How effective are narrative messages in changing attitudes and preferences for electric vehicles? A before-and-after stated choice experiment

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SHORT SUMMARY

Attitudinal change is an important factor in increasing electric vehicle (EV) acceptance and accelerating their market adoption. This paper aims to understand the processes underlying changes in attitudes and preferences towards EVs by examining individual responses to narrative-based persuasion messages, which psychological research has shown to be an effective technique to change attitudes. To represent the diversity of information individuals may encounter, we investigate the role of appeal (rational vs. emotional) and type (positive vs. negative) in narrative messages. We analyse data from a "before-and-after" stated choice (SC) experiment administered to a sample of vehicle owners in England. Participants first completed an SC experiment and an attitudinal questionnaire. In a follow-up survey, participants allocated to experimental groups were exposed to a narrative-based message about EVs before repeating the SC experiment and attitudinal questionnaire, while a control group received no messages. Our results demonstrated that narrative messages can be effective in changing attitudes and preferences toward EVs. These results can therefore help shape policy measures to support the transition toward sustainable mobility.

Keywords: Electric vehicles, Discrete choice model, Hot coherence, Experimental study, Before and after study, Narrative messages

1 INTRODUCTION

Psychological factors including attitudes, perceptions, emotions, and social factors such as social image, self-identity and social influence, have a significant incidence on the acceptance of alternative fuel vehicles (AFVs), including both electric vehicles (EVs) and plug-in hybrid electric vehicles (HEVs) (Bhat & Verma, 2022). Issues like driving range anxiety, lack of experience or previous knowledge about AFVs, low environmental awareness, and low technology affinity, have often been highlighted as factors inhibiting AFV adoption (Pamidimukkala et al., 2024). Attitudinal change is required to increase the acceptability of AFVs and boost their market diffusion.

Persuasive communication can be a powerful strategy to achieve attitudinal change (Green & Brock, 2000; Petty & Briñol, 2012). There are two main persuasive communication strategies: advocacy-based (also known as *argumentation*) and narrative-based (also called *storytelling*). Advocacy-based persuasion involves an argument, or putting forth claims and supporting evidence linked by rational or logical coherence. Advocacy-based messages have been by far the primary strategy for persuasive communication used in the transport resaerch context, and specifically for EV adoption (Barth et al., 2016; Chung & Chon, 2024; Decrinis et al., 2023; Lee et al., 2021; Sunde, 2014; White & Sintov, 2017).

In contrast, narrative-based persuasion is based on descriptions of causally and chronologically related events played out by sentient characters (Bilandzic & Busselle, 2013). There is significant evidence that exposure to narratives based on stories, testimonial, opinions, and examples, can have a greater effect on changing individual beliefs about a product or object than advocacy-based messages (Green & Brock, 2000). Nevertheless, narrative-based messaging has been rarely used in the context of AFV adoption (Cherchi, 2017; Karpinska-Krakowiak et al., 2023; Lee, 2015).

In this paper, we investigate the efficacy of narrative messages in shifting attitudes and preferences towards AFVs focusing on the causal mechanisms through which an attitudinal change elicited by a narrative message can also induce shifts in preferences. We analyse data from a "before-and-after" stated choice (SC) experimental survey, administered to a sample of vehicle owners in England along with an attitudinal questionnaire. The survey included four different narrative messages combining two *appeals* (emotional or rational) and two *types* (positive and negative) of messages. We estimate a discrete choice model that incorporates the *hot coherence* (HOTCO) model, a type of cognitive consistency theory (Thagard, 1989, 2006) to investigate changes in attitudes and preferences.

Understanding the mechanisms of attitudinal change due to communication and information exchange is crucial for designing effective policy measures, improving their social acceptability and ensuring their long-term impact.

2 EXPERIMENTAL DESIGN

We designed and administered two surveys (henceforth referred to as *Before* and *After*) to a sample of vehicle owners[1]. The surveys were implemented using SurveyEngine (SurveyEngine, 2022), a Web-based data collection platform compatible with both laptop and mobile devices. Participants were recruited from a pool of England residents on the Prolific (2014) platform who, in a brief pre-screening

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

question, indicated that they had at least one car available and were involved in the car purchase decisions in their household.

