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Heterogeneity in preferences for alternative fuel vehicles: A latent class choice model including psychological factors

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Context

- Typically, choice modelling studies address preference heterogeneity using methods such as:
  - Deterministic and random heterogeneity.
  - Latent class-choice models with psychological variables.
  - Hybrid latent variable-choice models with psychological variables.
- Psychological effects are often studied using **attitude-behaviour link** theories, including constructs such as:
  - General or alternative-specific attitudes (e.g. pro-environmental or pro-innovation).
  - Behavioural intentions.
  - Mediators and moderating factors including habit, inertia, social influence, affective appraisal.

Context

- Attitude-behaviour link theories offer a simplified representation of decision-making, as they:
  - Consider independent evaluations for each attitudinal component.
  - Assume linear and unidirectional links between them.
  - Neglect the interaction between determinants and outcomes of the behavioural decision.
- This can hamper the analysis of complex decisions (e.g. vehicle purchases).
- **Theories of cognitive consistency** challenge these assumptions.

Aims and contributions

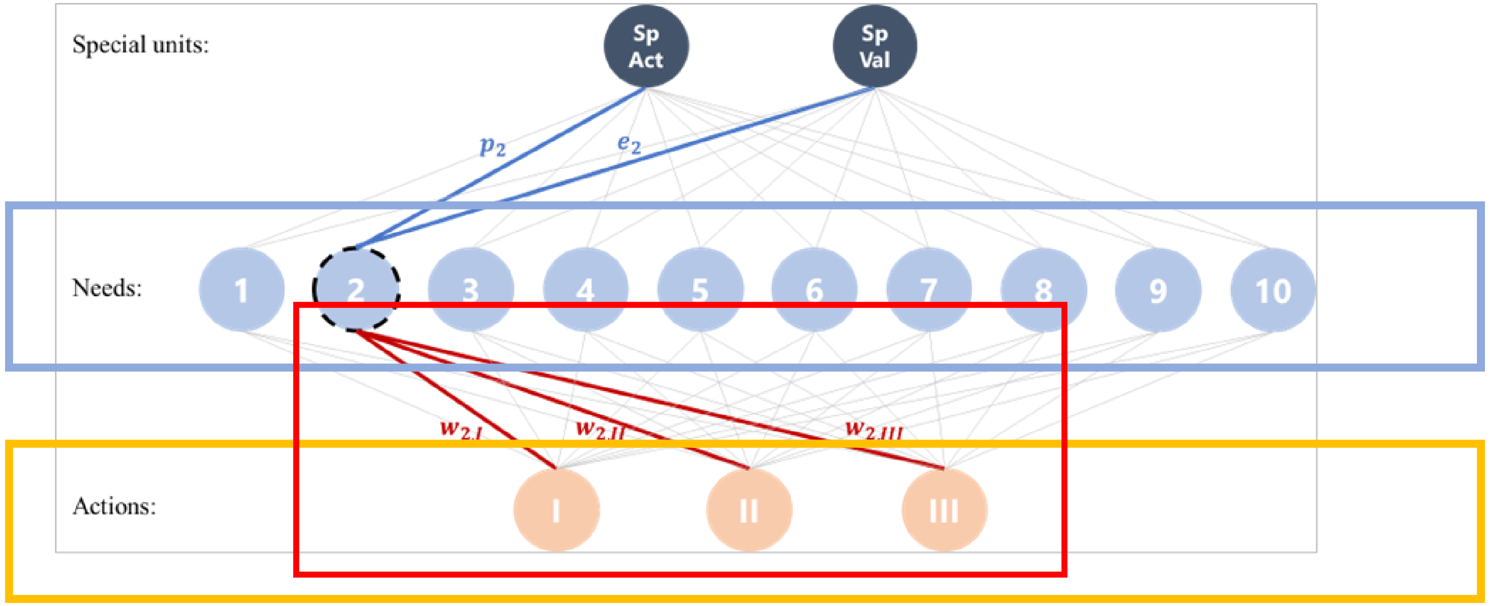
- **Aim**: To study the impact of the decision-making process in EV choices, following the theory of cognitive consistency.
- To do this, we:
  - Design a **stated choice (SC) experiment and attitudinal questionnaire** to collect information about a sample of households …
  - …implement the **Hot Coherence (HOTCO)** framework to understand attitudinal and emotional evaluations of vehicle fuel types in the sample…
  - …incorporate these results into a **latent class-discrete choice model** to analyse preferences for fuel types…
  - …**validate** our specification using an independent dataset.

