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The role of emotional coherence in electric vehicle purchasing decisions

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ABSTRACT

Cognitive consistency theories offer a solid background to understand the effects of latent psychological constructs in decision-making. These theories model decision-making as the product of a dynamic and recursive process in which individual elements are evaluated toward a decision and this emerging decision returns to its individual elements. In this study, we use the Hot Coherence (HOTCO) cognitive consistency theory to analyse the choice between electric, hybrid-electric, and petrol vehicles. We apply the model to a sample of respondents from England households with one or more cars. The HOTCO model offers a more nuanced representation of the decision-making process – compared with traditional attitude-behaviour link theories – by incorporating non-linear and multidimensional interactions between its components. Our results suggest that positive attitudes and emotional appraisals for electric and hybrid-electric vehicles are shaped by similar motivators, and respondents perceive them as capable of satisfying the same set of needs. In addition, environmental awareness and pro-innovative orientation are the two motives that generate the greater differences in attitudinal evaluations of petrol vehicles, compared with alternative fuels.

1. Introduction

Latent psychological constructs, including attitudes towards the environment, innovation-oriented beliefs, and social influence, have been widely acknowledged as relevant motivators for electric vehicle (EV) purchases (e.g., Adnan et al., 2016; Axsen & Kurani, 2014; Beck et al., 2017; Bennett & Vijaygopal, 2018; Bhat et al., 2021; Broadbent & Wiedmann, 2021; Franke et al., 2011; Haustein & Jensen, 2018; Jensen et al., 2014; Junquera et al., 2016; Liao et al., 2017; Maybury et al., 2022; Mohamed et al., 2016; Morton et al., 2016; Rainieri et al., 2023; Schmalfuß et al., 2017; van Heuveln et al., 2021; Westin et al., 2018; Wicki et al., 2022). Studies addressing the effect of psychological factors in EV adoption behaviour tend to rely on the Theory of Planned Behaviour (TPB; Ajzen, 1991) and other similar theories (e.g., Theory of Interpersonal Behaviour, Protection Motivation Theory and Symbolic Self-Completion Theory). Sovacool (2017) reviews a list of psychological theories used to model this issue. In the TPB, attitudes, subjective norms, and perceived behavioural control influence behavioural intention which, in turn, is the most proximal determinant of behaviour. The TPB is the most widely used and validated; however, behaviour is likely to depend upon factors outside those included in this theory, such as emotions, situational elements, or prior experience. Although these factors are accounted for in certain extensions of the TPB (Ajzen, 1991), they

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are still often neglected in applications. Other theories, for example, the Theory of Interpersonal Behaviour (Triandis, 1977), incorporates aspects like the frequency of past behaviour and emotions into the evaluation, whereas the Symbolic Self-Completion Theory focuses on individuals adopting behaviours that are symbolically related to what they perceive as their "ideal" self (Wicklund & Gollwitzer, 1982). In the Protection Motivation Theory (Rogers, 1983), a behavioural response is adopted only when perceptions of response efficacy and self-efficacy outweigh the response costs of the behaviour. Importantly, all these attitude-behaviour link theories consider independent evaluations of each component and assume linear and unidirectional links between psychological constructs (e.g., attitudes influence intentions, and intentions) predict behaviour. Some researchers, however, argue that human decision-making is substantially affected by mutual interactions among the components of the cognitive representation (Simon & Stenstrom, 2015). This is particularly crucial for complex decisions – such as the purchase of a vehicle – in which individuals must simultaneously assess several factors whose effects are not necessarily linear or additive, but rather interact with each other to generate cognitive evaluations.

Cognitive consistency theories of behaviour have been proposed in response to these challenges (see Simon & Holyoak, 2002, for a review). According to cognitive consistency theories, a cognitive state (e.g., decision) is determined by a dynamic and recursive process in which individual elements are evaluated toward a decision and this emerging decision updates the individual elements. The assumption of mutual interdependency among the elements of thought forming states of "order and coherence" originated several theoretical frameworks (Glöckner & Betsch, 2008), but largely abandoned because they "failed to yield a general account of the mechanisms by which attitudes are formed and decisions are made" (Simon & Holyoak, 2002, p. 283).

Cognitive consistency theories were reformulated with the advent of connectionist theories of cognition. The most important of these is the Hot Coherence (HOTCO) model (Thagard, 1989, 2006; Thagard & Millgram, 1997), which represents individual decision-making as a connectionist network consisting of motivation and behavioural-response nodes that interact with each other to produce a consistent assessment. The HOTCO model explains behaviour as the result of this interaction. HOTCO models have been used in contexts as diverse as ethical justification, cognitive dissonance, and democratic deliberation (Thagard, 2006; Thagard & Verbeurgt, 1998). A handful of studies have used the HOTCO model to explain decision-making processes in the context of pro-environmental behaviour specifically in the transport context. Wolf et al. (2015) used the HOTCO model in the context of an agent-based model to understand attitudes towards electric vehicle adoption, while Schröder and Wolf (2017) used the same model to understand pro-environmental transport behaviour. More recently, Liang et al. (2022) used a HOTCO network to model agent decision-making behaviour in an agent-based model to simulate the effectiveness of policy measures on the use of green space. These studies focused on communication issues and network diffusion. Because of that, the researchers used the output of the HOTCO simulation – activations and valences – essentially as proxy for behaviour in their diffusion models but did not analyse the determinants of the adoption decision in terms of the structure of the coherence networks.

The primary aim of this paper is to model vehicle purchasing decisions using the HOTCO model to understand and analyse the motivating factors of a transport decision. We derive three specific objectives related to this aim: first, to understand the cognitive consistency of the decision-making process from an individual's perspective; second, to identify the most relevant determinant factors of the electric vehicle-purchasing decision; and third, to investigate the interactions and interdependencies between psychological constructs in this process.

We apply the HOTCO model to the choice of vehicle fuel type among three possible alternatives (electric vehicle, EV; plug-in hybrid-electric vehicle, HEV; and internal combustion engine vehicle, ICE), using a sample of vehicle owners residing in England. The HOTCO model is particularly well-suited to address this issue from a psychological perspective, as vehicle choice is a complex decision-making problem with several motivating factors that require simultaneous evaluation. Unlike traditional attitude-behaviour link theories (e.g., Ajzen, 1991; Triandis, 1977), the HOTCO model iteratively assesses the interactions between individuals' evaluations of needs (motives) and their evaluations of actions to build a consistent mental representation of the decision. Psychological theories using linear and unidirectional links between constructs cannot account for these complex interactions (e.g., Simon & Holyoak, 2002; Thagard, 2006). Thus, using this multidimensional and integrated analysis in understanding a choice problem is the main contribution of this paper to the literature.

As far as we are aware, our study is the first to analyse vehicle choice as a coherence problem, understanding its psychological motivators and studying their interrelations, and the role of attitudinal and emotional appraisals in the purchase decision. The outcomes from this analysis can potentially strengthen policy design in terms of acceptability, by focusing on the dimensions that are more relevant in shaping attitude formation and change, and effecting behavioural changes that are perceived as consistent in terms of coherence maximisation.

The remainder of the paper is organised as follows. First, Section 2 presents a brief overview of cognitive consistency models in general, and of the HOTCO model in particular, focusing on its advantages in addressing complex decisional behaviour. Section 3 introduces the survey used to collect the required information along with descriptive analyses of the sample. Next, Section 4 presents the methodology used to calibrate the HOTCO networks and analyse their outcomes. Finally, the results of this analysis are provided in Section 5, with some closing remarks and conclusions in Section 6.

2. Theory and calculation

2.1. HOTCO model

The HOTCO model (Thagard, 1989; 2006; Thagard & Millgram, 1997) is a cognitive consistency theory implemented as a parallel constraint satisfaction model. The theory assumes that individuals make decisions by maximising the *coherence* of their current beliefs and emotions in terms of maximal satisfaction of multiple constraints derived from mental representations of the decision-making process (Thagard, 2001).

The elements in a HOTCO mental representation include certain *needs* to be satisfied as well as possible *actions* to be undertaken. A need is said to be "coherent" with an action if the action facilitates the satisfaction of the need. 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. Conversely, if the action is deemed as detrimental to the satisfaction of the need, it is said to be "incoherent" with it. In our context, 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.

When a need coheres with an action, there is a positive constraint between them; conversely, a negative constraint exists between them if they are not coherent. Positive constraints can be satisfied by accepting both elements (the action and the need) or rejecting both, while a negative constraint can be satisfied by accepting one and rejecting the other. The coherence problem consists of dividing the set of elements (actions and needs) in the mental representation into accepted and rejected sets in a way that satisfies the most constraints (Thagard & Verbeurgt, 1998). The problem is modelled using a connectionist network to organise the mental representation of the decision-making problem. In such a network, neuron-like units (nodes) represent elements (*actions* and *needs*) while excitatory and inhibitory links between nodes represent positive and negative constraints (Thagard, 2006). In the HOTCO algorithm, activation, understood as an indicator of the level of acceptability of each node, is spread through the network in a way that activates some nodes and deactivates others. At the end of this process, each node will have a certain degree of activation (Thagard, 2001), and the resulting network will involve the best possible satisfaction of all the given constraints in parallel.

Sociologists distinguish between "cold" and "hot" cognition, which differ in that the latter includes an emotional component (Abelson & Rosenberg, 1968). In deliberative (or "cold") decision making, the final state of a network only depends on the intrinsic importance the respondent gives to each motive, and in the perceived links between the actions and the satisfaction of each need. Emotions can be modelled within a coherence network assuming that nodes can have, in addition to acceptability, an emotional valence. In this context, valence is understood as a positive or negative emotional appraisal, and can represent likability, desirability, or any other positive/negative evaluation. Just as they are linked by positive and negative deliberative constraints, units can also be linked by positive and negative valence constraints, and valence can be spread through the network in a similar manner as activation. However, valence spread depends in part on activation spread, as the emotional appraisal of an element does not just depend on the appraisals of the elements that constrain it, but also on their acceptability (Thagard, 2001, 2006). In our context, attaching a negative emotional appraisal to the action of purchasing an EV depends both on the relevant needs (for example, pro-environmental attitude) having a negative valence, and on the acceptability (activation) of pro-environmental behaviour in the current context.

The simultaneous spread of activation and valence defines a "hot" cognition model. Understanding the decision-making process with a HOTCO model involves a simultaneous consideration of the deliberative and emotional components within the network representation, with emotional coherence essentially distorting the rational deliberation by allowing emotional appraisal into the evaluation of evidence (Thagard, 2021). As a result of the calibration process, each node is given a certain level of cognitive activation, a measure of its acceptability; and a valence, measuring its emotional response.