During the *Before* survey (N = 555), participants completed a five-part questionnaire consisting of: 1) a *car characterisation* questionnaire, including details about current and past cars in the household; 2) a *SC experiment*; 3) an *emotional coherence* questionnaire; 4) a set of *electric charger awareness* questions; and 5) a *socioeconomic characterisation* questionnaire. After one month, participants who provided valid and complete responses in the *Before* survey were invited to participate in the *After* survey (N = 445). Participants were first exposed to persuasive messages and then completed the SC experiment (Part 2) and the emotional coherence questionnaire (Part 3) for a second time. Each participant in the *After* survey was randomly allocated to one of five groups – four *treatment* groups containing one of the four narrative messages (2 appeals × 2 types), plus a *control* group who was not presented any narrative message and therefore only completed the HOTCO questionnaire and the SC experiment. The layout of the messages in the survey is presented in Figure 1. A full description of the survey and data collection process can be found in Domarchi et al. (2025).

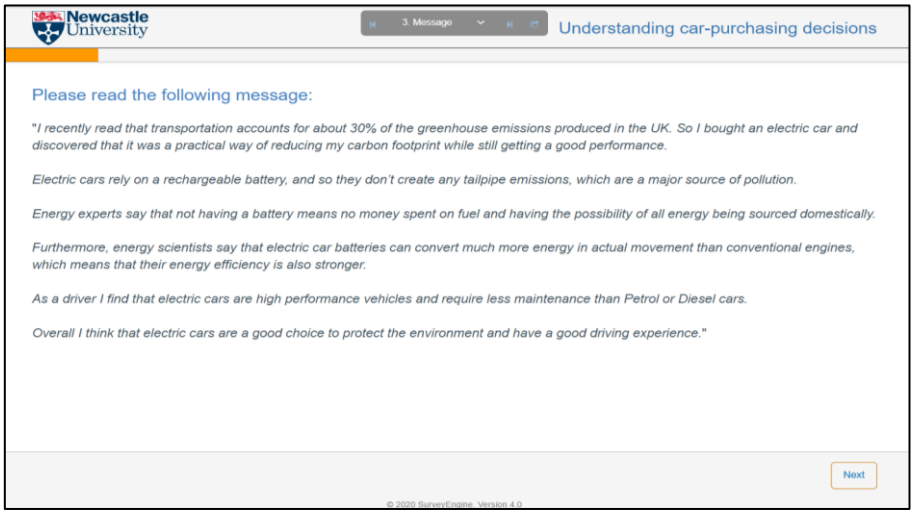


Figure 1. Narrative message – Presentation example (Screenshot)

The attitudinal information required to represent the choice problem in the context of a HOTCO connectionist network consists of a list of motives (*needs*) to be satisfied by the purchase of a car, as well as three possible outcomes of the purchase decision (*actions*); in this case, EV, HEV, and internal combustion engine (ICE) vehicles. We identified a list of ten *needs* to be satisfied by vehicle purchases that might be important for consumers in England, using an exploratory survey. The *needs* are listed in Table 1.

Table 1. HOTCO questionnaire – Final list of motives ("needs") for vehicle type choice

Need	**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*

Participants completed five ten-item questionnaires (one per each *need*). These measured the inputs required to build a HOTCO connectionist network for each participant. They included: priority scores (one questionnaire) and emotional scores (two questionnaires) for each need, measuring attitudes and affective evaluations, plus three questionnaires measuring facilitation links between each *need* and the three *actions.* Facilitation scores measure the degree to which each action is perceived as coherent with the satisfaction of each need. All items used a five-point Likert scale.

In the HOTCO algorithm, *needs* and *actions* interact in an iterative process to produce a consistent assessment. The HOTCO output consists of *activations* (an overall attitudinal evaluation of each alternative) and *valences* (the emotional appraisal of each alternative). Both are measured in scales ranging from -1 (alternatives perceived as "incoherent" with the mental representation of the decision-making process) to +1 (alternatives perceived as "coherent"). Details about the HOTCO algorithm can be found in Thagard (2006) and Thibault (2013), with its adaptation to this case study reported in Domarchi et al. (2024) and Domarchi et al. (2025).