Hot coherence model

- The **Hot coherence (HOTCO)** model (Thagard, 1989; 2006) is a cognitive consistency theory.
- It represents decision-making as a **connectionist network.**
- **Needs** (motivation nodes) and **actions** (behavioural-response nodes) interact with each other.
- When faced with a decision, individuals attempt to maximise the **coherence** between their beliefs and the possible actions.

Modelling framework

- A connectionist network and its **inputs**:



Needs to be satisfied.

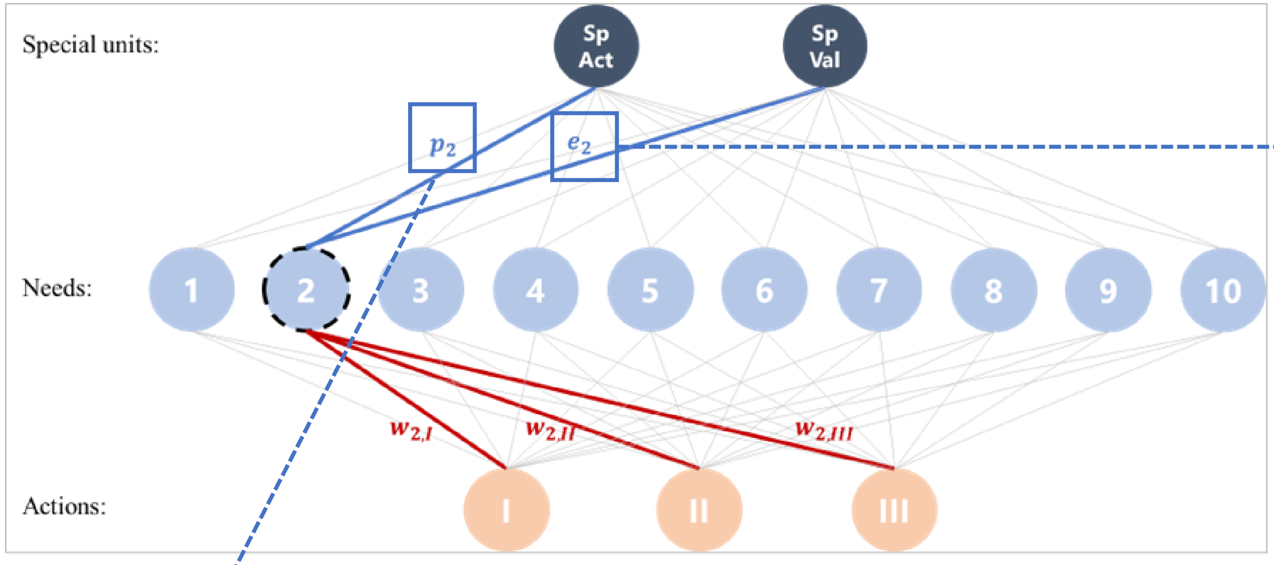
Possible **actions** to undertake.

Facilitation weights linking needs and actions:

- **Positive** if the action facilitates the need (**coherence**).
- **Negative** if the action impedes the need (**incoherence**).

Modelling framework

- A connectionist network and its **inputs**:



Emotional score: Emotional assessment of the need.

Priority: Intrinsic importance of the need.

Modelling framework

The HOTCO algorithm:

- **Activation** (attitudinal evaluation) and **valence** (emotional appraisal) are spread **iteratively** through the network.
- At each iteration, the nodes **update** their activation and valences (in parallel).
- The process is repeated until the network is "settled".

Update rule for activations:

$$ACT_n(c+1) = ACT_n(c)(1-d) + net_n \cdot (ceiling - ACT_n(c)) \text{ if } net_n > 0\text{, and}$$

$$ACT_n(c+1) = ACT_n(c)(1-d) + net_n \cdot (ACT_n(c) - floor) \text{ otherwise.}$$

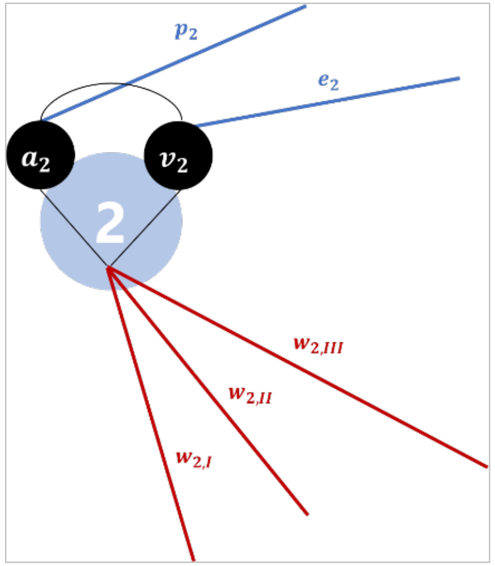
$$net_n = \sum_m w_{mn} \cdot ACT_n(c) + \sum_m w_{mn} \cdot ACT_n(c) \cdot VAL_n(c)$$

