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Author(s):
Bernardic, Ursa; Cerruti, Davide; Filippini, Massimo; Savelsberg, Jonas; Ugazio, Giuseppe

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De-biasing electric vehicle adoption with personalized nudging

Ursa Bernardic[1], Davide Cerruti[1], Massimo Filippini[1], Jonas Savelsberg[2], Giuseppe Ugazio[3]

[1]Center for Energy Policy and Economics, ETH Zürich.
[2]Energy Science Center, ETH Zürich.
[3]Geneva Finance Research Institute, University of Geneva.

Abstract

Replacing combustion engine vehicles with battery electric vehicles (BEV) is essential to achieving climate objectives and advancing sustainable transportation, aligning with the United Nations Development Goals and the Paris Agreement. In this project, we identify three perception biases linked to EV adoption and address them with personalized non-monetary information treatments to increase the adoption of BEVs among owners of internal combustion engine vehicles. In a randomized controlled trial with 3181 car owners, we measure the extent of perception biases about range anxiety, charging anxiety, and total cost of ownership (TCO). We find that individuals have strong misperceptions related to these three aspects. In a randomized control trial setting, we then introduce three personalized information interventions to correct each of these biases, based on actual driving and parking behavior. Our results show that these treatments, and especially the TCO information treatment, are effective in increasing purchase preferences toward BEVs.

1 Introduction

Battery electric vehicles (BEV) are a central pillar to decarbonizing road transport, a sector that accounts for over 22% of global energy-related emissions [1]. While advances have been made in overcoming financial and technological hurdles to BEV adoption, psychological barriers in car owners' minds persist and demand more attention. A yearly survey from the UK repeatedly highlights the role of range anxiety, and charging anxiety as the most common barriers to BEV adoption [2]. Similarly, a recent research has highlighted how perceived high purchase prices, and limited driving range represents common barriers in BEV adoption [3]. Related to the last barrier, several studies show that BEVs can already cover a vast majority of trips [4–6]. Moreover, BEVs are nearing cost parity with internal combustion engine vehicles (ICEV) and are often less expensive when considering the total cost of ownership [7]. However, some studies (to find and cite these studies) show a lack of knowledge of potential car buyers on fuel cost savings and advantages in total cost of ownership of BEV. We believe that addressing perceived barriers such as range anxiety, charging anxiety, and cost of ownership through informational treatments is pivotal in increasing BEV adoption. [6, 8, 9].

Common strategies to boost BEV adoption include financial incentives such as purchase subsidies or tax benefits, expanding charging infrastructure, and adjusting traffic regulations [10]. Another approach involves employing behavioral nudges, recognized as effective tools for policymakers in capturing consumer attention [11]. However, recent critiques have highlighted concerns about the universal application of nudges, as they may yield unintended consequences and backfire for certain groups [12]. This occurs due to the inherent diversity within populations that can lead to differing responses to nudges [13]. To address this problem, authors such as [14] proposed using personalized nudging,an approach that we adopted in this paper.

In the first part of the paper we assess the extent of perception biases linked to BEV adoption through a detailed survey. In the second part of the paper, we conduct a randomized control trial (RCT) among owners of ICEVs to assess the impact of personalized information treatments in reducing biases.

Based on insights from previous studies, we focus on three main compatibility biases: 1) Range compatibility: misconceptions of the share of car trips within a year that could be completed with a given battery range; 2) Charging compatibility: misconceptions of the number of charges needed per week for an electric car with a given battery range; and 3) Total cost of ownership (TCO) compatibility: misconceptions of the total cost of owning and using a compact gasoline and a compact electric car over four years.[1]

Specifically, we have implemented a survey with 3181 car owners from the United Kingdom. Within this survey we first elicit to what extent car owners over- or underestimate the range, charging and TCO compatibility of BEVs with their own behavior. In the second part of the survey, we use a stated choice randomized controlled trial to determine whether providing personalized information on range, charging, and total

[1] In this paper, we define the concept of compatibility bias as "the discrepancy between perceived and actual compatibility with drivers' mobility needs" [6]

cost of ownership (TCO) based on respondents' driving behavior has an impact on their intention to purchase a battery electric vehicle (BEV).