2.2. HOTCO algorithm

Fig. 1 shows a generic network with 10 *needs* nodes (light blue circles numbered from 1 to 10) and 3 *action* nodes (light orange circles numbered I, II, and III). Actions and needs are connected by excitatory or inhibitory links, depending on the extent to which the individual perceives that each action is excited or inhibited by each need. In addition, *Needs* nodes are also connected to a special

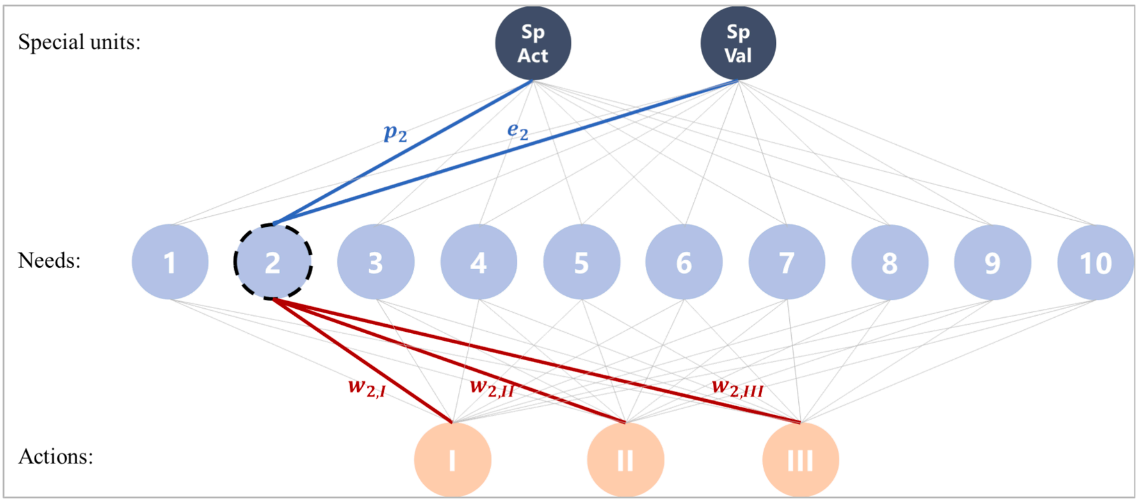


Fig. 1. Representation of a generic hot coherence network.

activation node (SpA; with activation always equal to $+1$) with an excitatory link whose weight is proportional to the importance (priority) given to the need by the individual. The *Needs* nodes are also connected to a special valence node (SpV; with valence always equal to $+1$) with a link whose weight depends on the emotional appraisal of the need. In practice, these two special nodes store information about the relevance of each motive to the respondent, independently from their perceived relationship with any behavioural outcome (action).

Fig. 1 highlights the connections of Need 2 with the three action nodes ($w_{2,I}$, $w_{2,II}$, $w_{2,III}$), as well as with the special activation and valence units (p_2, e_2). These attributes are network inputs. Fig. 2 presents a zoom in on Need 2, revealing its two main outputs (activation, a_2; and valence, v_2). The priority weight p_2 directly influences the activation flow, while the emotional weight e_2 has a direct effect on the valence flow; however, the two outputs (a_2 and v_2) also interact with each other. The weights of the links between the *Action* nodes and the *Needs* nodes ($w_{2,I}$, $w_{2,II}$, $w_{2,III}$) are the same for both outputs (activations and valences).

The HOTCO algorithm is executed in a process where activations and valences are spread through the network. Convergence is a cyclic process where each node updates its activations and valences in parallel with all other units on every cycle. With this method, activations and valences depend on their previous value on the cycle as well as the combined stimulus received from all the connected nodes (Thibault, 2013). On every cycle, the activation of node *j*, a_j is updated according to the sigmoid activation function proposed by McClelland and Rumelhart (1981):

$$a_j(t+1) = \begin{cases} a_j(t)\cdot(1-d) + net_j\cdot\left(ceiling - a_j(t)\right) & \text{if } net_j > 0, \text{ and} \\ a_j(t)\cdot(1-d) + net_j\cdot\left(a_j(t) - floor\right) & \text{otherwise.} \end{cases} \tag{1}$$

In this expression, *d* is a decay parameter which symbolises the loss of information between two consecutive cycles and is usually taken to be equal to 0.05. In addition, activations are constrained to the $[-1;+1]$ range so that *floor* is the minimum activation (-1) and *ceiling* is the maximum activation ($+1$). The net input to a node is calculated as:

$$net_j = \sum_i w_{ij}\cdot a_i(t) + \sum_i w_{ij}\cdot a_i(t)\cdot v_i(t) \tag{2}$$

In this expression, w_{ij} is the weight between nodes *i* and *j*, while $v_i(t)$ represents the valence of node *i* during cycle *t*. The link weight will be positive if there is an excitatory relationship between nodes *i* and *j* and negative if there is an inhibitory relationship. Node valences, on the other hand, are updated with the following formula:

$$v_j(t+1) = \begin{cases} v_j(t)\cdot(1-d) + netval_j\cdot\left(max - v_j(t)\right) & \text{if } netval_j > 0, \text{ and} \\ v_j(t)\cdot(1-d) + netval_j\cdot\left(v_j(t) - min\right) & \text{otherwise.} \end{cases} \tag{2}$$

Here, $netval_j$ is the net valence input to the unit, and is calculated as:

$$netval_j = \sum_i w_{ij}\cdot a_i(t)\cdot v_i(t) \tag{4}$$

These equations denote that valence flow is spread through the network by interacting with the activation values of the nodes, and that the net input to each node depends on both the activations and the valences of all the connected nodes. The process is carried out until the network has reached a "settled" status – i.e., when the change in activations and valences between two successive iterations is lower than a certain predefined threshold – which usually happens after a few hundred iterations.

The resulting activations and valences can be analysed from a cognitive consistency perspective. Actions and needs with positive activations will cohere and will therefore be seen as consistent from a cognitive perspective; similarly, activations and needs with a positive valence will be perceived as consistent from an emotional perspective. These actions should be "accepted" by the decision-maker, i.e., they should be the most likely outcome of the decision-making process. Conversely, actions and needs with negative activations and valences will cohere, and it is likely that the decision-maker will "reject" this outcome.

3. Materials and methods

A survey was designed to collect the information required to analyse vehicle fuel type purchase decisions. The survey was used to collect the information required to calibrate the HOTCO networks, as well as basic socioeconomic and geographic location characteristics of each household. The details are described in the next sections.

3.1. Identification of motives

The first step to build HOTCO networks was to identify the main motives of vehicle purchases in England. As this is the first application of the HOTCO framework to model a vehicle choice decision in this market, no pre-existing list of motives was found in the literature. Wolf et al. (2015) and Schröder and Wolf (2017) are the only articles that used the HOTCO model in the transport context, but the list of motives in their papers refer to the German market. In addition, these studies only provided a list of the motive labels without a description of the motives.

To overcome this issue, we surveyed the literature and identified 22 studies that included attitudinal questions that measure motives for car purchasing in the context of developed economies. We summarised and standardised the questions and generated a list of 20 possible motives to test. We carried out a preliminary survey to obtain an importance rating for each motive on a 5-point Likert

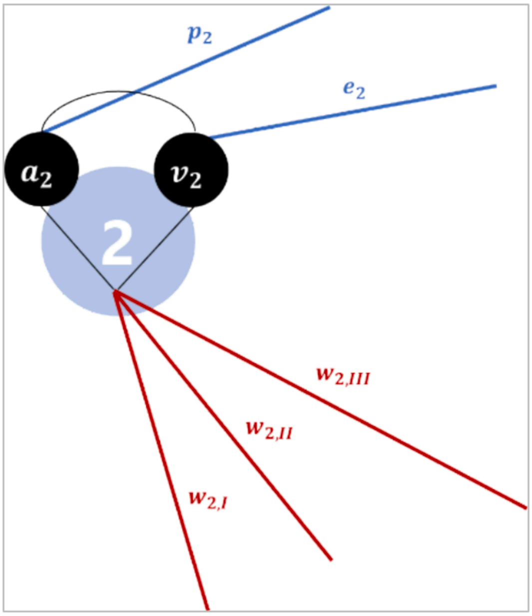


Fig. 2. Hot coherence network – Zoom in on Node 2.

scale. The data obtained from this preliminary survey (N = 359) were first analysed with exploratory and confirmatory factor analyses to identify the factors representing latent motives.[1] Two structural equation models (SEM) were then estimated (one for the short-term and one for the long-term) to link the importance ratings for each item with assessments of short- and long-term EV purchase intentions for respondents. Table 1 lists the 20 motives tested and their exact wording in the survey. Several specifications of direct and indirect effects were tested. The results of the best SEM model for short-term and long-term EV purchase intention are depicted in Fig. 3A and Fig. 3B, respectively. The SEM outputs are also summarised in the last two columns of Table 1, which indicate if each motive has a statistically significant influence in either short- or long-term EV purchase intention. All the selected factors have a *Z*-test higher than 1.96 ($p < 0.05$) in the SEM analysis. Influence can be either indirect (i.e., as part of a latent factor), or direct. Motives written in bold in Table 1 – all incident in purchase intentions – were chosen as *needs* nodes to build the HOTCO network.

The results show that Factors 3 ("Car affinity") and 5 ("Level of service") have a significant effect in explaining both short-term and long-term EV purchase intention. Factor 1 ("Symbolic"), on the other hand, only has a significant effect on the long-term purchase intention. This could be the case because respondents may not understand that deriving symbolic meanings – such as pride, self-identification, or self-expression – from owning a vehicle is achievable over time. On a similar note, more immediate motives like flexibility, convenience, and range/independence, in Factor 2 ("Instrumental") are significant at 90 % confidence only for the short-term purchase intention. While Factor 4 ("Economic/Environmental") did not appear to have a significant effect on either specification, some of its components have a direct effect in purchase intentions. Specifically, environmental awareness is highly positive and significant in explaining intention in both the short- and the long-term, while a higher awareness for performance and purchase cost reduce this intention.

