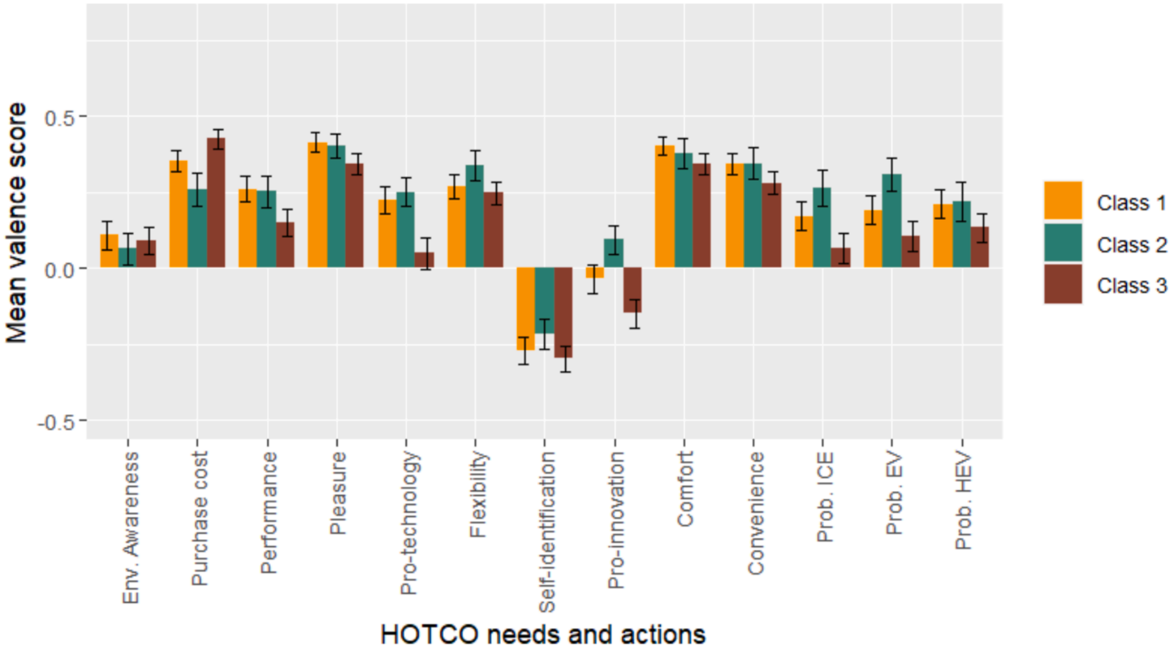

Fig. 7. Latent class choice model – Weighted mean valence scores by class.

HEV, as well as the highest scores for most attributes (crucially including environmental awareness, pro-technology orientation, and pro-innovation), revealing a highly coherent decision network that favours AFV adoption, with both activations and valences playing a role in their choices (both significant at 90 % confidence). Importantly, this is the only one of the three classes where the "pro-innovation" dimension has a positive activation and valence score, indicating that users in this class are motivated by being pioneers in adopting new technologies. This group should be the first to massively adopt AFVs and they are probably in that process – it must be noted that 21.2 % of households in this class *already* own an EV or an HEV.

- **Class 3 ("Sceptics" – 37.6 %).** Respondents in this class has a comparatively higher proportion of children, live in more densely populated areas, and have the lowest level of income across all three classes. They are the least likely to own an AFV currently (only 5.7 % of respondents in this class have one) or to have bought their current cars as new. Individuals in the class have the highest activation and valence scores for purchase costs, while their evaluation of dimensions such as environmental awareness, comfort, and convenience is the lowest across the three classes. Their choices are also less affected by their HOTCO evaluations than Class 2, with only valences playing a significant role at 90 % confidence. These are rational users without a specific intention to adopt the more innovative alternatives, and a majorly rational approach towards choices that reveals a strong concern about the costs involved.

As discussed, the main sources of class heterogeneity in the model are purchase price, EV annual operation costs, and driving range of HEV and ICE vehicles (as indicated by the superscripts next to the parameter values in Table 7). In other cases, there is significant variability when comparing one class with the other two; for example, the charging distance parameter is only significant for Class 3. In fact, *all* attributes are statistically significant for this class, which is consistent with their definition as "sceptics", or users who are highly aware of every aspect of their purchase decision, and therefore highly rational or less likely to be influenced by attitudinal or emotional attributes. Conversely, EV driving range is non-significant for uses in Class 2 who, as "innovators", appear to be less concerned about instrumental and operational attributes of their decision, and more driven by their pro-innovation character. In fact, none of the class-specific price coefficients are significant for this class. These attributes are very significant for both "potential innovators" in Class 1 and "sceptics" in Class 3, which highlights the more rational focus of these respondents in terms of their decision-making. There appears to be no significant class differences with respect to charging time, annual vehicle mileage, HOTCO activations and valences, and the two new vehicle inertia parameters.

All the retained parameters have the expected sign, and we have retained some key parameters (such as those related to prices, costs, and driving ranges) even if they were not statistically significant at 90 %. The purchase price and annual operation cost parameters are significant in two of the three classes.