Three alternatives were included in the SC experiment: EVs, HEVs, and ICE cars plus an "opt-out" alternative to preserve the realism of the choice. As the price and operational characteristics of these vehicles are extremely variable across the market, we built fifteen different survey designs, based on five different vehicle segments (small cars, medium cars, large cars, SUVs, and sports/luxury cars) and three possible purchasing options (new only, second-hand only, or a combination of both). Respondents were asked two screening questions before the SC experiment and were allocated to a specific design based on the responses. The SC tasks included five attributes: purchase cost, annual operation cost, driving range, distance to recharge/refuel, and charging time. We used the NGene software (ChoiceMetrics, 2018) to generate an efficient design (Rose & Blimier, 2009). Each respondent was presented with nine choice situations in random order. Further details about the experiment are reported in Domarchi et al. (2025).

3 METHODOLOGY

We specify a discrete choice model that identifies preference parameters affected by the narrative messages. The utility functions have the following generic expression:

$$U_{jqt} = V_{jqt} + H_{ACT,jqt} + H_{VAL,jqt} + \sigma_j \cdot \eta_{jq} + \varepsilon_{jqt} \quad \textbf{(1)}$$

V_{jqt} is the observed utility of alternative j as perceived by individual q in choice task t, and has the following components:

$$V_{jqt} = \left(a_j + \sum_{g=1}^{4} \alpha_{jg} \cdot r_{gq} \right) + \sum_{k=1}^{K} \left(\left(\beta_{jk} + \sum_{g=1}^{4} \beta_{jgk} \cdot r_{gq} + \sum_{l} \beta_{jkl} \cdot s_{lq} \right) \cdot X_{jqkt} \right) + \sum_{w=1}^{W} \left(\left(\gamma_w + \sum_{g=1}^{4} \gamma_{gw} \cdot r_{gq} + \sum_{l} \gamma_{wl} \cdot s_{lq} \right) \cdot I_{jqwt} \right) \quad \textbf{(2)}$$

Here, X_{jqkt} is the value of attribute k belonging to alternative j presented to individual q in choice task t. β_{jk} are coefficients associated with attribute k and alternative j (generic for all respondents), β_{jgk} are

group-specific coefficients associated with allocation to group *g* (as indicated by dummy variable r_{gq}), and β_{jkl} are parameters measuring systematic taste variation (Ortúzar & Willumsen, 2024).due to participants belonging to sociodemographic group *l* (as indicated by dummy variable s_{lq}). Next, I_{jqwt} are a set of inertia *dummy* variables taking the value 1 when participants choose the same fuel type (EV, HEV, or ICE *w* = 1) or the same purchase condition (new vehicle, *w* = 2) of one of their current vehicles. These inertia variables are associated with generic coefficients γ_w, group-specific coefficients γ_{gw}, and systematic taste variation coefficients γ_{wl}. Finally, a_j are alternative-specific constants associated with alternative j (EV, HEV, or ICE; the opt-out alternative is used as reference), and a_{jg} are group-specific coefficients measuring the variation in these constants arising from being allocated to group *g*.

The second and third terms in expression (2), $H_{ACT,jqt}$ and $H_{VAL,jqt}$ are related to the HOTCO outputs (activations and valences), associated with each alternative (EV, HEV, or ICE):

$$H_{ACT,jqt} = \left(\theta_{ACT} + \sum_{g=1}^{4} \theta_{ACT,g} \cdot r_{gq} + \sum_{l} \theta_{ACT,l} \cdot s_{lq} \right) \cdot \left(ACT_{jqt} + \sigma_{ACT,jq} \cdot \zeta_{ACT,jq} \right) \quad \textbf{(3)}$$

$$H_{VAL,jqt} = \left(\theta_{VAL} + \sum_{g=1}^{4} \theta_{VAL,g} \cdot r_{gq} + \sum_{l} \theta_{VAL,l} \cdot s_{lq} \right) \cdot \left(VAL_{jqt} + \sigma_{ACT,jq} \cdot \zeta_{ACT,jq} \right) \quad \textbf{(4)}$$

Here, ACT_{jqt} and VAL_{jqt} are activations and valences associated with alternative j for individual q in choice situation *t*. As before, coefficients θ_{ACT} and θ_{VAL} capture the baseline preferences for activation and valences, respectively, while $\theta_{ACT,g}$ and $\theta_{VAL,g}$ measure the change in preferences due to being allocated to group *g*. Systematic taste variations were also tested for these attributes.