We find that current car owners have remarkable psychological biases regarding range, charging and TCO compatibility. Our personalized information interventions aimed to counter each of these biases show a relevant impact: the range and charging compatibility treatments increased BEV purchase intentions by about 8 percentage points, while the TCO treatment increased BEV purchase intention by about 14 percentage points, compared to the control group. Together, these results suggest that personalized information provided through our intervention played a significant role in increasing BEV purchase intentions and highlight how insights from compatibility biases may complement existing policies in the promotion of BEV adoption.

To the best of our knowledge, our paper is the first to quantify not only range anxiety but also charging anxiety and to develop an effective informational treatment to correct it. Furthermore, testing three different psychological barriers to BEV adoption allows us to compare the effect of bias correction on buying intentions. Therefore, this paper contributes to a broad literature that uses information treatments to study limited knowledge and perceptual biases in individuals' decision-making across different contexts, from financial literacy to the energy efficiency gap. We also contribute to a growing body of nudging research studying the role of personalization and customization of treatment information.

The remainder of the paper is organized as follows. In Section 2 we review the existing literature; in Section 3 we describe the personalized information treatments developed for this study, the experimental design and sample characteristics; in Section 4 we present our measurements of perceptual biases and estimates of the treatment effects. Section 5 includes a discussion of the findings and presents our conclusions.

2 Literature Review

At least two branches of the literature are relevant for this study. On one side, we have studies dealing with the analysis of the barriers to adopting BEV, whereas on the other side, we have the literature on nudges and, more specifically, on information nudges.

A complex interplay of economic, financial, technological, and psychological factors seems to contribute to the slower adoption rate of BEVs [15]. Extensive research examining EV adoption behaviors consistently highlights the primary obstacles, notably the high initial cost, limited driving range, and charging inconveniences [3, 16, 17].

Range anxiety, defined as the apprehension about inadequate battery capacity to reach a destination, is a prevalent concern within the literature [18]. Studies have demonstrated significantly lower preferences for alternative fuel vehicles compared to conventional technology, mainly due to restricted driving range and considerable refueling durations [19]. Similarly, concerns about safety, reliability, and range emerge as top issues in public perception studies [20]. The concept of range anxiety fluctuates with varying levels of EV experience, yet remains unclear. While some studies suggest a decrease in range anxiety over time with increased EV experience [21–23], others paradoxically observed an increase in range anxiety with greater EV familiarity [24].

Charging time and vehicle-to-grid capability emerge as pivotal factors influencing consumer decisions [25]. The preference for home charging stems from concerns regarding relatively lengthy charging durations [5, 16, 26]. Patt et al. [27] found that the availability of private charging infrastructure significantly determined consumer willingness to purchase BEVs, with dedicated parking spaces and private charging access increasing inclination towards buying a BEV. Inconvenience associated with charging is a leading reason for electric vehicle owners discontinuing their use [28, 29]. However, findings from Melliger et al. [4], Needell et al. [5] suggest that a majority of trips could have been covered by electric vehicles.

Additionally, while there's a common belief that BEVs incur higher expenses due to initial capital outlay, studies demonstrate that their operational costs can be lower than those of conventional vehicles [30, 31]. TCO considerations typically favor BEVs over ICEV vehicles [29]. Yet, consumer choices primarily focus on the purchase price of BEVs, leading to skewed perceptions and slower growth of BEVs [**?**]. Furthermore, consumer myopia concerning future fuel costs significantly impacts TCO assessments [32]. Studies reveal a tendency to undervalue future fuel expenses, focusing more on immediate costs [33]. Limited understanding of electricity prices in contrast to gasoline prices further complicates the intuitive grasp of relative costs [34, 35].

As outlined above, consumers are primarily concerned with BEV compatibility about range, charging, and TCO. Perceived compatibility of a given BEV with consumers' mobility needs and lifestyles is considered one of the most important predictors of BEV purchase intention and adoption [36]. However, studies have shown that such anticipatory perception of consumers can be biased [6]. For example, consumers underestimate their compatibility with BEV regarding range concerns. In contrast, actual range compatibility showed that most of the trips could already be met with available and increasingly affordable BEV [5]. Correcting such systematic compatibility underestimations for range concerns, increased willingness to pay [6], while other compatibility biases have remained relatively understudied. More importantly, no interventions exist that address charging and TCO compatibility biases.