In the case of Class 3, there is a significant negative effect of the charging distance variable in choice probabilities. The effect is mitigated when respondents declared having a charging point available either at home or at their place of work/study. User sensitivities to driving range are positive and significantly different for EVs and HEVs/ICEs, as expected in the design. As also expected, the coefficients for the sensitivity to charging time are negative and significant for all three classes. In addition, a higher use of the car (as indicated by the highest number of miles driven during the year), increases the probability of choosing the conventional fuel alternatives (ICE).

The alternative specific attitudinal and emotional evaluations play a significant role in increasing choice probabilities in two of the three classes (innovators and laggards), with activation playing a significantly higher role for respondents in Class 2, and valence in Class 3. As previously mentioned, these variables appear to have no effect in car purchasing decisions for Class 1 users, with the valence score only significant at 90 % confidence, somewhat reinforcing the definition of decision-makers in this class as rational users with a positive disposition towards innovative alternatives, but who also seem to be less influenced by emotional or attitudinal evaluations.

Individuals across all three classes experiment show some level of inertia in their decision, with users who have bought new cars in the past more likely to buy them new in the future.

4.3. Post-estimation analysis

The models were validated against the dataset obtained with the follow-up survey, conducted one month after the main data collection stage, using an identical questionnaire. The validation dataset contains 819 observations from 91 respondents (we excluded 2 respondents with invariant responses).

Validation indicators are reported in Table 10. These include the first preference recovery, the Brier score, the mean absolute error, and the ρ^2 indicator measured against the market share models. The results are compared with those obtained using the baseline model (the MMNL model that does not consider latent classes).

The chosen specification (LCCM) performs the best across all indicators except for the mean absolute error in the prediction of fuel types, obtaining a lower Brier score, a higher first percentage recovery, as well as a higher ρ^2 indicator. This indicates that the increase in the number of parameters is compensated by a significantly better level-of-fit. These results confirm that the LCCM is an efficient method to capture user heterogeneity in the context of this dataset and reinforces the predictive ability of the model.

To illustrate the potential interpretations allowed by our model, we built a set of forecasting scenarios and estimated how the HOTCO model captures changes in attitudes towards EVs, and in the effect of these changes in EV choice probabilities. This application allows assessing how changes in attitudes toward transport needs and motives (measured as changes in HOTCO input scores for each participant) translate into attitudinal and emotional evaluations of EVs (measured as HOTCO output scores for activations and valences) and, more importantly, into EV choice probabilities. This analysis is feasible because, in our framework, individual-specific attitudes are linked to attitudes toward alternatives, which in turn serve as determinants of choice probabilities. Such an analysis is not possible with conventional HLCM specifications based on traditional attitude-behaviour link theories, where the relationships between questionnaire scores, latent variables, and choice probabilities are less transparent and harder to interpret.

The four forecasting scenarios for each car purchasing motive were identified considering four possible types of variation in the HOTCO inputs:

1) An increase of 0.5 points in the *priority* score for the motive.
2) An increase of 0.5 points in the *emotional* score for the motive.
3) An increase of 0.5 points in the *facilitation link* between EV and the motive, in the same way as (1).
4) A combination of the three effects, (1), (2), and (3).

HOTCO inputs were originally measured in a 5-point Likert scale and later transformed to the scale ranging from -1 to $+1$, required by the model. The 0.5-point increases in the transformed scale are therefore equivalent to each respondent in the dataset increasing their ratings by one point in the original 5-point Likert scale (compared to the initial rating), except for those respondents who had already provided the highest possible rating in the scale.

We use the validation dataset for this application. After the inputs are changed, we run the HOTCO networks for each individual in the sample and use the results in the LCCM to obtain class-specific choice probabilities for each observation. As class membership probabilities depend on HOTCO outputs, these are also updated when the inputs change. It should be noted that the forecasting scenarios are generated by simulating small shifts in the evaluation of a single need, one at a time. However, each run of the HOTCO algorithm produces new activations and valences for *all* ten needs and three action nodes (i.e. the whole network is updated). This is a significant advantage of HOTCO over attitude-behaviour link theories, as these only allow for a linear, piecemeal analysis of their components in predictive mode. Full results for the 40 simulations (10 needs $\times$ 4 scenarios) are summarised in Appendix 1.

Table 11 provides an excerpt of this table, containing only the four motives that generate the highest changes in EV choice probabilities in the predictions. When ranking the motives in terms of the changes they generate in EV choice probabilities due to the combined effect of changes in all three HOTCO inputs, the four most relevant motives are environmental awareness, pleasure/enjoyment, pro-technological orientation, and convenience. The table lists the mean changes in activations and valences for EVs, the mean changes in choice probabilities for all three vehicle types, and the mean changes in class membership probabilities for each need.

These results allow evaluating the process through which an attitudinal change can produce changes in EV choice probabilities. Increases in priority and emotional scores only generate a mild effect in EV choice probabilities, while an increase in the score for the link between the motive and EV produces a slightly higher increase. The combined effect of the three HOTCO inputs increasing at the same time yields the highest growth in EV choice probabilities for each scenario. Taking the first need listed in Table 11 as an example, the HOTCO theory reveals that a more positive individual attitude towards the environment, or a higher emotional evaluation of environmental awareness, are not enough on their own to produce a significant change in the propensity to buy an EV (the associated changes in EV choice probabilities amount to 0.2 and 0.3 percentage points respectively for this effect). Individuals also need to perceive that the action provides a reasonable alternative to satisfy this need, i.e., that EVs are a good car purchasing option when

Table 10
Validation indicators.