Update rule for valences:

$$VAL_n(c+1) = VAL_n(c)(1-d) + netval_j \cdot (ceiling - VAL_n(c)) \text{ if } netval_n > 0\text{, and}$$

$$VAL_n(c+1) = VAL_n(c)(1-d) + netval_n \cdot (VAL_n(c) - floor\ ) \text{otherwise.}$$

$$netval_n = \sum_m w_{mn} \cdot ACT_n(c) \cdot VAL_n(c)$$



- Each node ends up with an **activation** and a **valence** score .
- The final network is said to represent a **coherent** mental representation of the decision.

Data (1) – *Basics*

- We conducted a **survey** with the Prolific panel in 2022–23 to study vehicle type choice between three options: EV, HEV, ICE (Petrol/Diesel).
- Participants came from households in England which currently own at least one car. They were only included if they take part in the car purchase decision.

Dimension	Variable	Level	Main Survey	Reference (NTS 2021-R)
Sample size	Total respondents	–	620	–
	Number of complete responses	–	555	–
	Mean response time (minutes)	–	14	–
Cars	% of households by number of cars	0	–	–
		1	52.3	56.3
		2	37.8	35.9
		3 or more	9.9	7.8
	Mean cars per household	–	1.60	1.53
	% of households by number of driving licences	1	26.7	38.3
		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

Dimension	Variable	Level	Main Survey	Reference (NTS 2021-R)
Cars	% of households by annual income (Thousands of £)	<15	5.8	11.9
		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
	% 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
	% of urban households	–	69.0	74.0

Data (2) – *HOTCO questionnaire and inputs*

- Motives for car purchase were sourced from the literature and validated with an exploratory survey.

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

- Inputs for each need: priority, emotional evaluation, facilitation weights with each alternative (EV, HEV, ICE).

Data (3) – *Stated choice experiment*

- **15 possible designs (Ngene):** Five vehicle segments x Three purchase options (new, 2nd hand, both).
- **Nine choice situations** (simulated car purchases).
- **Five attributes** in each choice situation.
- We used **Survey Engine** to administer the survey.

	Petrol	Electric	Hybrid-electric	None
Upfront cost *Includes purchase price plus any taxes, rebates, or subsidies that may apply.*	$32,000	£32,000	£31,000	
Operation cost (per 100 miles) *Expenses for fuel or electricity*	£16.5	£6.6	£5.1	
Distance to recharge/refuel *Average distance from home to the nearest charging station.*	0.8 miles	1.1 miles	0.8 miles	
Driving range *Maximum number of miles before recharge/refuel.*	480 miles	500 miles	885 miles	
Charging time *Time to get the vehicle charged up to 80% of its capacity (tank/battery).*	3 minutes	20 minutes	3 minutes	
Which would you choose?	○	○	○	○

Modelling framework

- **Latent class-choice model**. Class-specific conditional choice utilities:

  - We model a mixed multinomial logit (MMNL) structure, considering correlation between choices by the same individual.
  - The utility functions have the following generic form:

$$U_{jqts} = \underbrace{V_{jqts}} + \underbrace{\varepsilon_{jqts}} + \underbrace{\sigma_j \cdot \eta_{jq}}$$

j: alternative
q: individual
t: choice task
s: class

Class-specific utility. Depends on alternative attributes, systematic heterogeneity, **plus** HOTCO variables.

Random component of the utility function. Conditional to the realisation of the error term, the probabilities have an MNL form.

Panel effect. Random term distributed Normal with mean 0 and variance to be estimated.

Modelling framework

- **Latent class-choice model.** Class-specific conditional choice utilities:

  - We treat the HOTCO terms for the **need** nodes as "latent variables" (unobserved initially but measured as a combination of the HOTCO inputs that were collected using the questionnaire), considering alternative-specific error terms:

$$V_{jqts} = \underbrace{V'_{jqts}}_{} + \underbrace{\theta_{ACT,s}}_{} \cdot \left(\underbrace{ACT_{jq}}_{} + \underbrace{\sigma_{ACT,j} \cdot \zeta_{ACT,jq}}_{}\right) + \underbrace{\theta_{VAL,s}}_{} \cdot \left(\underbrace{VAL_{jq}}_{} + \underbrace{\sigma_{VAL,j} \cdot \zeta_{VAL,jq}}_{}\right)$$

j: alternative
q: individual
t: choice task
s: class

Deterministic utility. Depends on alternative attributes and systematic heterogeneity.