As in Domarchi et al. (2025), we treat activations and valences as latent variables (unobserved initially but measured as a combination of the HOTCO inputs that were collected using the questionnaire). We model three error components for activations $\zeta_{ACT,jq}$ (one for each alternative *j*) and three for valences, $\zeta_{VAL,jq}$.

The two final terms in equation (1) are: ε_{jqt}, the random component of the utility function, varying across alternatives j, individuals q and choice situations t, and $\sigma_j \cdot \eta_{jq}$, an error component associated with alternative j distributed Normal IID across individuals, but constant across all choice situations (i.e. across both surveys). All four alternative-specific variances ($\sigma_{EV}, \sigma_{HEV}, \sigma_{ICE}$ and $\sigma_{opt-out}$) are identifiable and can be estimated (Walker et al., 2007). If we assume an IID EV distribution for the ε_{jqt} term, the conditional choice probability of choosing a sequence of choices is given by the product (over the SC tasks) of multinomial logit probabilities, conditional on the realisation of the error terms ζ and η. The unconditional choice probabilities are then given by the integral of this product over the domains of ζ and η. We estimated the models by simulated maximum likelihood with Pandas Biogeme (Bierlaire, 2020).

4 RESULTS AND DISCUSSION

Model results

The coefficients in our discrete choice model specification are presented in Table 2. The parameters associated with vehicle attributes have the expected signs, with negative marginal utilities for price, operation cost, charging distance, and charging time, and positive coefficients for range. Importantly, while there is a negative valuation of the distance required to reach a charging station, the effect disappears for respondents who either have a charging point at home/at work or are aware of the location of a charging point nearby. Respondents who drive more miles annually are more likely to choose petrol or Diesel vehicles. This result might be related to the extended belief that AFVs might be less reliable for longer distance journeys (Krisher, 2023). There is also evidence of inertia effects in the choice experiment, with respondents more likely to choose a fuel type if they already own a vehicle with the same fuel type, and respondents who have previously bought new vehicles more likely to select this purchase option in the experiment. The mean values of both HOTCO outputs have both positive coefficients, although only valence is significant in the baseline model. As these are random parameters with alternative-specific variances, they reveal significant preference heterogeneity.

The effects of the messages on preference parameters are limited. As expected, there are no significant effects on any preference parameters for respondents in the control group. Message 1 (positive and rational) induces a negative variation in the parameter, which implies a higher marginal utility of income. Exposure to Message 2 (negative and rational) is associated with a decrease in the HEV/ICE range parameter (albeit only for female respondents), and a significant increase in the new vehicle inertia parameter. The effect of Message 3 is significant mostly in the vehicle range attribute. The positive portrait of EVs in this message is associated with a reduced concern for EV range, but the effect is limited to female respondents and those who reside in Greater London. The most significant effect of Message 4 (negative and emotional) appears in the importance of fuel type inertia, with a lower effect in preferences for EV range.

The most significant effects of the messages appear on the HOTCO parameters. All four messages are associated with changes in preferences for HOTCO activation compared to the base case; however, the effect is not significantly different across groups ($p > 0.05$ for all pairwise comparisons). This suggests that the effects of attitudinal factors on choice probabilities change are linked to mere exposure to narrative messages, regardless of their type. Conversely, although both rational messages (1 and 3) significantly shift the mean values of the valence coefficient distributions to the left, the positive message is associated with a statistically more pronounced effect This implies that focusing on more concrete aspects of EV operation in the messages, shifts the focus of the decision to these aspects, and reduce the importance of the emotional dimension. The effect is not symmetric in the emotional appeal as messages 2 and 4 do not significantly change the HOTCO mean values of the valence coefficients.