Name (Range)	Desirable value	Baseline	LCCM
First preference recovery (%)	Closer to 100 %	66.2	**67.4**
Brier score (0 – 2)	Closer to 0	0.450	**0.448**
Mean absolute error (0 % –100 %)	Closer to 0 %	**0.9**	1.5
ρ^2 (market share)	Higher	0.428	**0.461**

Table 11
Forecasting scenarios for the most important car purchasing motives.

Motive	Sc.	Change	Change in HOTCO outputs for EV		Percentage change in choice probabilities			Percentage change in class membership probabilities		
			Activation	Valence	EV	HEV	ICE	Class 1	Class 2	Class 3
Environmental Awareness (1)	1–1	+ *Priority*	+0.026	0.000	+0.2	+0.1	−0.3	+0.8	−1.0	+0.2
	1–2	+ *Emotional*	+0.024	+0.016	+0.3	+0.1	−0.4	+0.7	−0.5	−0.2
	1–3	+ *EV link*	+0.032	+0.057	+0.5	−0.3	−0.2	+0.4	−0.3	−0.1
	1–4	*Combined*	+0.092	+0.091	+1.2	−0.1	−0.9	+0.9	−0.4	−0.5
Pleasure/Enjoyment (4)	4–1	+ *Priority*	+0.007	+0.009	+0.3	−0.3	+0.0	+0.0	+0.5	−0.5
	4–2	+ *Emotional*	+0.002	+0.011	+0.4	−0.3	−0.2	−0.1	1.0	−0.9
	4–3	+ *EV link*	+0.067	+0.058	+1.0	−0.4	−0.4	+0.7	−0.3	−0.4
	4–4	*Combined*	+0.086	+0.082	+1.4	−0.9	−0.5	−0.4	+2.2	−1.8
Pro-technological Orientation (6)	6–1	+ *Priority*	+0.007	+0.008	+0.2	+0.2	−0.2	+1.2	−2.4	+1.2
	6–2	+ *Emotional*	+0.006	+0.012	+0.7	+0.0	−0.5	+6.2	−2.0	−4.2
	6–3	+ *EV link*	+0.066	+0.087	+1.0	−0.6	−0.3	+1.6	−0.6	−1.0
	6–4	*Combined*	+0.093	+0.091	+1.6	−0.5	−0.7	+8.3	−3.0	−5.3
Convenience (10)	10–1	+ *Priority*	+0.016	+0.012	+0.2	−0.3	+0.1	−1.0	+0.7	+0.3
	10–2	+ *Emotional*	+0.010	+0.002	+0.5	−0.2	−0.3	+5.2	+0.6	−5.8
	10–3	+ *EV link*	+0.044	+0.044	+0.8	−0.4	−0.3	+1.4	−0.5	−0.9
	10–4	*Combined*	+0.080	+0.074	+1.2	−0.8	−0.4	+4.6	+3.0	−7.6
Combined A	CA	(1) + (8)	+0.160	+0.151	+2.6	−1.1	−1.1	+6.8	−0.7	−6.1
Combined B	CB	(1) + (4) + (6) + (10)	+0.231	+0.240	+3.7	−2.2	−1.2	−3.0	6.2	−3.2

environmental issues are a high concern. A change in this perception causes a slightly higher increase in EV choice probabilities (0.5 percentage points). However, the combined effect of both increases produces an increment of 1.2 % in EV choice probabilities.

All these results indicate that measures aimed to stimulate the adoption of EV technology should not be solely directed towards changes in general attitudes at the individual level, independent of coherence considerations. They might be more effective if they also account for how EVs can be beneficial in satisfying each need, approaching the decision-making process from a coherence perspective. These more complex changes in perspective can generate stronger effects on choice probabilities, as they are both necessary to achieve coherence networks with higher EV activations and valences. It must also be noted that some motives can bring about more significant changes in terms of class profiling. For example, the combined change in HOTCO inputs related with the pro-technological orientation motive increases the share of respondents belonging to *Class 1* ("possible innovators") by 8.3 %, while significantly reducing the other two classes; in particular, the proportion of sceptics is reduced by 5.3 %. The remaining motives cause somewhat lower variations in the class profiles.

All the changes in probabilities are relatively modest compared to those that can be obtained by variations of the economic/ instrumental attributes such as purchase prices or driving ranges.[5] Still, attitudinal effects can produce relevant shifts when combined, as can be seen in the final two scenarios in Table 11 where EV probabilities increase by 2.6 and 3.7 percentage points, and the class membership probabilities are reconfigured so that there are fewer sceptics and more innovators and potential innovators in the sample. This is derived from the strong increases in EV activation and valence, which arise from the combined effect of more positive perception of these needs. These effects can be significant, as they entail a change in the decision-making framework for at least some individuals in the sample.