Class-specific HOTCO activation coefficient. Generic for all alternatives.

HOTCO activation for alternative (**action node**) j by individual q

Alternative-specific **activation error term** distributed Normal wih mean 0, variance to be estimated.

Class-specific HOTCO valence coefficient. Generic for all alternatives.

HOTCO valence for alternative (**action node**) j by individual q

Alternative-specific **valence error term** distributed Normal wih mean 0, variance to be estimated.

Results (1) – *Class-specific probability functions*

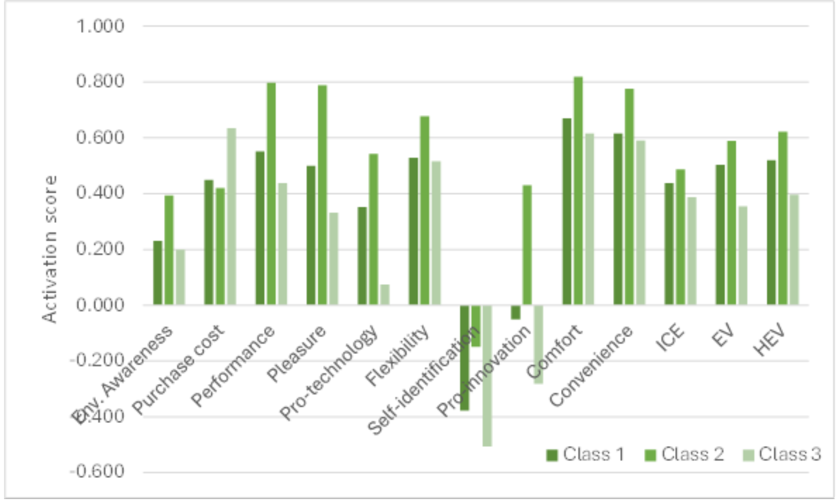
Type	Attribute	Alternative	Baseline model	Latent class choice model			
				Generic	Class-specific		
					Class 1 (46.8%)	*Class 2* (15.5%)	*Class 3* (37.8%)
			Coef. (T-Test)	Coef. (T-Test)	Coef. (T-Test)	Coef. (T-Test)	Coef. (T-Test)
Vehicle attributes	Alternative-specific constants	EV	10.075 (10.59)	–	12.223 (8.56)	2.545 (1.33)	19.798 (9.98)
		HEV	10.433 (11.96)	–	12.3 (10.73)	4.873 (3.60)	18.351 (11.18)
		ICE	8.550 (9.72)	–	10.074 (8.15)	2.337 (1.41)	16.205 (9.82)
	Purchase price (*Thousands of GBP*)	EV; HEV; ICE	–0.168 (–14.34)	–	–0.149 (–9.61)	–0.020 (–1.07)	–0.595 (–8.78)
	Annual operation cost (*Thousands of GBP*)	EV	–2.959 (–8.45)	–	–4.889 (–7.54)	–0.383 (–0.59)	–3.304 (–4.77)
		HEV; ICE	–2.169 (–9.51)	–	–3.158 (–6.21)	–0.574 (–1.06)	–2.617 (–6.36)
	Distance to charge (*Miles*)	EV; HEV; ICE	–0.456 (–4.41)	–	–	–	–1.279 (–4.72)
	Distance to charge x Charger awareness	EV	0.395 (2.56)	–	–	–	0.834 (1.94)
	Driving range (*Hundreds of miles*)	EV	0.297 (9.97)	–	0.445 (4.60)	0.425 (2.36)	0.263 (1.66)
		HEV; ICE	0.410 (7.59)	–	0.292 (4.48)	0.169 (1.51)	0.435 (6.03)
	Charging time (*Hours*)	EV; HEV; ICE	–0.800 (–8.70)	–	–1.218 (–6.62)	–0.592 (–2.12)	–0.882 (–2.67)
	Annual mileage (*Thousands of miles*)	ICE	0.601 (3.41)	–	0.274 (1.19)	0.524 (1.06)	1.428 (1.96)
Inertia	New vehicles	EV; HEV; ICE	0.402 (2.39)	–	0.516 (2.13)	1.291 (3.18)	1.278 (2.27)
HOTCO parameters	Activation	EV; HEV; ICE	0.569 (3.53)	–	0.404 (1.29)	4.685 (3.41)	0.437 (1.10)
	Valence	EV; HEV; ICE	1.094 (4.85)	–	–	2.331 (1.60)	1.793 (2.55)
Random term variances	Panel effects	Opt-out	4.977 (11.11)	5.457 (12.62)	–	–	–
		EV	–0.508 (–1.70)	1.613 (10.75)	–	–	–
		HEV	0.555 (4.49)	0.164 (0.48)	–	–	–
		ICE	–1.183 (–2.96)	–1.282 (–3.19)	–	–	–
	Activation error component	EV	0.433 (0.32)	0.192 (2.01)	–	–	–
		HEV	–0.056 (–0.20)	0.628 (2.87)	–	–	–
		ICE	–1.000 (–1.08)	–0.082 (–1.07)	–	–	–
	Valence error component	EV	–1.359 (–4.52)	–0.565 (–1.81)	–	–	–
		HEV	–0.265 (–1.29)	0.095 (0.66)	–	–	–
		ICE	0.755 (2.45)	–0.851 (–2.38)	–	–	–