Table 2. Discrete choice modelling results (Robust *t*-test in parenthesis)

Variable	Alternative	Interaction	Baseline	Variations for each experimental group				
				Control	M1	M2	M3	M4
Alternative-specific constants								
Mean	Opt-out	–	0	–	–	–	–	–
	EV	–	7.819 (12.59)	0.274 (0.58)	1.292 (1.09)	-0.731 (-1.09)	1.035 (1.89)	-0.563 (-1.2)
	HEV	–	8.803 (15.36)	0.311 (0.67)	0.569 (0.52)	-1.325 (-2.32)	-0.712 (-1.07)	-0.328 (-0.69)
	ICE	–	6.22 (9.45)	0.745 (1.45)	-0.308 (-0.25)	-0.918 (-1.51)	-0.991 (-1.45)	-1.788 (-2.09)
Standard deviation (Panel effect)	Opt-out	–	4.116 (10.94)	–	–	–	–	–
	EV	–	0.324 (1.5)	–	–	–	–	–
	HEV	–	0.005 (0.03)	–	–	–	–	–
	ICE	–	0.615 (2.46)	–	–	–	–	–
Alternative attributes								
Price (x GBP 1,000)	EV, HEV, ICE	–	-0.177 (-17.25)	–	-0.061 (-2.17)	–	–	–
Operational cost (x GBP 1,000/Year)	EV, HEV, ICE	–	-2.275 (-11.00)	–	–	–	–	–
Driving range (x 100 miles)	EV	Base	0.470 (9.35)	–	–	–	–	–
		× *Gender = Female*	–	–	–	-0.245 (-2.49)	-0.243 (-2.30)	–
		× *Region = Gr. London*	–	–	–	–	-0.341 (-2.21)	-0.36 (-2.11)
	HEV, ICE	Base	0.321 (8.80)	–	–	–	0.151 (1.73)	–
		× *Cars > 1*	0.067 (2.54)	–	–	–	–	–
		× *Ethnicity = Non-white*	-0.077 (-2.29)	–	–	–	–	–
		× *High education*	-0.087 (-3.02)	–	–	–	–	–
		× *Not currently working*	0.082 (2.20)	–	–	–	–	–
		× *Gender = Female*	–	–	–	–	-0.125 (-1.67)	–
Charging distance (miles)	EV, HEV, ICE	Base	-0.372 (-4.24)	–	–	–	–	–
		× *Charger awareness*	0.265 (2.00)	–	–	–	–	–
Charging time (hours)	EV, HEV, ICE	Base	-1.073 (-9.38)	–	–	–	–	–
		× *Cars > 1*	0.224 (1.51)	–	–	–	–	–
		× *Household with kids*	0.341 (2.43)	–	–	–	–	–
Annual mileage (x 1,000 miles)	ICE	–	0.054 (6.78)	–	–	–	–	–
Inertia parameters								
Fuel type inertia	EV, HEV, ICE	–	0.773 (3.12)	–	–	–	–	1.363 (2.05)
New vehicle inertia	EV, HEV, ICE	–	0.479 (3.27)	–	–	0.980 (2.57)	–	–

Variable	Alternative	Interaction	Baseline	Variations for each experimental group				
				Control	M1	M2	M3	M4
HOTCO activation								
Mean	EV, HEV, ICE	Base	0.165 (1.07)	–	0.399 (1.90)	0.511 (2.54)	0.384 (2.94)	0.356 (2.67)
Standard deviation (Error component)	EV	–	-2.855 (-2.71)	–	–	–	–	–
	HEV	–	1.143 (1.25)	–	–	–	–	–
	ICE	–	-2.752 (-2.48)	–	–	–	–	–
HOTCO valence								
Mean	EV, HEV, ICE	Base	0.887 (3.43)	–	-1.363 (-3.99)	-0.334 (-1.23)	-0.581 (-2.11)	-0.337 (-1.21)
Standard deviation (Error component)	EV	–	1.625 (3.69)	–	–	–	–	–
	HEV	–	0.693 (2.69)	–	–	–	–	–
	ICE	–	1.427 (3.76)	–	–	–	–	–
Level-of-fit indicators								
Log-likelihood (*)	-6296.85							
Log-likelihood (market shares)	-8627.72							
Rho-square (market shares)	0.270							
Number of parameters	64							
AIC	12721.71							
BIC	13168.83							