5. Conclusions

Compared to the TPB (Ajzen, 1991) and other similar theories (e.g. Triandis, 1977; Wicklund & Gollwitzer, 1982; Rogers, 1983), cognitive consistency allows considering the non-linear and multidimensional interaction between the elements that constitute the mental representation of the decision-making process. Among the few models proposed to model the cognitive consistency theory, HOTCO is an attractive method to address the effect of attitudinal and emotional variables in individual choices because it yields a

[5] We simulated scenarios with EV purchase prices and operational costs reduced by 10%, and ranges increased by 10%. In these scenarios, EV choice probabilities increased by 4.4%, 1.4%, and 1.9%, respectively.

complete profile of each user's attitudinal and emotional appraisals towards behavioural motives and possible courses of action and it produces a simple representation of the relationship between the basic attitudinal scores provided by the respondent, and his/her propensity towards each behavioural outcome. This latter property is key for prediction, as it makes possible to test the effect of attitudinal changes (for example, due to learning or social interaction) on these propensities and, in turn, on choice probabilities, while prediction of latent variables in hybrid choice models is problematic due to the nature of the indicators.

The HOTCO score parameters confirms that attitudinal and affective appraisals play a key role in the choice of fuel type and vehicle segment. User profiles indicate that diffusion in the English market is already past its initial stages, as two of the three classes appear prone to innovation. In terms of the classifications of adopters in Rogers (2003) innovation diffusion theory, Class 2 is likely to include the reduced group of *early innovators* and the more numerous segment of *early adopters*, while Class 1 should include the larger part of the *early majority* which has already started to evaluate the possibility of considering the purchase of AFVs.

In addition, findings from our simulation highlight how the elements in the purchase decision interact to produce updated evaluations of the alternatives. According to the HOTCO framework, individuals first build the mental representation of the purchase decision problem in terms of their attitudes and emotional responses towards their transport needs. Their psychological evaluations of each alternative are mediated by their perceptions on how effective each vehicle type can be in satisfying these needs. Our model shows that these evaluations also sensibly affect their preferences. Coherence maximisation implies that individuals need to "make sense" of how the alternatives available can satisfy their needs. As shown in our scenario analysis, if individuals do not perceive EVs as effective means to fulfil their need of protecting the environment, they will not choose them, even if they have a strong pro-environmental attitude. These coherence effects can be crucial for policy formulation, as decision-makers are more likely to select options that are coherent with their beliefs and motivations. The efficiency of policy interventions will depend on the degree to which they are perceived as coherent by decision-makers. From the perspective of car manufacturers and sellers, awareness campaigns that highlight the connection between EVs and factors such as driving pleasure, convenience, technological appeal, and environmental awareness can significantly influence EV choice. Our analysis reveals that, while the individual impact of these factors may be modest, their cumulative effect can lead to a substantial increase in the EV choice probabilities. The combined influence of these factors can be comparable to the effects of practical improvements like extended driving range or reduced charging times. However, differently from previous research using TPB or TAM, our results show that for these effects to materialize, it is crucial that consumers perceive a strong and coherent alignment between EVs and these motivating factors. This suggests that campaign aimed at promoting EV adoption should thus clearly and effectively communicate this connection to achieve the desired outcomes.

There are some potential limitations in our study. First, while our sample represents the target population relatively well in some key dimensions, it is recruited from an online platform, which somewhat limits the generalisability of our findings. As the aim of this paper is mostly methodological, we do not claim our sample to be representative of the population. A larger and more representative sample might be required to obtain more generalisable conclusions. Second, while the HOTCO framework represents an attractive option to model decision-making from a psychological perspective, our data does not allow comparing the results with more traditional attitude-behaviour link theories in terms of their ability to represent this aspect in a choice modelling context. A more specific data collection framework that includes the HOTCO questionnaire alongside TPB-compatible attitudinal questionnaire would potentially enable these comparisons, and we suggest this as possible further research in this topic. Third, from a practical standpoint, the large number of inputs required to model decision-making using HOTCO increases the questionnaire complexity and places a greater burden on respondents. While we did not observe significant evidence of respondent fatigue in either the HOTCO input questionnaire or the stated choice experiment, the length of the questionnaire can pose challenges for survey administration. This makes adapting HOTCO to other research contexts somewhat difficult. The use of HOTCO requires also a sequential estimation of the hybrid choice models, because at the moment it is not possible to estimate it jointly with the discrete choice part. Finally, our framework for integrating activations and valences into the discrete choice modelling assumes that coherence evaluation precedes choice. As activation and valence can be influenced by the same factors that affect choice, our latent variable might be endogenous to choice (e.g. Chorus & Kroesen, 2014). Further work is required to postulate a modelling framework that allows for simultaneous estimation of the HOTCO outputs and the preference parameters, avoiding this source of endogeneity. The question of how well such a modelling framework would represent the decision-making problem is open. Further theoretical work, possibly of a qualitative nature, might be required to combine cognitive consistency and utility maximisation, as they are, in principle, difficult to reconcile. Exploring such a unified theory is also proposed as further research derived from this paper.

CRediT authorship contribution statement

Cristian Domarchi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisabetta Cherchi:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Quoc C. Vuong:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation.

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Appendix A. – Full simulation results

The following table contains the full results of the 42 simulation scenarios, as explained in section 4.3.

Forecasting scenarios for the all the car purchasing motives.