As previously mentioned, we cannot directly compare our list of motives with previous studies. Wolf et al. (2015) and Schröder and Wolf (2017) did not describe their questions in detail, but five of their motives (eco-friendliness, costs, driving experience, image, and comfort) are similar to the ones of interest in our study and we have included them in our survey. Other motives seem to refer to constructs similar to those of interest for our study, albeit with a different label: our flexibility motive is similar to their independence motive, and pleasure/enjoyment might be associated with their (no) stress. Pro-technological orientation, performance and convenience are new motives identified specifically in our study and form part of the connectionist network in our specification – as they were significant in our SEM specification. Finally, security was the only element mentioned in Wolf et al. (2015) that was not a significant motive for our study.

3.2. Survey design

The main survey was aimed to build the HOTCO networks considering the ten chosen motives (bolded in Table 1) as *needs* nodes, and three possible *action* outcomes of the purchase decision: electric vehicle (EV), plug-in hybrid-electric vehicle (HEV), and petrol vehicle with an internal combustion engine (ICE). Questionnaire design and survey administration are discussed in the following sections.

[1] The results of these analyses can be found on the Appendix.

Table 1
List of motives for vehicle purchases.

Motive	Survey question	Short-Term Effect	Long-Term Effect
Dimension: Pro-environmental			
Environmental awareness	***An environmentally friendly car***	Direct	Direct
Dimension: Emotional			
Pleasure/Enjoyment	***A car that makes you enjoy the driving experience***	Indirect	Indirect
Comfort	***A car that makes you feel comfortable when driving***	Indirect	–
Dimension: Symbolic			
Pride	*A car that makes you feel proud*	–	–
Self-identification	***A car that distinguishes you from others***	–	Indirect
Self-expression	*A car that allows you to express yourself*	–	–
Status	*A car that gives you social prestige*	–	–
Car looks	*A car that looks good*	–	–
Dimension: Innovative identity			
Pro-technological orientation	***A car with advanced technological features and gadgets***	Indirect	Indirect
Pro-innovative orientation	***A car that satisfies your curiosity for innovation***	Indirect	Indirect
Dimension: Car authority identity			
Car expert orientation	*A car whose features you can analyse in detail and consult vehicle catalogues and/or online information*	–	–
Dimension: Instrumental			
Range/Independence	*A car that offers independence for carrying out your daily activities*	–	–
Operation cost	*A car with a low operation cost (including taxes, parking fees, tolls, permits, insurances, and fuel/charging cost)*	–	–
Purchase cost	***A car with a low purchase cost***	Direct	Direct
Mechanical issues	*A car that has a low occurrence of mechanical issues or failures*	–	–
Convenience	***A car that provides a convenient mean to carry out your daily activities***	Indirect	–
Flexibility	***A car that provides flexibility for your daily activities***	Indirect	–
Performance	***A car that offers a good performance, in terms of speed, acceleration, handling, and brakes***	Direct	Direct
Durability	*A car with a long service life*	–	–
Safety and security	*A car that provides safety and security when driving*	–	–

3.2.1. Questionnaire design

According to the requirements of the HOTCO algorithm, respondents were required to provide three types of input: priority and emotional ratings (for the *needs* nodes), and facilitation weights (links between *needs* and *action* nodes). All these items were measured using a 5-point Likert scale, and later rescored to vary between –1 to +1.

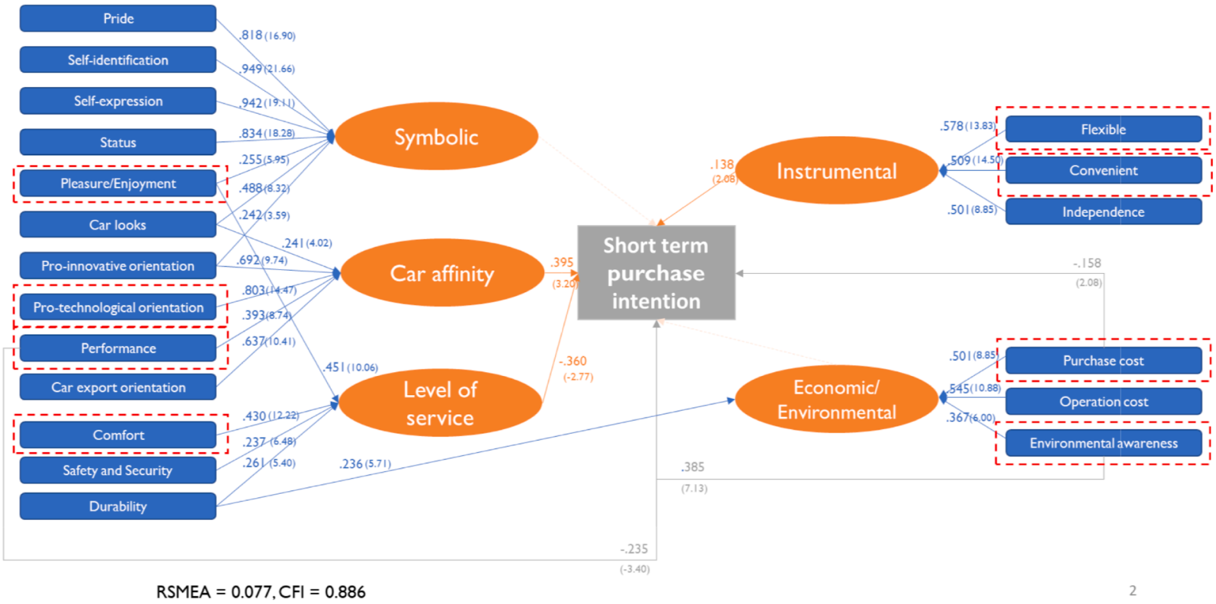
Priority refers to the desirability that each motive has to the participant "for intrinsic or other non-coherence reasons" (Thagard & Millgram, 1997, p. 3). It was measured using an importance rating question, i.e., "Please rate the following elements according to their importance to you when you decide which type of car to buy", with a Likert scale ranging from "Not important at all" to "Very important". The emotional score is a composite of two of the dimensions defined in Bradley and Lang (1994): pleasure (happy/unhappy) and 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 Likert scale ranged between "To no extent" and "To a very large extent", and the emotional score is the arithmetic mean of these two dimensions. Finally, the weights of the 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 vehicle, electric vehicle or hybrid-electric vehicle]". The Likert scale is the same used for the emotional scores, ranging between "To no extent" and "To a very large extent".

As can be noted with these definitions, the complete calibration of a HOTCO network requires 10 + 20 + 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. The survey was implemented in the Survey Engine platform (SurveyEngine, 2022). A screenshot of the survey is depicted in Fig. 4.

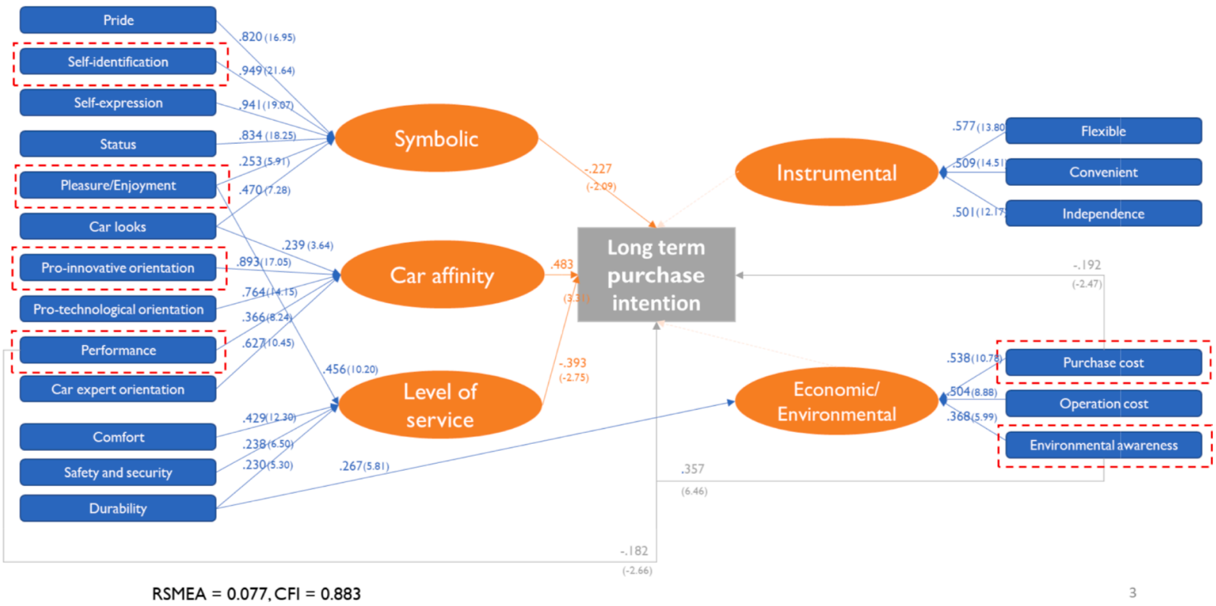
3.2.2. Sample characteristics

These questions were part of a larger survey that also included questions about each vehicle currently in the household, detailed socioeconomic characterisation of the household and its residents, as well as a stated choice experiment whose results are reported in Domarchi et al. (2024).

Our survey was aimed at individuals over the age of 18 living in households in England with at least one vehicle, who declared participating in the household vehicle purchasing decision. As per the Office of National Statistics, there are approximately 24.4 million households in England (Department for Levelling Up Housing and Communities, 2023), and the National Travel Survey (NTS, Department for Transport, 2021) estimates that around 78 % of them own at least one car. The size of the target population is therefore



a) SEM for short-term EV purchase intention



b) SEM for Long-term EV purchase intention

Fig. 3. Structural Equation models (SEM) for EV purchase intention from the preliminary survey. Individual motives are illustrated as blue rectangles, chosen motives are highlighted by red dashed outlines, and latent factors are orange ovals. *Z*-tests are given in parenthesis (all $ps < 0.05$). The figure includes two indicators of model fit – the root index of the mean square error of approximation (RMSEA, better model fit if closer to 0) and the Comparative Fit Index (CFI, better fit if closer to 1).