Behavioral nudges are recognized as effective tools for policymakers in capturing consumer attention [11]. However, recent critiques have highlighted concerns about the universal application of nudges, as they may yield unintended consequences and backfire for certain groups [12]. This occurs due to the inherent diversity within populations can lead to differing responses to nudges [13], and therefore personalized nudging has been proposed [14]. Using customized information on monetary savings Boogen et al. [37] conducted a field study with in-home visits of households in Switzerland, finding that treated households who received customized information on monetary savings adopted more efficient appliances and reduced the intensity of use of certain appliances. In a similar vein, Blasch et al. [38] and Blasch et al. [39] found that displaying information on energy consumption in monetary terms on energy labels (rather than in terms of kWh), as well as of education programs on how to calculate lifetime costs and the use of lifetime cost calculators, enabled respondents in Switzerland to identify appliances having the lowest lifetime cost correctly. In a study evaluating the efficacy of labels for cars in Switzerland, Alberini et al. [40] concluded that while consumers were willing to pay more for more fuel-efficient cars, it was not clear whether the fuel economy labels had any additional effects on the prices of cars. Cerruti et al. [41] showed the role of policy awareness for BEV fiscal incentives, and how informational treatment about the presence of the fiscal program increases the awareness and increases BEV choices in explaining the impact of policy measures in Switzerland. Building on the above findings, this study examines biases related to BEV adoption and tests whether personalized nudges might be a promising avenue to promote BEV adoption and widespread electrification of personal vehicles.

3 Experimental design

Our study is based on a large-scale survey of 3181 UK online participants who own a car (56% female, mean age 39) organized over two weeks. The questionnaire used in the survey consists of four main sections: (1) respondents' perceptions of BEV compatibility with their own behaviour and expected costs, (2) detailed driving and parking diaries to elicit actual behaviour, (3) a randomised controlled trial to test the effect of three personalised information treatments on range anxiety, charging anxiety and total cost of ownership, and (4) a short socio-demographic survey. The experiment was pre-registered on OSF [42].

After giving consent, participants were asked to estimate, in random order, perceived range compatibility, perceived charging compatibility, and perceived total cost of ownership. Perceived range compatibility was measured by asking respondents to estimate the proportion of car journeys they could make in a year with a given battery range. Each respondent had to indicate a percentage using a slider for battery ranges from 420 miles to 70 miles in 50-mile increments. Perceptions of charging compatibility were assessed by asking respondents to estimate how many times per week they would need to charge an electric car with a given battery range. This required each respondent to indicate the number of times per week they would need to recharge on a scale of 0 to 10, using a slider for battery ranges from 420 miles to 70 miles in 50-mile increments. Finally, respondents were asked to estimate the total cost of owning and using a compact petrol car (e.g. VW Golf) and a compact BEV (e.g. VW ID.3) over a four-year period.

Fig. 1: Annual vehicle mile comparison survey and [2]

Subsequently, in order to determine respondents' actual behavior, they were asked to complete a weekly diary of their driving behavior during an average week in the year 2022. In this diary, they could record up to six one-way journeys for each day of the week. The weekly driving diary was followed by a long-distance driving diary in which respondents could record up to 18 long-distance journeys of more than 120 miles. Based on the information collected, we estimated annual mileage and provided respondents with an overview of our estimate and a comparison with the annual mileage they reported at the start of the survey, allowing them to adjust their entries. Compared to the UK average annual mileage of 6,600 miles in 2022 [2], we find a median annual mileage of 6,610 miles in our survey. Figure 1 compares the respondents' annual mileage derived from the diary with the annual mileage for different segments according to [2] and underlines the quality of our measure. Following the driving diary, a detailed parking diary was used to record the time a car was parked at different locations such as the respondent's workplace, supermarkets or other locations. Respondents were given live feedback on how many hours of parking and driving per week their responses indicated. For both diaries, respondents were given practice diaries to test their understanding before being given the personal diary used in the study.Comparing perceived and actual BEV compatibility allows us to identify the presence and size of perception biases.