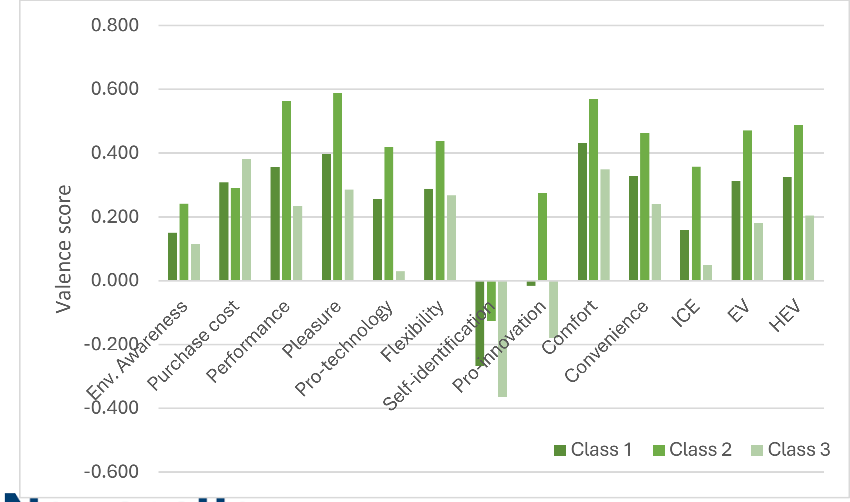
Results (2) – *Class membership functions + Model fit*

Type	Attribute	Baseline model	Latent class choice model			
			Generic	Class-specific		
				Class 1 (46.8%)	*Class 2* (15.5%)	*Class 3* (37.8%)
		Coef. (T-Test)	**Coef.** (T-Test)	**Coef.** (T-Test)	**Coef.** (T-Test)	**Coef.** (T-Test)
	Class-specific constant	–	–	–	–7.546 (–2.48)	–
Individual attributes	Gender (Male = 1)	–	–	–	1.607 (2.06)	–
Household attributes	Number of driving licences	–	–	–	0.815 (1.61)	–
	Number of employed people	–	–	–	–1.354 (–2.43)	–0.348 (–2.34)
	Household has bought a car new	–	–	–	–	–0.810 (–2.30)
	Household owns a medium car	–	–	–	1.165 (1.52)	–
	Household owns a large car	–	–	–	1.899 (1.84)	–
	Household owns a SUV/MPV	–	–	–	1.640 (1.68)	–
HOTCO attributes	Activation 2: Purchase price	–	–	–	–	1.235 (3.23)
	Activation 3: Driving performance	–	–	–	1.817 (1.52)	–
	Activation 4: Technological features	–	–	–	2.755 (2.34)	–
	Activation 5: Driving enjoyment	–	–	–	–2.044 (–2.58)	–
	Activation 8: Curiosity for innovation	–	–	–	1.344 (2.37)	–
	Activation 10: Convenience	–	–	–	2.817 (1.92)	–
	Valence 5: Driving enjoyment	–	–	–	–	–1.027 (–2.38)
	Valence 6: Flexibility	–	–	–	–	1.324 (1.78)
	Valence 10: Convenience	–	–	–	–	–1.320 (–2.00)