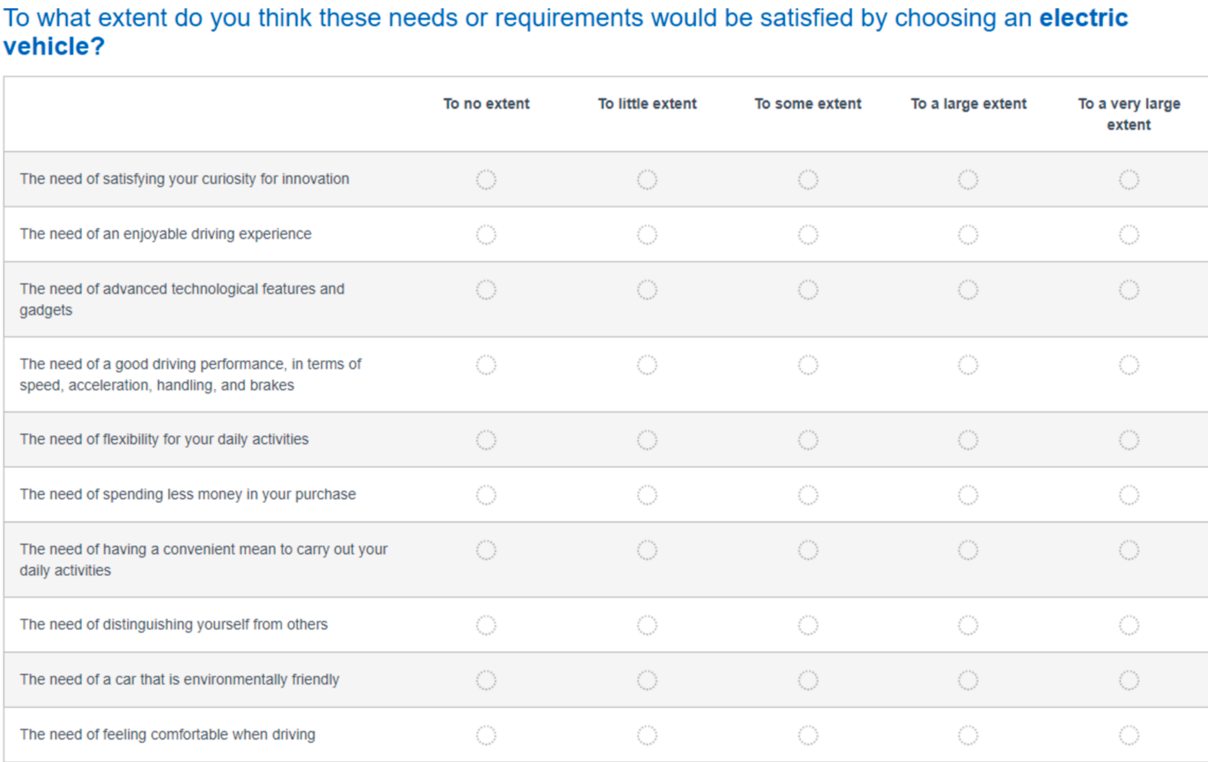


Fig. 4. Screenshot of the facilitation links questions.

equal to around 19 million households.

Participants were recruited from a pool of England residents who self-registered on the Prolific platform (Prolific, 2014). In a brief pre-screening question, they also declared having at least one car available and participating in car purchase decisions in their household.[2] As Prolific is an online panel composed of voluntary participants with internet access, our sample does not aim to be statistically representative of the target population. However, the pool of Prolific participants is large and may be varied enough to be used as a proxy for the target population. Thus, if the main characteristics have similar distributions in the sample and the target population, we can be confident that the results can still be used to draw valid conclusions about the target population.

We aim to estimate mean activations and valences in our settled networks from a random sample of the target population. Thus, for our power calculation, we used estimated mean values of approximately 0.5, high variability (coefficient of variation close to 100 %),[3] and with a maximum error of 5 %. This calculation yielded a minimum required sample size of 384 respondents.

The survey was collected between November and December 2022. Table 2 presents a descriptive summary of the sample. To analyse its representativeness, the survey is compared with the 2021 subset of the NTS sample (Department for Transport, 2021) – the latest year available in this dataset – albeit excluding car-less households, to make it comparable with the target population of the present study.

The sample in our survey has more people per household on average, they own more vehicles and hold more licenses than the NTS sample ($ps < 0.001$). The sample in our survey and the NTS sample do not differ significantly in terms of mean income. In addition, the proportion of alternative fuel vehicles (AFVs) in the sample are compatible with the shares of licenced vehicles for the same period in England (Department for Transport, 2022), 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. Overall, the sample we collected has the right characteristics to study car purchase decisions involving vehicle replacements and additions, and choices between different fuel types. In particular, the distribution of fuel types in the sample and mean income are similar to those in the target population. Thus, the study can help us understand the decision-making process in the context of transport decisions.

2 The data collection process design received ethical approval from Newcastle University (Ref N 7076/2020).

3 These values were sourced from two pilot surveys with an aggregate sample size of 94 individuals, which were conducted to test the instrument, its parameters, and the HOTCO algorithm (see Domarchi, 2023 for details).

Table 2
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	–	–
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 size (persons)	–	*2.82*	*2.42*	$t(df = 4478) = 4.88$, $p < 0.001$
	% of urban households	–	69.0	74.0	–

4. Results

The HOTCO algorithm was implemented in a custom function written in R, whose code is provided in the appendices. The algorithm requires initialising calibration parameters, whose values are presented in Table 3. Most of these parameters were adapted from the recommendations in Thagard (2006) and Thibault (2013).

The results of this implementation are presented in two main sections: inputs and outputs. The first section presents the analyses of the survey responses to the priority, emotion, and facilitation weights that are used as input to setup the individual HOTCO network parameters. The second section discusses the outputs of the calibrated connectionist networks, including activations and valences for both *needs* and *actions* units.

4.1. Inputs

In what follows, the HOTCO inputs are presented in a descriptive analysis, highlighting their means and standard deviations, based on the values recorded in the survey. The inputs reveal how participants separately assess each of the ten needs, and how they perceive the effectiveness of each alternative in satisfying them. These are the key elements that determine the mental representation of the decision in terms of coherence maximisation. The scores are treated as continuous variables, with all the Likert scale values varying from -1 to $+1$ (in 0.5 steps). Fig. 5 illustrates the mean score for priority and emotional values for each need, and Fig. 6 illustrates the mean score for facilitation weights for the same needs as a function of fuel type. The error bars in both figures represent the 95 % confidence interval.

Comfort and convenience exhibit the highest priority scores (>0.6), suggesting that they are generally acknowledged as the most relevant motives for vehicle choice. Driving performance ($M = 0.505, SD = 0.420$), flexibility ($M = 0.498, SD = 0.376$), purchase cost ($M = 0.495, SD = 0.411$), and pleasure/enjoyment ($M = 0.473, SD = 0.425$), also have a high share of respondents rating them as “important” or “very important”. Conversely, self-identification ($M = -0.412, SD = 0.547$) and pro-innovative orientation ($M = -0.155, SD = 0.537$) are rated as non-relevant when defining priorities.

Interestingly, the concepts seem to elicit weaker emotional responses, with only purchase cost ($M = 0.129, SD = 0.569$), pleasure/enjoyment ($M = 0.143, SD = 0.551$), and comfort ($M = 0.132, SD = 0.547$) scoring higher than 0.1 in the score that combines the responses to the “happy/sad” and “excited/calm” questions. The scores for environmental awareness ($M = -0.205, SD = 0.568$) and pro-technological orientation are rather surprising ($M = -0.223, SD = 0.558$) and may reflect the increased feelings of negative polarity (*sad / calm*) derived from the process of choosing a vehicle.

Table 3
Parameters of the HOTCO algorithm implementation.

Parameters	Abbreviation	Value
Initial activations	$a_i(0), i = 1, \cdots, 13$	0.01
Initial valences	$v_i(0), i = 1, \cdots, 13$	0.01
Maximum activation or valence	*ceiling*	1
Minimum activation or valence	*floor*	−1
Decay parameter	*d*	
Maximum number of iterations	–	300
Convergence threshold	–	0.001

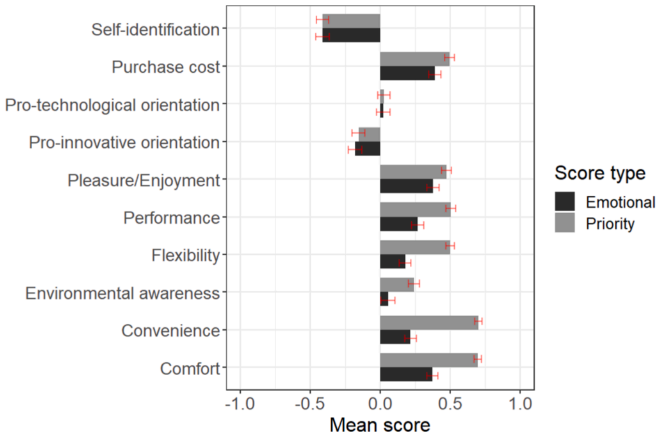


Fig. 5. Mean priority and emotional scores for each motive.

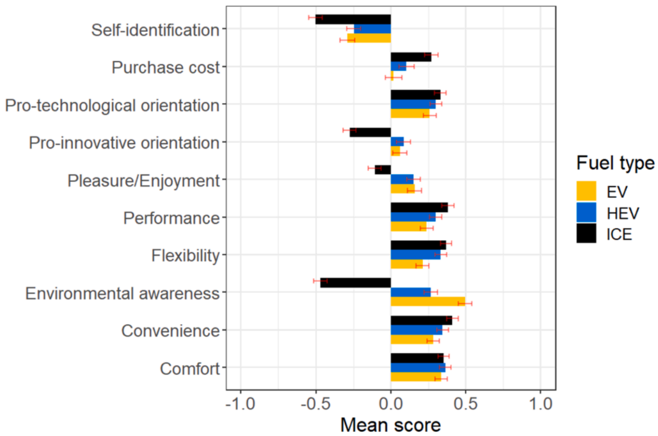


Fig. 6. Mean facilitation weights for each motive.

The results show that the highest rated needs in terms of priority are also the ones that elicit stronger positive emotional evaluations. While, from a linear and unidirectional perspective, these motives should be expected to drive the decision-making process, the input scores do not depend on any coherence effect. Facilitation weights provide further insights into how well each alternative satisfies each motive. Specifically, respondents believe, on average, that EVs are the most effective option to facilitate the need for environmental awareness ($M = 0.495, SD = 0.548$), followed by HEVs ($M = 0.267, SD = 0.518$). ICE vehicles are deemed as impeding it ($M = -0.468, SD = 0.527$). A similar – and expected – result is observed in the case of pro-innovative orientation, where there is a negative average weight for ICE vehicles ($M = -0.275, SD = 0.528$). Conversely, EVs and HEVs are more neutral in this evaluation ($M = 0.060, SD = 0.587$ and $M = 0.086, SD = 0.562$, respectively). A reduction of purchase costs is perceived as being facilitated by ICE vehicles ($M = 0.269, SD = 0.536$), with EVs and HEVs scoring lower in this item. Notably, there are some relevant differences in the pleasure/enjoyment dimension, which, on average, is perceived as slightly facilitated by both EVs ($M = 0.159, SD = 0.548$) and HEVs ($M = 0.153, SD = 0.527$), and moderately inhibited by ICE vehicles ($M = -0.107, SD = 0.537$).