Motive	Sc.	Change	Change in HOTCO outputs for EV		Percentage change in choice probabilities			Percentage change in class membership probabilities		
			Activation	Valence	EV	HEV	ICE	Class 1	Class 2	Class 3
Environmentalawareness (1)	1–1	+ *Priority*	+0.026	+0.000	+0.2	+0.1	−0.3	+0.8	−1.0	+0.2
	1–2	+ *Emotional*	+0.024	+0.016	+0.3	+0.1	−0.4	+0.7	−0.5	−0.2
	1–3	+ *EV link*	+0.032	+0.057	+0.5	−0.3	−0.2	+0.4	−0.3	−0.1
	1–4	*Combined*	+0.092	+0.091	+1.2	−0.1	−0.9	+0.9	−0.4	−0.5
Purchase cost (2)	2–1	+ *Priority*	−0.007	−0.001	+0.1	−0.3	+0.0	−0.4	+1.1	−0.7
	2–2	+ *Emotional*	−0.011	+0.004	+0.2	−0.2	−0.1	+0.0	+0.4	−0.3
	2–3	+ *EV link*	+0.013	+0.054	+0.8	−0.4	−0.3	+0.1	+0.1	−0.2
	2–4	*Combined*	+0.052	+0.064	+0.9	−0.7	−0.2	−1.4	+2.9	−1.6
Performance (3)	3–1	+ *Priority*	+0.004	+0.005	−0.2	+0.1	+0.1	−1.7	−0.4	+2.1
	3–2	+ *Emotional*	−0.002	−0.011	−0.4	+0.1	+0.3	−1.8	−0.4	+2.2
	3–3	+ *EV link*	+0.067	+0.050	+0.8	−0.4	−0.3	+0.2	−1.0	+0.8
	3–4	*Combined*	+0.078	+0.054	+0.5	−0.4	−0.2	−2.4	−1.5	+3.9
Pleasure/Enjoyment (4)	4–1	+ *Priority*	+0.007	+0.008	+0.0	−0.1	+0.1	−0.4	1.1	−0.7
	4–2	+ *Emotional*	+0.002	+0.008	+0.1	−0.1	+0.0	+0.1	+0.3	−0.4
	4–3	+ *EV link*	+0.068	+0.062	+0.9	−0.4	−0.4	+0.7	−0.5	−0.2
	4–4	*Combined*	+0.099	+0.100	+1.0	−0.7	−0.2	−0.2	+1.5	−1.2
Pro-technologicalOrientation (5)	5–1	+ *Priority*	+0.007	+0.009	+0.3	−0.3	+0.0	+0.0	+0.5	−0.5
	5–2	+ *Emotional*	+0.002	+0.011	+0.4	−0.3	−0.2	−0.1	+1.0	−0.9
	5–3	+ *EV link*	+0.067	+0.058	+1.0	−0.4	−0.4	+0.7	−0.3	−0.4
	5–4	*Combined*	+0.086	+0.082	+1.4	−0.9	−0.5	−0.4	2.2	−1.8
Flexibility (6)	6–1	+ *Priority*	+0.007	+0.008	+0.2	0.2	−0.2	+1.2	−2.4	+1.2
	6–2	+ *Emotional*	+0.006	+0.012	+0.7	0.0	−0.5	+6.2	−2.0	−4.2
	6–3	+ *EV link*	+0.066	+0.087	+1.0	−0.6	−0.3	+1.6	−0.6	−1.0
	6–4	*Combined*	+0.093	+0.091	+1.6	−0.5	−0.7	+8.3	−3.0	−5.3
Self-identification (7)	7–1	+ *Priority*	−0.001	+0.004	+0.3	+0.0	−0.2	+0.4	−0.3	−0.1
	7–2	+ *Emotional*	−0.006	−0.002	−0.4	+0.0	+0.3	−5.5	−1.6	+7.1
	7–3	+ *EV link*	+0.052	+0.046	+0.6	−0.3	−0.3	+0.0	−0.9	+0.9
	7–4	*Combined*	+0.084	+0.070	+0.1	−0.3	+0.2	−6.7	−0.2	+6.8
Pro-innovativeorientation (8)	8–1	+ *Priority*	−0.006	+0.009	+0.0	+0.2	−0.2	+0.0	−0.2	+0.2
	8–2	+ *Emotional*	+0.002	+0.030	+0.0	+0.1	+0.0	+0.1	−0.4	+0.3
	8–3	+ *EV link*	+0.008	+0.071	+0.6	−0.4	−0.2	+0.1	+0.3	−0.4
	8–4	*Combined*	+0.023	+0.083	+0.7	−0.3	−0.3	+0.3	+0.1	−0.4
Comfort (9)	9–1	+ *Priority*	+0.007	+0.008	+0.3	−0.2	+0.0	+0.5	−0.1	−0.4
	9–2	+ *Emotional*	−0.001	+0.003	+0.1	+0.2	−0.2	+1.0	−1.4	+0.4
	9–3	+ *EV link*	+0.064	+0.060	+1.1	−0.7	−0.3	+1.2	−0.7	−0.4
	9–4	*Combined*	+0.087	+0.081	+1.1	−0.5	−0.4	+0.2	+0.5	−0.7
Convenience (10)	10–1	+ *Priority*	+0.016	+0.012	+0.2	−0.3	0.1	−1.0	+0.7	+0.3
	10–2	+ *Emotional*	+0.010	+0.002	+0.5	−0.2	−0.3	+5.2	+0.6	−5.8
	10–3	+ *EV link*	+0.044	+0.044	+0.8	−0.4	−0.3	+1.4	−0.5	−0.9
	10–4	*Combined*	+0.080	+0.074	+1.2	−0.8	−0.4	+4.6	+3.0	−7.6
Combined A	CA	(4) + (8)	+0.160	+0.151	+2.6	−1.1	−1.1	+6.8	−0.7	−6.1
Combined B	CB	(4) + (6) + (8) + (10)	+0.231	+0.240	+3.7	−2.2	−1.2	−3.0	6.2	−3.2