***M1: Positive, Rational; M2: Positive, Emotional; M3: Negative, Rational; M4: Negative emotional**

Post-estimation

We use an independent dataset of England households sourced from the National Travel Survey to generate forecasts with our model (Domarchi & Cherchi, 2024). To obtain values for HOTCO inputs, each household in the validation dataset was matched to its closest counterpart in the survey using a fast nearest neighbour search algorithm, with a distance measure based on sociodemographic attributes[2]. The validation dataset comprises 235 records, and its market shares differ from those observed in the stated choice experiment; for example, only 4.2% of the vehicles in the dataset are AFVs.

We use our model to predict choice probabilities for each fuel type in eight policy scenarios. *Scenario 0* assumes that households were not exposed to any message, and thus they keep their HOTCO inputs and outputs, and preference parameters, as in the base case scenario. In the remaining seven scenarios (1 – 7), we randomly allocate households in the dataset to one of the messages, as in Table 3:

[2] Further details are provided in Domarchi (2023).

Table 3. Forecasting scenario definitions

Policy scenario	Specification	Share of the population exposed to each message type				
		Control	M1	M2	M3	M4
1	Mostly positive	10%	35%	10%	35%	10%
2	Mostly negative	10%	10%	35%	10%	35%
3	Rational and positive	10%	50%	20%	10%	10%
4	Emotional and positive	10%	20%	50%	10%	10%
5	Rational and negative	10%	10%	10%	50%	20%
6	Emotional and negative	10%	10%	10%	20%	50%
7	Reduced information	60%	10%	10%	10%	10%

***M1: Positive, Rational; M2: Positive, Emotional; M3: Negative, Rational; M4: Negative emotional**

Table 4 reports the changes in mean choice probabilities with respect to the predicted probabilities for Scenario 0, along with the mean direct arc EV demand elasticities, and their respective confidence intervals. Although not an economic measure, we also included HOTCO outputs (activation and valence) in these calculations, mainly to illustrate their overall impact in choice probabilities

Table 4. Changes in probabilities, mean activations, and mean valences under each policy scenario

Variable	Fuel type	Policy scenario						
		1	2	3	4	5	6	7
Change in probabilities (percentage points w/r to scenario 0)	EV	+5.4* [+4.1, +6.6]	+5.0* [+3.8, +6.2]	+5.4* [+4.2, +6.7]	+4.6* [+3.4, +5.8]	+4.7* [+3.4, +5.9]	+2.5* [+1.4, +3.6]	+1.9* [+0.8, +2.9]
	HEV	-3.6* [-5.0, -2.1]	-6.5* [-8.0, -5.0]	-3.4* [-5.0, -1.9]	-7.2* [-8.7, -5.6]	-3.6* [-5.1, -2.2]	-2.9* [-4.3, -1.4]	-1.8* [-3.2, -0.4]
	ICE	-1.9* [-3.0, -0.7]	+1.2 [0.0, +2.5]	-2.2* [-3.3, -1.0]	+2.2* [+0.9, +3.6]	-1.2 [-2.4, +0.0]	+0.2 [-1.0, +1.4]	-0.2 [-1.4, +1.0]
Direct elasticity	Purchase price	-1.27* [-1.39; -1.16]	-1.22* [-1.33; -1.12]	-1.31* [-1.43; -1.19]	-1.23* [-1.35; -1.12]	-1.26* [-1.37; -1.16]	-1.29* [-1.40; -1.18]	-1.36 [-1.47; -1.25]
	Operational cost	-0.24* [-0.25; -0.22]	-0.24* [-0.25; -0.22]	-0.24* [-0.25; -0.22]	-0.23* [-0.24; -0.21]	-0.24* [-0.26; -0.22]	-0.25* [-0.27; -0.23]	-0.26* [-0.28; -0.24]
	Range	0.54* [0.52; 0.57]	0.51* [0.48; 0.54]	0.57* [0.55; 0.60]	0.51* [0.48; 0.54]	0.55* [0.52; 0.58]	0.61* [0.58; 0.64]	0.66* [0.64; 0.69]
	Charging distance	-0.35* [-0.36; -0.34]	-0.35* [-0.36; -0.34]	-0.35* [-0.36; -0.34]	-0.34* [-0.35; -0.33]	-0.36* [-0.37; -0.35]	-0.37* [-0.38; -0.36]	-0.39* [-0.40; -0.38]
	Charging time	-0.56* [-0.58; -0.54]	-0.56* [-0.58; -0.54]	-0.56* [-0.58; -0.54]	-0.55* [-0.57; -0.52]	-0.58* [-0.60; -0.56]	-0.59* [-0.62; -0.57]	-0.62* [-0.65; -0.60]
	Activation	0.13* [0.10; 0.16]	0.13* [0.11; 0.16]	0.13* [0.10; 0.16]	0.14* [0.11; 0.17]	0.13* [0.11; 0.16]	0.14* [0.11; 0.17]	0.08* [0.06; 0.10]
	Valence	0.05* [0.03; 0.08]	0.07* [0.05; 0.09]	0.03* [0.00; 0.05]	0.06* [0.03; 0.08]	0.08* [0.06; 0.10]	0.08* [0.05; 0.11]	0.16* [0.12; 0.20]