While the cleaner alternatives (EVs and HEVs) offer an effective choice to address individual concerns about the environment, they are not perceived as the cheaper option, or the one with the better performance or flexibility, with all these attributes better fulfilled by the traditional ICE vehicle. Interestingly, the motives that respondents deemed the most important when choosing a vehicle (comfort and convenience), appear to be similarly facilitated by all three alternatives. It should therefore be expected that their overall effect in the coherence outputs is less relevant.

4.2. Outputs

4.2.1. Individual level results

To illustrate the results obtained by running the HOTCO network for each individual in our sample and the information it provides, Fig. 7 depicts the activations on a settled HOTCO network (i.e., a HOTCO network in a settled status) for a single respondent. Nodes in green represent positive activations, while nodes in yellow represent negative activations. For easier visualisation, nodes with activation = 0 (null), are presented in white. 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. Results reported in Fig. 7 show that this respondent perceives that choosing an ICE facilitates their need for better driving performance, pro-technological orientation, flexibility, comfort, and convenience. Because these needs have positive activations, the resulting activation for ICE is high and positive. Conversely, this respondent perceives EVs as the only option that facilitates the need for comfort. However, since the rest of the EV facilitation weights are negative (i.e., the respondent does not feel the EV satisfies the other needs) the final EV activation is negative. In the case of HEVs, the combination of weights involves a final state of indifference (activation equal to 0), which means that this respondent does not have a particularly strong attitudinal evaluation towards HEVs in one direction or the other. It is interesting to note that two needs (pleasure/enjoyment and pro-innovative orientation) also have null final activations, and therefore appear to be irrelevant in the decision-making process for this respondent.

4.2.2. Aggregate level results

While similar analyses can be carried out at the individual level for all respondents, the aggregate outputs offer a more complete picture of the results. We start with a descriptive analysis of the resulting activations and valences for both *needs* and *action* nodes. Table 4 lists the mean and standard deviation of the resulting activations and valences calculated across respondents, for both the *needs* and *action* nodes.

We also compared activation and valence scores, and their correlation. Because these scores were not normally distributed, we used non-parametric Wilcoxon signed-rank tests and Spearman rho correlation tests. Table 4 also presents these additional analyses for each *needs* and *actions*. We note that for both *needs* and *action* motives, the emotional responses (valences) have lower scores (in absolute value) than activation responses (all $ps < 0.001$). This is a result of the HOTCO modelling structure, as the emotional response measured by valence scores is also dependent – and therefore moderated by – the attitudinal evaluation that the activation score measures.

We also compared the average activation and valence scores for different motives across respondents. Unlike the traditional attitude-behaviour link theories, the HOTCO network structure of coherence maximisation considers the interaction between the *needs* that are most likely to be satisfied by each respondent, and their inclination to engage in each *action* node, and allows evaluating the overall importance given to them by respondents.

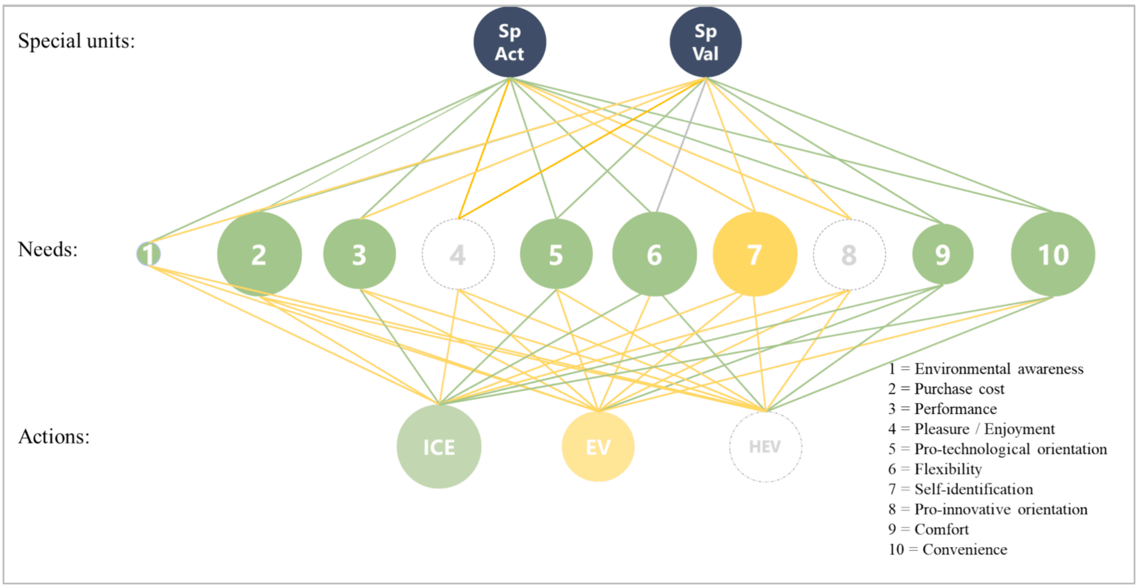


Fig. 7. Example of activations in a settled HOTCO network.

Table 4
Mean and standard deviation of activations and valences and correlation between activation and valence (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$).

Node Type	Node name	Activation		Valence		Wilcoxon signed-rank test (*p*-value)	Spearman's Rho
		Mean	SD	Mean	SD		
Needs	Environmental awareness	0.236	0.643	0.146	0.482	<0.001	0.913***
	Purchase cost	0.511	0.494	0.330	0.401	<0.001	0.870***
	Performance	0.542	0.486	0.338	0.420	<0.001	0.933***
	Pleasure/Enjoyment	0.469	0.527	0.378	0.370	<0.001	0.887***
	Pro-technological orientation	0.257	0.648	0.185	0.494	<0.001	0.929***
	Flexibility	0.541	0.454	0.300	0.407	<0.001	0.887***
	Self-identification	−0.388	0.608	−0.278	0.446	<0.001	0.831***
	Pro-innovative orientation	−0.070	0.681	−0.037	0.491	<0.001	0.871***
	Comfort	0.670	0.346	0.417	0.362	<0.001	0.914***
	Convenience	0.627	0.374	0.314	0.417	<0.001	0.893***
Actions	ICE	0.485	0.532	0.297	0.473	<0.001	0.679***
	EV	0.424	0.554	0.140	0.496	<0.001	0.764***
	HEV	0.445	0.569	0.276	0.475	<0.001	0.778***

For the *needs* nodes, comfort and convenience have the highest activations, with their mean scores significantly higher than the scores for all the other dimensions (all *ps* < 0.001). Purchase cost, performance, and flexibility also have high activations, albeit lower than those of comfort and convenience. However, they are also significantly higher than the activations for all the other needs (all *ps* < 0.001). Respondents would, on average, have a strong behavioural intention to satisfy these five needs compared to their intention to satisfy the other needs in their network. The same motives also appear to have the highest emotional responses (valences). While the valences for comfort and pleasure/enjoyment are significantly higher than for all the other motives (all *ps* < 0.001), and significantly different from each other, the valence scores for purchase cost, performance, and convenience do not differ from each other ($p < 0.05$ for the difference between convenience and performance, $p > 0.1$ for the other two pairwise comparisons). The three *action* nodes have the same mean activation value (between 0.424 and 0.485; all *ps* > 0.05). The valence, on the other hand, is significantly lower for EV compared to the other two vehicle types (*ps* < 0.01), which could indicate a certain degree of uneasiness in the emotional response towards the most innovative vehicle type (EV). Indeed, from an emotional point of view, there is a low evaluation of environmental awareness, pro-technological orientation, and pro-innovative orientation, three motives that most users would describe as more likely to be satisfied by EV acquisition. The resulting low EV valence is likely a result of this interaction. The ICE and HEV alternatives do not differ in the mean valence scores.

The lower mean valences result in several connectionist networks with high behavioural intentions accompanied by milder

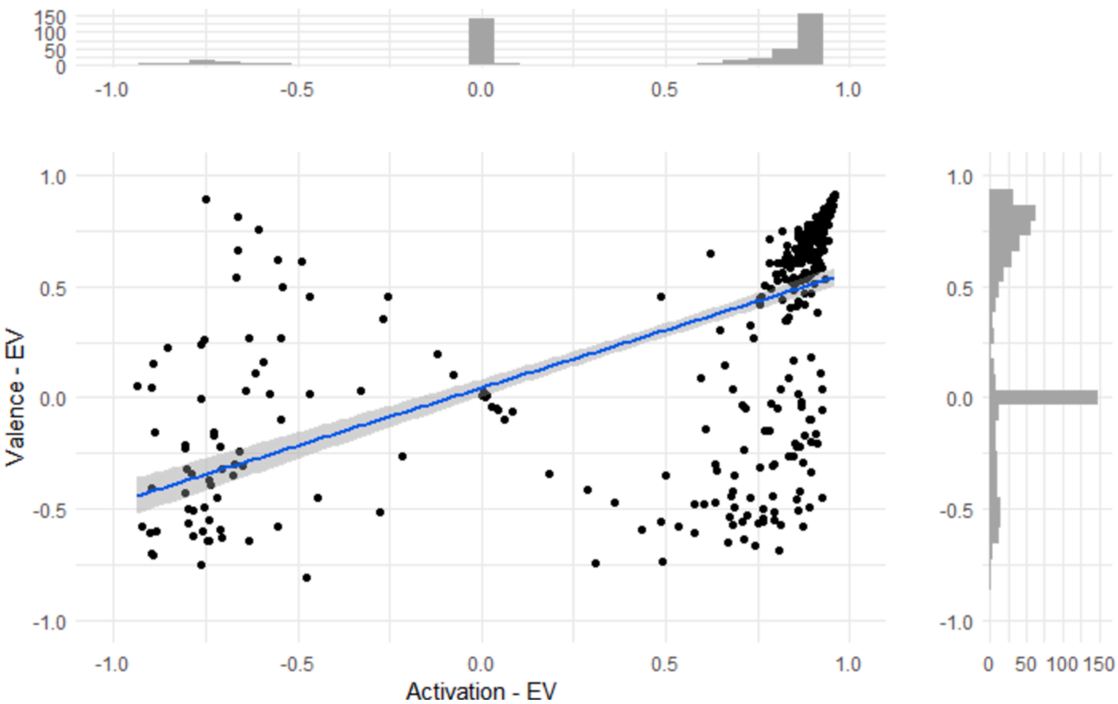


Fig. 8. Correlation between activations and valences for the EV action node.

emotional responses to certain items. It would appear that some respondents are aware of the importance of satisfying certain needs and thus are likely to choose an alternative that fulfils this objective, but doing so does not necessarily provide a significant increase in their happiness or arousal. The emotional response appears to impart a moderating effect to the strongest activation scores.