Appendix B. – HOTCO questionnaire

The attitudinal questionnaire in the survey included questions aiming to measure the required inputs to build the HOTCO connectionist networks, considering these ten motives as *needs* nodes, and three possible *action* outcomes of the purchase decision: EV, HEV, and petrol vehicle with an internal combustion engine (ICE). The format of the questions for each HOTCO input is summarised in Table B1:

Table B1
HOTCO – Questionnaire formulation.

Input type	Meaning	Question wording	Scale	N
Priority	Desirability of each need "*for intrinsic or other non-coherence reasons*" (Thagard and Millgram, 1997).	"*Please rate these items according to its importance to you when you decide which type of car to buy*".	5-point Likert scale from "Not important at all" to "Very important".	10

(*continued on next page*)

Table B1 (*continued*)

Input type	Meaning	Question wording	Scale	N
Emotional scale (1) Pleasure	Continuum between happiness and unhappiness.	*"To which extent do these items make you feel happy (instead or sad)".*	5-point Likert scale from "To no extent" to "To a very large extent".	10
Emotional scale (2) Arousal	Continuum between excitedness and calmness.	*"To which extent do these items make you feel excited (instead or calm)".*	5-point Likert scale from "To no extent" to "To a very large extent".	10
Facilitation links	Perception of connection between *needs* and *action* nodes.	"*To what extent do you think these needs or requirements would be satisfied by choosing a* [petrol vehicle, electric vehicle, hybrid-electric vehicle]".	5-point Likert scale from "To no extent" to "To a very large extent".	30

All these items were measured using a 5-point Likert scale and coded to ensure that the scores varied from –1 to + 1. The complete calibration of a HOTCO network requires 10 + 10 + 10 + 30 = 60 ratings by each respondent. All the sentences evaluating the same questions were placed in the same screen, so that all 10 items could be rated relatively quickly. In addition, all the motives were randomised for each evaluation question, to avoid any biases derived from question ordering. These questionnaires were included in both surveys (*Before* and *After*). Further details are discussed in Domarchi (2023) and Domarchi et al. (2024).

Data availability

Data will be made available on request.

References

Abotalebi, E., Scott, D.M., Ferguson, M.R., 2019. Why is electric vehicle uptake low in Atlantic Canada? A comparison to leading adoption provinces. J. Transp. Geogr. 74, 289–298. https://doi.org/10.1016/j.jtrangeo.2018.12.001.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Aravena, C., Denny, E., 2021. The impact of learning and short-term experience on preferences for electric vehicles. Renew. Sustain. Energy Rev. 152, 111656. https://doi.org/10.1016/j.rser.2021.111656.

Axsen, J., Bailey, J., Castro, M., 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.

Bansal, P., Kumar, R.R., Raj, A., Dubey, S.K., Graham, D.J., 2021. Willingness to pay and attitudinal preferences of Indian consumers for electric vehicles. Energy Econ. 100, 105340. https://doi.org/10.1016/j.eneco.2021.105340.

Bierlaire, M., 2023. *A short introduction to Biogeme. Technical report TRANSP-OR 230620*. Transp. Mobility Lab., ENAC, EPFL.

Caussade, S., de Dios Ortúzar, J., Rizzi, L.I., Hensher, D.A., 2005. Assessing the influence of design dimensions on stated choice experiment estimates. Transp. Res. B Methodol. 39 (7), 621–640. https://doi.org/10.1016/j.trb.2004.07.006.

ChoiceMetrics. (2018). Ngene 1.2 User Manual & Reference Guide.

Cherchi, E., Manca, F., 2011. Accounting for inertia in modal choices: some new evidence using a RP/SP dataset. Transportation 38, 679–695. https://doi.org/10.1007/s11116-011-9338-9.

Chorus, C.G., Kroesen, M., 2014. On the (im-)possibility of deriving transport policy implications from hybrid choice models. Transp. Policy 36, 217–222. https://doi.org/10.1016/j.tranpol.2014.09.001.

Commission of the European Communities (1999). Merger Procedure Article 6(1)(b) of Council Regulation (EEC) No 4064/89 – Decision on Case No IV/M.1406. HYUNDAI / KIA, (1999).

Cook, R.D., Nachtrheim, C.J., 1980. A comparison of algorithms for constructing exact D-optimal designs. Technometrics 22 (3), 315–324. https://doi.org/10.1080/00401706.1980.10486162.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319–340 https://doi.org/10.2307%2F249008.

Department for Transport. (2021). *National Travel Survey, 2002-2020 [data collection]* (SN: 5340; Version 14th Edition). https://doi.org/10.5255/UKDA-SN-5340-11.