	Baseline model	Latent class choice model
Log-likelihood (*)	–3806.9	–3524.1
Number of individuals	525	525
Number of observations	4,725	4,725
Number of parameters	25	66
ρ^2 (market shares)	0.415	0.452
Akaike Information Criterion (AIC)	7663.9	7182.2
Bayesian Information Criterion (BIC)	7825.4	7615.0

Results (3) – *Class profiling*





Attribute	**Units**	***Class 1* (46.8%)**	***Class 2* (15.5%)**	***Class 3* (37.8%)**
Mean predicted choice probabilities				
ICE	–	0.095	0.158	0.143
EV	–	0.435	0.351	0.346
HEV	–	0.430	0.414	0.436
Sociodemographic attributes				
Population density	*Persons/hectare*	26.8	24.7	28.3
% of women	–	67.1	41.7	67.8
Annual income	*Thousands of GBP*	61.3	59.6	51.9
Car attributes				
Number of cars	–	1.7	1.8	1.5
% of households owning an EV/HEV	%	7.9	21.2	5.7
% of cars bought as new	–	33.0	42.8	15.7
Annual mileage driving (by car)	*Thousands of miles*	17.1	17.8	16.2

- **Class 1: Possible innovators**. High income, high EV probability. Relatively low activations and valences.
- **Class 2: Innovators**. Not majorly concerned with costs. High activations and valences for EVs, environmental awareness, and pro-innovation character. Over 21% already own an EV/HEV.
- **Class 3: Sceptics**. Low-income households in densely populated areas. Concerned about cost factors (high activations and valences).

Results (4) – *Post-estimation*

- **"Pseudo-elasticities"** – Even if elasticities do not have a real meaning with SC data, we computed them as they provide a sense of attribute importance:

Type	Attribute	Class 1	Class 2	Class 3	Model
Own	Purchase price (*Thousands of GBP*)	–0.710	–0.086	–1.900	**–1.034**
	Annual operation cost (*Thousands of GBP*)	–0.485	–0.035	–0.290	**–0.355**
	Driving range (*Hundreds of miles*)	0.611	0.494	0.290	**0.483**
	Distance to charge (*Miles*)	–	–	–0.309	–0.112
	Charging time (*Hours*)	–0.158	–0.062	–0.103	–0.127
	HOTCO activation	0.034	0.483	0.029	**0.104**
	HOTCO valence	–	0.139	0.072	**0.040**
Cross – HEV	Purchase price (*Thousands of GBP*)	0.176	0.033	0.551	0.274
	Annual operation cost (*Thousands of GBP*)	0.191	0.042	0.154	0.160
	Driving range (*Hundreds of miles*)	–0.118	–0.075	–0.162	–0.127
	Distance to charge (*Miles*)	–	–	0.067	0.023
	Charging time (*Hours*)	0.005	0.003	0.004	0.004
	HOTCO activation	–0.012	–0.195	–0.013	–0.041
	HOTCO valence	–	–0.046	–0.023	–0.013
Cross – ICE	Purchase price (*Thousands of GBP*)	0.428	0.038	1.050	0.601
	Annual operation cost (*Thousands of GBP*)	0.298	0.033	0.185	0.219
	Driving range (*Hundreds of miles*)	–0.348	–0.125	–0.358	–0.330
	Distance to charge (*Miles*)	–	–	0.128	0.049
	Charging time (*Hours*)	0.016	0.005	0.009	0.012
	HOTCO activation	–0.032	–0.290	–0.025	–0.067
	HOTCO valence	–	–0.076	–0.046	–0.023

Discussion

- HOTCO considers the effects of attitudes and emotional appraisal in decision-making, lifting the restriction of linear and unidirectional links between constructs.
- The latent class analysis identifies decision-making profiles that might get overlooked by generic models.
- Both can be useful for policy and addressing user heterogeneity.
- Specifically, "Possible innovators" are worried about the environmental effects of car purchases but appear constrained by cost and operative concerns. They are likely the group to which measures should be targeted.

Limitations and further research

- Integrating the HOTCO paradigm into discrete choice models might not be as straightforward. Further theoretical work is still required.
- HOTCO requires a great amount of information to build the connectionist networks. Simplified questionnaires might be explored.
- **Further research**:
  - HOTCO outputs have previously been used to model communication processes and attitudinal change over time (e.g., Wolf *et al.*, 2015).
  - An application considering the HOTCO model and a latent class choice model inside an agent-based model is underway!

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Thank you!

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