The study of correlation between activations and valences in *needs* nodes is another advantage of the HOTCO network as a method to represent a decision in this context. It allows analysing the degree of coherence between the attitudinal and emotional appraisals of both *needs* and *actions*, generating a clearer picture of how "coherent" these evaluations might appear and, more interestingly, a sense of how strong the evaluations of *actions* are for each respondent. Activations and valences tend to be highly correlated in the *needs* nodes, with only pleasure/enjoyment, flexibility, comfort, and convenience having a correlation coefficient lower than 0.8. This is an expected result as, by definition, the net flow of valence into each node includes the net flow of activation, and these nodes receive the flow from the special units directly. More interestingly, the correlation is lower for the *action* nodes, as their activations and valences are the result of several interaction processes including all 10 needs simultaneously. Furthermore, the correlation appears to be lower for ICE vehicles compared to EVs and HEVs. To explore this finding, scatter plots of activations and valences are presented in Fig. 8 (for EVs), Fig. 9 (HEVs), and Fig. 10 (ICE vehicles). These allow visualising the relation between both coherence evaluations for all the individuals in the sample. In the figures, the solid blue line reflects the best fitting regression line, with grey shading indicating the variability of the fit. The lower correlation for ICE vehicles may be found as several respondents seem to assign negative valences to ICE vehicles, even if their activations are positive.

The figures also depict the marginal distribution of each coherence measure, revealing that a large number of neutral activations (activation = 0) and valences (valence = 0) are present in the survey results for all three fuel types. In general terms, large activations seem to be positively correlated with large valences; however, this is not the case for negative values, and pairings between opposite scores (positive valences with negative activations and vice-versa) are frequently observed in the dataset. This effect is more pronounced for ICE vehicles than for EVs and HEVs.

4.2.3. Main motives

The identification of the *needs* nodes with a higher influence in the outputs on the *action* nodes is of special interest to understand the determinants of the vehicle purchasing decision. The HOTCO model allows studying these effects at an individual level, by directly examining the activations and valences of each node in the settled network for each respondent. To evaluate the aggregate influence of each *need* node (motive) on each *action* (fuel type) node, we estimate models that explain the variability in activations and valences for each *action* node, as a function of activations and valences in *need* nodes. As the resulting distributions of activations and valences are not normally distributed, we study this effect by estimating a series of six logistic regression models: one for each of the three actions (EV, HEV, and ICE), combined with one of the two types of outputs (activations and valences). It must be noted that the HOTCO inputs were measured using 5-point Likert scales, and later rescored to vary between –1 to +1. The HOTCO outputs are thus continuous

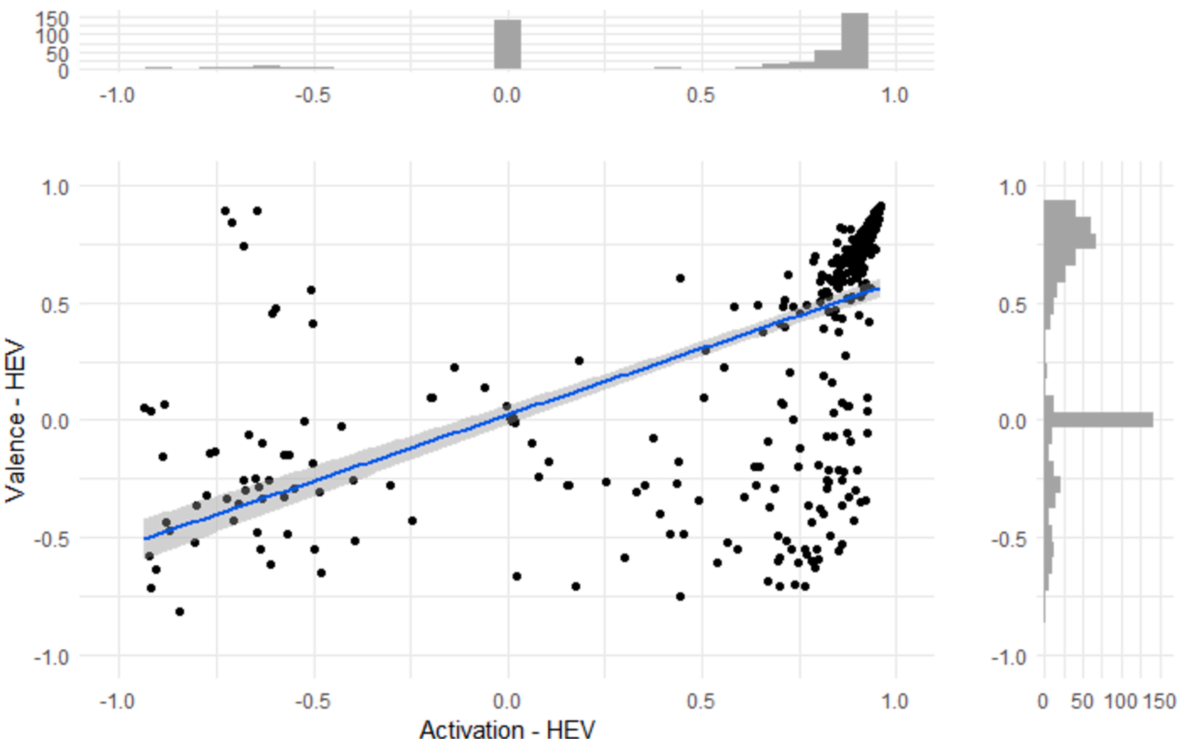


Fig. 9. Correlation between activations and valences for the HEV action node.

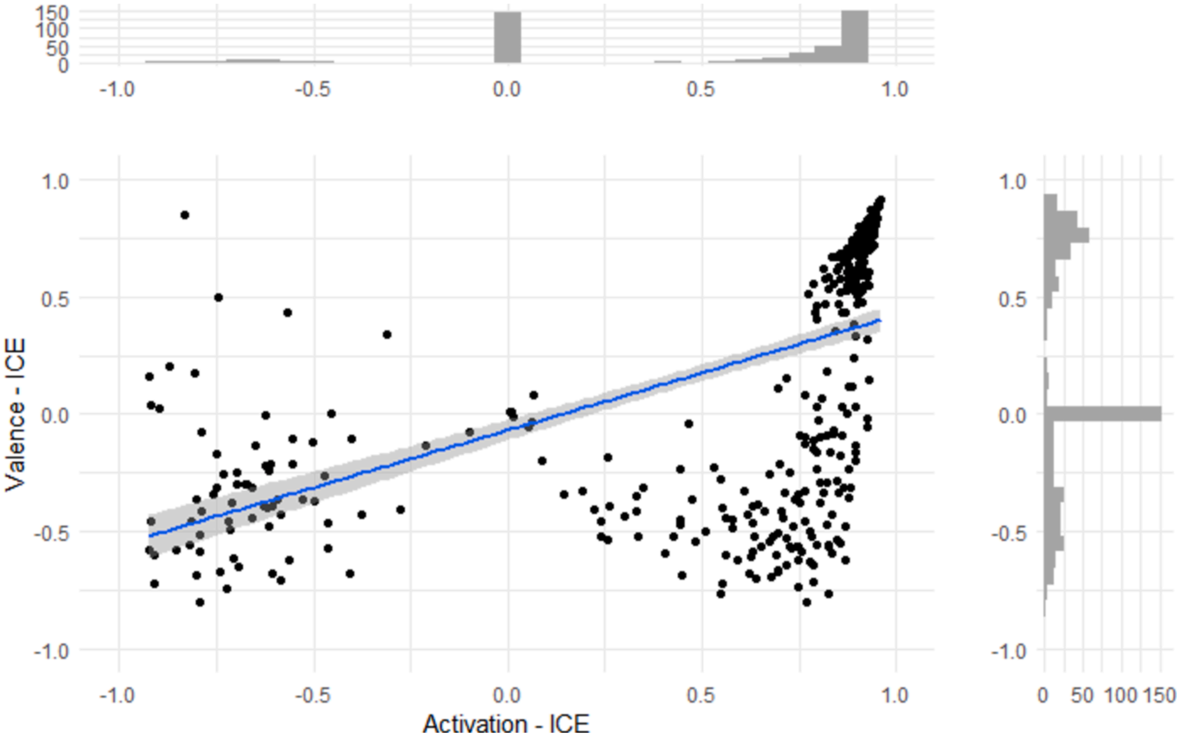


Fig. 10. Correlation between activations and valences for the ICE action node.

variables varying from –1 to +1.

In each of these models, the dependent variable is a dummy which takes the value 1 if the output (activation or valence) for that specific action (EV, HEV, or ICE) is positive, and 0 otherwise. The dependent variables are the corresponding outputs (activations or valences) for each *need* node. The resulting coefficients can thus be interpreted as the marginal increase in the log-odds ratio of the dependent variable, as a result of a unit increase in the corresponding variable. More importantly for our analysis, if a coefficient has a positive and significant score, the *need* node will increase the probability of a positive outcome in the corresponding action and, conversely, a negative and significant score will decrease it.

The results of these six logistic regression models are presented in Table 5 and Table 6, which also include the *Z*-tests and *p*-values of the regression coefficients. As the χ^2 tests for the deviances of all six models are statistically significant, all models perform significantly better than the null models.

First, considering Table 5, we note that activation scores for ICE vehicles are mostly uncorrelated with scores for the *needs* nodes, with a positive correlation with pro-technological orientation and convenience, and a negative correlation with pleasure/enjoyment and also, crucially, with environmental awareness. The rest of the motives are non-significant in explaining the variability of ICE activation scores. Notably, activation scores for EVs and HEVs are explained by the same sets of needs, as they both have a positive correlation with convenience, pro-innovative orientation, pro-technological orientation, and environmental awareness; and a negative correlation with self-identification, pleasure/enjoyment, and purchase cost. These results indicate that EVs and HEVs are perceived as similar alternatives, with respondents not differentiating them in terms of the role they play in fulfilling their transport needs. However, the residual deviances are rather high, suggesting that the models account for up to 17 % of the deviance.