Department for Transport. (2022a). *TAG Data Book [data collection]*. https://www.gov.uk/government/publications/tag-data-book.

Department for Transport. (2022b). *VEH1153: Vehicles registered for the first time by body type and fuel type: Great Britain and United Kingdom [data collection]*. https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables.

Department for Transport. (2024). *VEH1153: Vehicles registered for the first time by body type and fuel type: Great Britain and United Kingdom [data collection]*. https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables.

Domarchi, C. (2023). Integrated diffusion and choice models for innovative transport alternatives: An application to the electric vehicle market. Phd Thesis. Newcastle University.

Domarchi, C., Cherchi, E., 2023. Electric vehicle forecasts: a review of models and methods including diffusion and substitution effects. Transp. Rev. 43 (6), 1118–1143. https://doi.org/10.1080/01441647.2023.2195687.

Domarchi, C., Cherchi, E., 2024. Role of car segment and fuel type in the choice of alternative fuel vehicles: a cross-nested logit model for the English market. Appl. Energy 357, 122451. https://doi.org/10.1016/j.apenergy.2023.122451.

Domarchi, C., Vuong, Q.C., Cherchi, E., 2024. The role of emotional coherence in electric vehicle purchasing decisions. Transport. Res. F: Traffic Psychol. Behav. 107, 997–1014. https://doi.org/10.1016/j.trf.2024.10.018.

Ferguson, M.R., 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. Part D: Transp. Environ. 58, 208–224. https://doi.org/10.1016/j.trd.2017.12.006.

Ghasri, M., Ardeshiri, A., Rashidi, T.H., 2019. Perception towards electric vehicles and the impact on consumers' preference. Transp. Res. Part D: Transp. Environ. 77, 271–291. https://doi.org/10.1016/j.trd.2019.11.003.

Giansoldati, M., Rotaris, L., Scorrano, M., Danielis, R., 2020. Does electric car knowledge influence car choice? Evidence from a hybrid choice model. Res. Transp. Econ. 80, 100826. https://doi.org/10.1016/j.retrec.2020.100826.

Glöckner, A., Betsch, T., 2008. Modeling option and strategy choices with connectionist networks: towards an integrative model of automatic and deliberate decision making. MPI Collective Goods Preprint 2008 (2), 1–28. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1090866.

Glöckner, A., Hilbig, B.E., Jekel, M., 2014. What is adaptive about adaptive decision making? A parallel constraint satisfaction account. Cognition 133, 641–666. https://doi.org/10.1016/j.cognition.2014.08.017.

Gong, S., Ardeshiri, A., Rashidi, T.H., 2020. Impact of government incentives on the market penetration of electric vehicles in Australia. Transp. Res. Part D: Transp. Environ. 83, 102353. https://doi.org/10.1016/j.trd.2020.102353.

González, R.M., Marrero, A., Cherchi, E., 2017. Testing for inertia effect when a new tram is implemented. Transp. Res. A Policy Pract. 98, 150–159. https://doi.org/10.1016/j.tra.2017.02.007.

Hidrue, K., Parsons, G.R., 2015. Is there a near-term market for vehicle-to-grid electric vehicles? Appl. Energy 151, 67–76. https://doi.org/10.1016/j.apenergy.2015.04.051.

Higueras-Castillo, E., Kalinic, Z., Marinkovic, V., Liébana-Cabanillas, F.J., 2020. A mixed analysis of perceptions of electric and hybrid vehicles. Energy Policy 136 (4), 111076. https://doi.org/10.1016/j.enpol.2019.111076.

HM Government. (2021). *Transitioning to zero emission cars and vans: 2035 delivery plan*. Retrieved from https://www.gov.uk/government/publications/transitioning-to-zero-emission-cars-and-vans-2035-delivery-plan.

International Energy Agency. (2022). *Global EV Outlook 2022: Securing supplies for an electric future*. International Energy Agency. Retrieved 30 June 2022 from https://www.iea.org/reports/global-ev-outlook-2022.

Kim, S.H., Mokhtarian, P.L., 2023. Finite mixture (or latent class) modeling in transportation: trends, usage, potential, and future directions. Transp. Res. B Methodol. 172, 134–173. https://doi.org/10.1016/j.trb.2023.03.001.

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. Part D: Transp. Environ. 67, 685–702. https://doi.org/10.1016/j.trd.2018.10.010.

Jensen, A.F., Thorhauge, M., Mabit, S.E., Rich, J., 2021. Demand for plug-in electric vehicles across segments in the future vehicle market. Transp. Res. Part D: Transp. Environ. 98, 102976. https://doi.org/10.1016/j.trd.2021.102976.

Lane, B.W., Dumortier, J., Carley, S., Siddiki, S., Clark-Sutton, K., Graham, J.D., 2018. All plug-in electric vehicles are not the same: predictors of preference for a plug-in hybrid versus a battery-electric vehicle. Transp. Res. Part D: Transp. Environ. 65, 1–13. https://doi.org/10.1016/j.trd.2018.07.019.

Liao, F., Molin, E., van Wee, B., 2017. Consumer preferences for electric vehicles: a literature review. Transp. Rev. 37 (3), 252–275. https://doi.org/10.1080/01441647.2016.1230794.