Values marked with * are statistically different from the corresponding scenario 0 value at 95% confidence ($p < 0.05$).

As expected, the scenarios where positive information about EV is predominant (1, 3, 4), yield a statistically significant increase in EV choice probabilities (compared with scenario 0). The effects are slightly more pronounced for scenario 1, in which the rational component is more predominant, although this increase is not statistically different than the ones in the other two scenarios. Notably, scenarios 1 and 3, both of which assume a higher proportion of households receiving rational messages, also achieve significant reductions in ICE choice probabilities. In scenario 4, where the emotional information is more prevalent, the likelihood of buying an ICE car is also increased, and the strongest reduction in choice probabilities is observed for HEVs.

While negative information about EVs is predominant in scenarios 2, 5, and 6, the net effect of exposure to messages in the dataset is still a significant increase of EV choice probabilities. This is compensated by a significant reduction in HEV choice probabilities in all three scenarios, demonstrating a "cross" effect of similar respondent perceptions about EV and HEVs. In addition, scenarios 2 and 5 exhibit a

significantly higher probability of choosing ICE vehicles, another indicator of the cross effect of the messages. In scenario 7, where households receive no information, all changes in probabilities are smaller in magnitude, and ICE choice probabilities remain unchanged.

Elasticities of purchase price, driving range, charging distance, charging time, activation, and valence, are statistically different from their counterparts in the base case scenario, regardless of which message is predominant in each case. People are typically exposed to different types of information. Thus, these results suggest that in such more realistic situations, dynamic effects in elasticities can be expected – possibly due to repeated exposure to the choice problem – regardless of the type of information received.

5 CONCLUSIONS

Our results reveal significant effects of narrative messages, both in HOTCO outputs (activations and valences), and in preferences for fuel types. Message effects in preferences are relatively limited, with the most significant shifts found on the HOTCO coefficients. While all messages contribute to a change in preferences for activations (more related with attitudinal appraisals), only rational messages shift the mean values of valence coefficients to the left. Thus, the focus on more concrete aspects of EV operation in the information provided, could generate more significant effects on preferences for EVs compared with a more emotional-focused appeal. Our forecasting analysis confirms that providing positive information about the benefits of EVs can induce increased EV choice probabilities, regardless of message appeal. However, if the information provided is more strongly focused on the utilitarian and quantifiable benefits of owning an EV (rational appeal), the added benefit of reduced choice probabilities for ICE vehicles could be observed. In addition, the effect of negative messages about EVs appears at least partially neutralised by the provision of positively framed information. We observe increases in EV choice probabilities even in these more "pessimistic" settings. This hints at the importance of information and awareness campaigns to counterbalance the effects of negative publicity about EVs. Our work highlights the importance of public awareness about the advantages and benefits of EVs as a powerful tool for attitudinal change, which can have a significant effect on preferences towards this fuel type. Providing this information can significantly increase users' familiarity with cleaner transport alternatives in general, generating an environment that favours their willingness to consider these alternatives in their future purchasing decisions.

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