The activation results are mostly consistent with the analysis of valences in Table 6. Environmental awareness, performance, self-identification, and comfort are positively correlated with valence scores for ICE, while a significant negative correlation is detected with environmental awareness. The variability in EV and HEV valence scores is explained by the same set of factors: positive correlation with environmental awareness, performance, pro-technological orientation, comfort, and pro-innovative orientation. The only differences between EVs and HEVs appears in pleasure/enjoyment, which only has a significant effect (at 95 % confidence) in explaining valences for EVs, and convenience, which is only significant for HEV valences. Interestingly, purchase cost has no significant effect on the valence scores of any of the three alternatives. The residual deviances are lower than in the activation data, suggesting that the models account for up to 36 % of the deviance.

We conducted a series of tests to verify the assumptions of logistic regression in our models. The tests were based on Fox (2016) and Alkan et al. (2023) and were implemented using the car package (version 3.1.2) in R (Fox and Weisberg, 2019). Specifically, we checked for the following assumptions:

Table 5
Logistic regression models between activations in actions and needs nodes, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Motive	ICE		EV		HEV	
	Coef.	*Z*-test	Coef.	*Z*-test	Coef.	*Z*-test
Intercept	0.395	1.61	0.525	2.09*	0.271	1.07
Environmental awareness	−0.811	−4.59***	0.649	3.81***	0.360	2.10*
Purchase cost	−0.073	−0.36	−0.534	−2.29*	−0.479	−2.05*
Performance	−0.025	−0.09	0.617	2.22*	0.458	1.67
Pleasure/Enjoyment	−1.093	−3.49***	−1.208	−3.80***	−1.134	−3.56***
Pro-technological orientation	0.784	3.54***	1.171	5.13***	1.026	4.54***
Flexibility	0.114	0.37	−0.293	−0.92	0.013	0.04
Self-identification	0.118	0.64	−0.383	−1.81	−0.417	−1.96*
Pro-innovative orientation	−0.003	−0.01	0.681	3.00**	0.540	2.34*
Comfort	0.238	0.51	−0.452	−0.97	−0.117	−0.25
Convenience	0.856	2.16*	0.841	2.08*	1.027	2.56*
Null deviance	**736.22**		**736.18**		**711.95**	
Residual deviance	**683.29**		**608.61**		**609.64**	
χ^2 test	**52.9** ($\boldsymbol{p} < 0.001$)		**127.6** ($\boldsymbol{p} < 0.001$)		**102.3** ($\boldsymbol{p} < 0.001$)	

Table 6
Logistic regression models between valences in actions and needs nodes, *p < 0.05, **p < 0.01, ***p < 0.001.

Motive	ICE		EV		HEV	
	Coef.	*Z*-test	Coef.	*Z*-test	Coef.	*Z*-test
Intercept	−2.874	−8.15***	−0.778	−3.39***	−1.222	−4.87***
Environmental awareness	−0.913	−3.29**	0.790	3.19**	0.720	2.75**
Purchase cost	0.488	1.45	0.077	0.23	0.291	0.84
Performance	0.973	2.39*	1.230	3.21**	1.078	2.72**
Pleasure/Enjoyment	−0.296	−0.58	−1.000	−2.13*	−0.803	−1.59
Pro-technological orientation	0.628	1.70	1.319	3.85***	1.061	2.93**
Flexibility	0.869	1.47	−1.140	−2.17*	0.284	0.53
Self-identification	0.711	2.39*	0.134	0.41	−0.062	−0.18
Pro-innovative orientation	−0.039	−0.12	0.773	2.25*	0.737	1.98*
Comfort	3.361	4.34***	1.702	3.00**	1.470	2.47*
Convenience	0.642	1.09	0.870	1.71	1.093	2.09*
Null deviance	**750.91**		**765.74**		**765.06**	
Residual deviance	**477.72**		**520.19**		**534.41**	
χ^2 test	**273.2** ($\boldsymbol{p} < 0.001$)		**245.6** ($\boldsymbol{p} < 0.001$)		**230.7** ($\boldsymbol{p} < 0.001$)	

(1) *Independence of errors*. We calculated a Durbin-Watson test for serial correlation for all six models. The hypothesis of uncorrelated errors cannot be rejected for any of them.
(2) *Absence of multicollinearity*. We calculated generalised variance inflation factors (VIF) for all the variables in our models. The test does not find evidence of multicollinearity in any of the six models (all VIF < 4).
(3) *Lack of outliers*. We conducted a Bonferroni test to identify mean-shift outliers. We identify no outliers in any model, except for one data point in the ICE valence model. We re-run the model excluding this value and obtained remarkably similar results (in terms of coefficients, p-values, and deviance value) compared with the original model estimate with the full dataset.
(4) *Linearity*. We analysed linearity between the logistic function of the predicted probabilities and each dependent variable, using partial residual plots. Based on visual inspection, we found that, out of the 60 variables used in the six models, 11 variables in three models appear to violate this assumption – three in the EV activation model, four in the HEV activation model, and four in the EV valence model. We did not detect any non-linearities in the other models. The effects of non-linearity seem relatively limited, although the results may need some caution when interpreting.

Finally, we also tested whether socioeconomic factors have an impact on the activation and valences for EV. The results show that socioeconomic factors do not have an impact on the activation of each type of fuel.[4] This does not mean that they do not have an impact on the purchase choice, but this is not measured in this model.

[4] The results of these models are available upon request.

5. Discussion

The analysis of the HOTCO data reveals that both activation and valence measure different constructs in the HOTCO model. Discrepancies between the two are more common for ICE vehicles, in which 24.5 % of respondents have activations and valences with opposite signs – most frequently, positive activations and negative valences, The sign difference is less common for EVs (17.3 %) and HEVs (19.1 %). Although differences between fuel types are small, they may be linked with attitudinal accessibility. Specifically, as ICE vehicles are the most frequent fuel type in the sample (95.6 % of respondents declared owning one), they are an ordinary and well-known object, and attitudes towards them are more "accessible" (Fazio, 2007). Accessible attitudes tend to have a higher likelihood of being reconsidered when more information is added into the evaluation, therefore generating more complex patterns in the mental representation.

The overall assessment of the HOTCO networks and the interaction of *actions* and *needs* indicate that EVs and HEVs are perceived as similar alternatives, with respondents not differentiating them in terms of the role they play in fulfilling their transport needs, with the only possible exception of valences for the need for comfort and the pleasure/enjoyment respondents derive from driving their vehicles. This is a very important result that has not previously been addressed by the literature. While previous papers report different perceptions for both fuel types (e.g., Higueras-Castillo et al., 2020; Lane et al., 2018), they do so in the context of choice models that address preferences towards cost-related and operational attributes, which are likely to reveal more patently the practical differences between the two fuel types. Our study, however, focuses on attitudinal and emotional evaluations of EVs and HEVs, and reveals that both are perceived to be similar in terms of the needs they can satisfy. This might also explain the significantly higher market for HEVs respect to EVs. Our findings highlight the need for stronger differentiation between EV and HEV in public awareness campaigns, as HEVs are still at least partially fuel-powered and therefore should not be the preferred option in terms of fleet decarbonisation. Comfort needs may be a possible distinction between the two. It contributes to a positive emotional evaluation of HEVs, but not of EVs. This is likely related with the perceived discomfort derived from the behavioural changes that EV use requires, especially in terms of charging and recharging. Addressing this source of negative emotional appraisal can be crucial for improving attitudes towards EVs and favouring their adoption.

These findings can also be beneficial for policy making as they provide critical information about the factors contributing more significantly to a shift in the attitudes towards EVs and HEVs. Our results show that these factors are environmental awareness and pro-innovative orientation and – rather surprisingly – driving performance, a dimension that includes aspects such as speed, acceleration, handling, and brakes. While the first two factors refer mostly to personal values and beliefs, the latter relates more closely to interacting with the attitudinal object (in this case, the car), hinting that less environmentally driven or innovation-oriented individuals could also develop positive attitudes towards EVs and HEVs if their driving experiences are positive. Awareness campaigns highlighting the pleasure or enjoyment of driving an AFV could therefore play a significant role in attitudinal changes. Supply-side campaigns might also contribute to this goal, as the automotive industry can focus their marketing efforts on highlighting the aspects that might contribute more effectively in this direction.

6. Conclusions

In this paper, we employed the HOTCO framework to analyse the mental representation of the vehicle purchase decision. This implies measuring activations and valences for the connectionist networks that characterise attitudes and emotional appraisals towards transport needs and vehicle alternatives. These translate into activations and valences that, at the individual level, provide an indication of the mental representations of the decision process in terms of satisfying the constrains derived from individual evaluation of both needs and possible courses of actions. We collected a sample that represents households in England in terms of their geographic distribution, mean income, and shares of vehicle fuel type. This sample provided valuable insights for vehicle purchase decisions in these households.

Two important results emerge from the data analysis. First, the mean activation and valence scores for EVs and HEVs define remarkably similar connectionist networks for both vehicle types. This means that the motives that determine a positive attitude or emotional appraisal are similar, and that respondents appear to perceive both alternative as capable of satisfying the same set of needs. This is particularly important as EVs and HEVs have different attributes, yet their overall perceptions – at least in terms of the HOTCO survey – appear to be the same. Second, environmental awareness and pro-innovative orientation are the two motives that generate the greater differences in activation and valence scores for ICE vehicles, compared with EV/HEV scores. These could be understood as differentiating motives and are those who would generate a greater divergence in the evaluations of each mode. As expected, respondents who assign a higher importance to these needs are more likely to assign higher activation and valence scores for the cleaner fuel alternatives. Interestingly, the effect of purchase cost is inverse, i.e., respondents who assign a higher importance score to this motive are less likely to exhibit higher activation scores for alternative fuels. This effect, however, is only relevant at the activation level, and it does not appear in the emotional (valence) scores, suggesting that the economic factor is more likely to affect the decision at a rational – rather than emotional – level.