Liu, Y., Cirillo, C., 2018. Modeling green vehicle adoption: an integrated approach for policy evaluation. Int. J. Sustain. Transp. 12 (7), 473–483. https://doi.org/10.1080/15568318.2017.1393584.

Manca, F., Sivakumar, A., Daina, N., Axsen, J., Polak, J.W., 2020. Modelling the influence of peers' attitudes on choice behaviour: theory and empirical application on electric vehicle preferences. Transp. Res. A Policy Pract. 140, 278–298. https://doi.org/10.1016/j.tra.2020.08.016.

Ortuzar, J. de D. & Willumsen, L. G. (2024). *Modelling Transport* (5th ed.) Wiley and Sons.

Petty, R. E., & Wegener, D. T. (1998). Attitude change: Multiple roles for persuasion variables. In D. Gilbert, S. Fiske, & G. Lindzey (Eds.), *The Handbook of Social Psychology* (4th ed., Vol. 1). McGraw-Hill.

Rogers, R.W., 1983. Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation. In: Cacioppo, J.T., Petty, R. E. (Eds.), *Social Psychophysiology: A Sourcebook*. Guilford.

Rogers, E.M., 2003. *Diffusion of Innovations*, (5th ed.). Free Press.

Rose, J., Bliemer, M.J.C., 2009. Constructing efficient stated choice experimental designs. Transp. Rev. 29 (5), 587–617. https://doi.org/10.1080/01441640902827623.

Rotaris, L., Giansoldati, M., Scorrano, M., 2021. The slow uptake of electric cars in Italy and Slovenia. Evidence from a stated-preference survey and the role of knowledge and environmental awareness. Transp. Res. A Policy Pract. 144, 1–18. https://doi.org/10.1016/j.tra.2020.11.011.

Schröder, T., Wolf, I., 2017. Modeling multi-level mechanisms of environmental attitudes and behaviours: the example of carsharing in Berlin. J. Environ. Psychol. 52, 136–148. https://doi.org/10.1016/j.jenvp.2016.03.007.

Simon, D., Stenstrom, D.M., 2015. The coherence effect: Blending cold and hot cognitions. J. Pers. Soc. Psychol. 109 (3), 369–394. https://doi.org/10.1037/pspa0000029.

SurveyEngine. (2022). *SurveyEngine GmbH*. In https://surveyengine.com/.

Teoalida. (2021). European United Kingdom car database, January 2021 version [data collection]. https://www.teoalida.com/cardatabase/uk/.

Thagard, P., 1989. Explanatory coherence. Behav. Brain Sci. 12, 435–502. https://doi.org/10.1017/S0140525X00057046.

Thagard, P., 2001. How to make decisions: Coherence, emotion, and practical inference. In: Millgram, E. (Ed.), *Varieties of Practical Inference*. MIT Press, pp. 355–371.

Thagard, P., 2006. Hot Thought: Mechanisms and applications of emotional contagion. The MIT Press.

Thagard, P., Millgram, E., 1997. Inference to the best plan: A coherence theory of decision. In: Ram, A., Leake, D.B. (Eds.), *Goal-Driven Learning*. MIT Press, pp. 439–454.

Thibault, D. U. (2013). *ECHO: Explanatory Coherence by Harmony Optimization. A flexible implementation*. https://www.researchgate.net/publication/235418721.

Thiel, C., Schmidt, J., Van Zyl, A., Schmid, E., 2014. Cost and well-to-wheel implications of the vehicle fleet CO_2 emission regulation in the European Union. Transp. Res. A Policy Pract. 63, 25–42. https://doi.org/10.1016/j.tra.2014.02.018.

Triandis, H.C., 1977. Interpersonal Behavior Brooks/Cole Pub. Co.

Valeri, E., Cherchi, E., 2016. Does habitual behavior affect the choice of alternative fuel vehicles? Int. J. Sustain. Transp. 10 (9), 825–835. https://doi.org/10.1080/15568318.2016.1163445.

Walker, J. L. (2001). *Extended discrete choice models: integrated framework, flexible error structures, and latent variables* Massachusetts Institute of Technology]. Cambridge, Massachusetts, US. http://dspace.mit.edu/handle/1721.1/7582.

Walker, J.L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in Normal error component logit-mixture (NECLM) models. J. Appl. Economet. 22, 1095–1125. https://doi.org/10.1002/jae.971.

Wicki, M., Brückmann, G., Quoss, F., Bernauer, T., 2023. What do we really know about the acceptance of battery electric vehicles? – Turns out, not much. Transp. Rev. 43 (1), 62–87. https://doi.org/10.1080/01441647.2021.2023693.

Wicklund, R.A., Gollwitzer, P.M., 1982. Symbolic Self Completion, (1st ed.). Routledge.

Wolf, I., Schröder, T., Neumann, J., de Haan, G., 2015. Changing minds about electric cars: an empirically grounded agent-based modeling approach. Technol. Forecast. Soc. Chang. 94, 269–285. https://doi.org/10.1016/j.techfore.2014.10.010.

ZapMap.Com. (2024). *Public Charging Calculator*. Retrieved 11 September 2024 from https://www.zap-map.com/tools/public-charging-calculator/.