There are some potential limitations in our study. First, we recruited respondents from an online platform which may not fully represent the target population, as our sample only contained participants who self-register on Prolific and choose to participate in our study. Thus, our findings must be taken with caution. That said, our sample shares some common characteristics with the representative NTS sample. Second, the large number of questions required to measure all the inputs in the HOTCO network may increase questionnaire complexity and burden. While we did not detect significant respondent fatigue effects in the HOTCO input data, questionnaire complexity and length may still pose challenges for adapting the theory to other research problems. Third, the HOTCO model addresses attitudes towards several fuel types and their relationship with the satisfaction of transport needs. It focuses on attitudes towards each mode, but it could also be used to understand the influence of several factors in choosing an alternative. The same problem is commonly analysed using with the discrete choice modelling paradigm, based on the random utility theory (Domencich & McFadden, 1975; Williams, 1977). Although both modelling approaches address different components of the decision-making process, there is space for their integration to gain further insights on this behaviour. Finally, we did not find significant correlations between HOTCO outputs and any socioeconomic attributes, geographic location variables or other individual-specific characteristics. These attributes may have more nuanced effects on the final purchase decision. Thus, more research is required to accommodate these effects into a single framework.

Further research is also required to test the strength of the predictions obtained with the HOTCO model, especially in comparison with other theories addressing the attitude-behaviour gap, such as Planned-Behaviour, Interpersonal-Behaviour, Protection-Motivation, or Symbolic Self-Completion theories (see Sovacool, 2017, for a review). In addition, social-cultural attitudes, and technological-economic attributes of AFVs will change over time. Consequently, activations and valences may similarly evolve over time. Collecting longitudinal data on the same households may help to understand these trends and their relationship to purchasing behaviour. Finally, other cognitive consistency models have been proposed to simultaneously consider cognition and emotion, including the ITERA model (Nerb & Spada, 2001), the dynamic systems approach (Lewis, 2005), and the Ising model of explanatory coherence, recently implemented in Maier et al. (2023). Future research should focus on comparing the theoretical foundations of different studies that assess emotional coherence to improve our understanding of human decision-making.

CRediT authorship contribution statement

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

Declaration of competing interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2024.10.018.

Data availability

Data will be made available on request.

References

Abelson, R. P., & Rosenberg, M. J. (1968). Symbolic psycho-logic: A model of attitudinal cognition. *Behavioral Science, 3*(1), 1–13. https://doi.org/10.1002/bs.3830030102

Adnan, N., Nordin, S. M., Rahman, I., Vasant, P. M., & Noor, A. (2016). A comprehensive review on theoretical framework-based electric vehicle consumer adoption research. *International Journal of Energy Research, 41*(3), 317–355. https://doi.org/10.1002/er.3640

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alkan, Ö., Güney, E., & Kilinç, A. (2023). Predictors of online shopping behavior of women in Turkey: A model and empirical study. *International Journal of Contemporary Economics & Administrative Sciences, 13*(1), 410–442. https://doi.org/10.5281/zenodo.8429022

Axsen, J., & Kurani, K. S. (2014). Social influence and proenvironmental behavior: The reflexive layers of influence framework. *Environment and Planning B: Planning and Design, 41*, 847–862. https://doi.org/10.1068/b38101

Beck, M. J., Rose, J. M., & Greaves, S. P. (2017). I can't believe your attitude: A joint estimation of best worst attitudes and electric vehicle choice. *Transportation, 44*, 753–772. https://doi.org/10.1007/s11116-016-9675-9

Bennett, R., & Vijaygopal, R. (2018). Consumer attitudes towards electric vehicles: Effects of product user stereotypes and self-image congruence. *European Journal of Marketing, 52*(3–4), 499–527. https://doi.org/10.1108/EJM-09-2016-0538

Bhat, F. A., Verma, M., & Verma, A. (2021). Measuring and modelling electric vehicle adoption of Indian consumers. *Transportation in Developing Economies, 8*, 6. https://doi.org/10.1007/s40890-021-00143-2

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry, 25*(1), 49–59. https://doi.org/10.1016/0005-7916(94)90063-9

Broadbent, G. H., & Wiedmann, T. O. (2021). Electric vehicle uptake: Understanding the print media's role in changing attitudes and perceptions. *World Electric Vehicle Journal, 12*(4). https://doi.org/10.3390/wevj12040174

Department for Levelling Up Housing and Communities. (2023). *English Housing Survey 2022 to 2023 Headline Report*. https://www.gov.uk/government/statistics/chapters-for-english-housing-survey-2022-to-2023-headline-report.

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

Department for Transport. (2022). df_VEH0120_GB: Vehicles at the end of the quarter by licence status, body type, make, generic model and model: Great Britain [data collection]. https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-files.

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

Domarchi, C., Cherchi, E., & Vuong, Q. C. (2024, July 14-18). *Heterogeneity in preferences for alternative fuel vehicles: A latent class choice model including psychological factors* 17th International Conference on Travel Behaviour Research, Vienna, Austria.

Fazio, R. H. (2007). Attitudes as object-evaluation associations of varying strength. *Social Cognition, 25*(5), 603–637. https://doi.org/10.1521/soco.2007.25.5.603

Franke, T., Neumann, I., Bühler, F., Cocron, P., & Krems, J. F. (2011). Experiencing range in an electric vehicle: Understanding psychological barriers. *Applied Psychology, 61*(3), 368–391. https://doi.org/10.1111/j.1464-0597.2011.00474.x

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models* (3rd ed.). Sage.

Fox, J., & Weisberg, S. (2019). *An R Companion to Applied Regression* (3rd ed.). Sage.

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.

Haustein, S., & Jensen, A. F. (2018). Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior. *International Journal of Sustainable Transportation, 12*(7), 484–496. https://doi.org/10.1080/15568318.2017.1398790

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), Article 111076. https://doi.org/10.1016/j.enpol.2019.111076

Jensen, A. F., Cherchi, E., & Ortúzar, J. de D. (2014). A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation, 41*(5), 973–993. https://doi.org/10.1007/s11116-014-9517-6

Junquera, B., Moreno, B., & Álvarez, R. (2016). Analyzing consumer attitudes towards electric vehicle purchasing intentions in Spain: Technological limitations and vehicle confidence. *Technological Forecasting and Social Change, 109*, 6–14. https://doi.org/10.1016/j.techfore.2016.05.006

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. *Transportation Research Part D: Transport and Environment, 65*, 1–13. https://doi.org/10.1016/j.trd.2018.07.019

Liang, X., Lu, T., & Yishake, G. (2022). How to promote residents' use of green space: An empirically grounded agent-based modeling approach. *Urban Forestry & Urban Greening, 67*, Article 127435. https://doi.org/10.1016/j.ufug.2021.127435

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews, 37*(3), 252–275. https://doi.org/10.1080/01441647.2016.1230794

Maybury, L., Corcoran, P., & Cipcigan, L. (2022). Mathematical modelling of electric vehicle adoption: A systematic literature review. *Transportation Research Part D: Transport and Environment, 107*, Article 103278. https://doi.org/10.1016/j.trd.2022.103278

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. *Psychological Review, 88*(375–407). https://doi.org/10.1037/0033-295x.88.5.375

Mohamed, M., Higgins, C. D., Ferguson, M. R., & Kanaroglou, P. (2016). Identifying and characterizing potential electric vehicle adopters in Canada: A two-stage modelling approach. *Transport Policy, 52*, 100–112. https://doi.org/10.1016/j.tranpol.2016.07.006

Morton, C., Anable, J., & Nelson, J. D. (2016). Assessing the importance of car meanings and attitudes in consumer evaluations of electric vehicles. *Energy Efficiency, 9*, 495–509. https://doi.org/10.1007/s12053-015-9376-9

Prolific. (2014). *Prolific (www.prolific.co)*. Retrieved 1 April 2022 from https://www.prolific.co.

Rainieri, G., Buizza, C., & Ghilardi, A. (2023). The psychological, human factors and socio-technical contribution: A systematic review towards range anxiety of battery electric vehicles' drivers. *Transportation Research Part F: Traffic Psychology and Behaviour, 99*, 52–70. https://doi.org/10.1016/j.trf.2023.10.001

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

Schmalfuß, F., Mühl, K., & Krems, J. F. (2017). Direct experience with battery electric vehicles (BEVs) matters when evaluating vehicle attributes, attitude and purchase intention. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 47–69. https://doi.org/10.1016/j.trf.2017.01.004

Schröder, T., & Wolf, I. (2017). Modeling multi-level mechanisms of environmental attitudes and behaviours: The example of carsharing in Berlin. *Journal of Environmental Psychology, 52*, 136–148. https://doi.org/10.1016/j.jenvp.2016.03.007

Simon, D., & Holyoak, K. J. (2002). Structural dynamics of cognition: From consistency theories to constraint satisfaction. *Personality and Social Psychology Review, 6*(4), 283–294. https://doi.org/10.1207/S15327957PSPR0604_03

Simon, D., & Stenstrom, D. M. (2015). The coherence effect: Blending cold and hot cognitions. *Journal of Personality and Social Psychology, 109*(3), 369–394. https://doi.org/10.1037/pspa0000029

Sovacool, B. K. (2017). Experts, theories, and electric mobility transitions: Toward an integrated conceptual framework for the adoption of electric vehicles. *Energy Research & Social Science, 27*, 78–95. https://doi.org/10.1016/j.erss.2017.02.014

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

Thagard, P. (1989). Explanatory coherence. *Behavioral and Brain Sciences, 12*, 435–502. https://doi.org/10.1017/S0140525X00057046

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

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

Thagard, P. (2021). The cognitive science of COVID-19: Acceptance, denial, and belief change. *Methods, 195*, 92–102. https://doi.org/10.1016/j.ymeth.2021.03.009

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

Thagard, P., & Verbeurgt, K. (1998). Coherence as constraint satisfaction. *Cognitive Science, 22*(1), 1–24. https://doi.org/10.1016/S0364-0213(99)80033-0

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

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

van Heuveln, K., Ghotge, R., Annema, J. A., van Bergen, E., van Wee, B., & Pesch, U. (2021). Factors influencing consumer acceptance of vehicle-to-grid by electric vehicle drivers in the Netherlands. *Travel Behaviour and Society, 24*, 34–45. https://doi.org/10.1016/j.tbs.2020.12.008

Westin, K., Jansson, J., & Nordlund, A. (2018). The importance of socio-demographic characteristics, geographic setting, and attitudes for adoption of electric vehicles in Sweden. *Travel Behaviour and Society, 13*, 118–127. https://doi.org/10.1016/j.tbs.2018.07.004

Wicki, M., Brückmann, G., & Bernauer, T. (2022). How to accelerate the uptake of electric cars? Insights from a choice experiment. *Journal of Cleaner Production, 355*, Article 131774. https://doi.org/10.1016/j.jclepro.2022.131774

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. *Technological Forecasting and Social Change, 94*, 269–285. https://doi.org/10.1016/j.techfore.2014.10.010