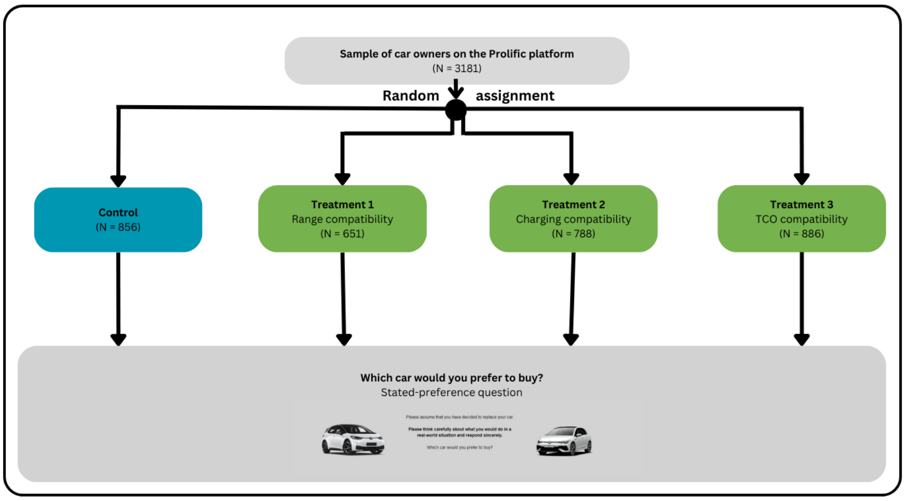
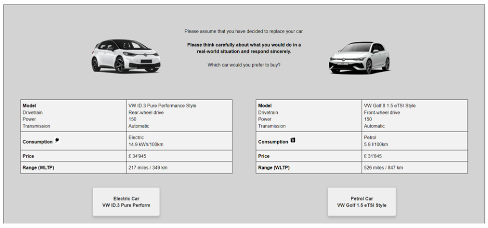


Fig. 2: Experimental design.

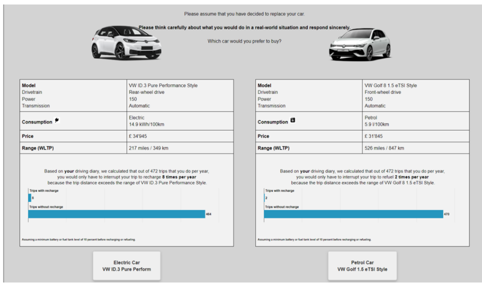
3.1 Interventions

To address the perception biases mentioned above we organized a randomized control trial using personalized information treatments. The treatments are based on respondents' stated car usage behavior. All participants were asked to decide between a small

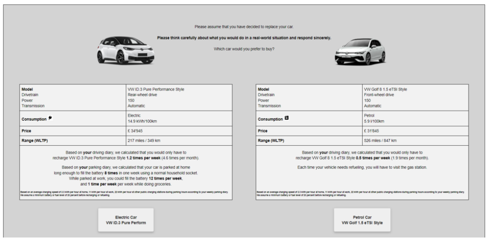
BEV (VW ID.3) and a small ICEV (VW Golf 8) in a stated choice framework. While respondents in the baseline group (Fig. 3a) only received some general car information such as model name, consumption, price and range, participants in the treatment groups received information comparing the number of charging instances needed per week to the number of possible charging instances at different locations where they park their car according to their parking diary (Treatment 1, Fig. 3b), or comparing the number of trips where they would have to recharge to the number of trips where they would not have to recharge (Treatment 2, Fig. 3c), or a comparison of the total cost of ownership for both vehicles (Treatment 3, Fig. 3d). All treatments were optimised for optimal understanding during an extensive pre-test phase.



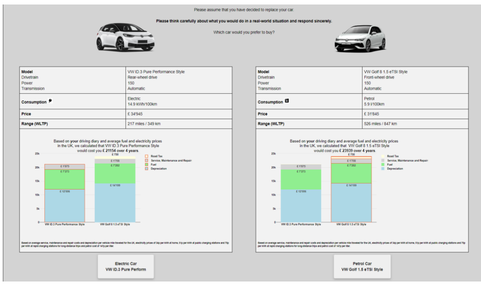
(a) Baseline decision.



(b) Treatment 1: Decision with range anxiety treatment.



(c) Treatment 2: Decision with charging anxiety treatment.



(d) Treatment 3:Decision with total cost treatment.

Fig. 3: Choice cards and treatments used in the randomized experiment.

Baseline information was taken from official price and specification guides for both models for the year 2022 from the manufacturer for the UK market. For treatment 1, the number of charging instances needed per week was calculated based on the total distance driven based on the weekly driving diary divided by the cars battery range reduced less 20 percent to account for the fact that respondents would never fully empty their battery but keep the state of charge between 20 and 100 percent. The number of possible charging instances was based on time parked at different locations according to the parking diary and fixed charging speeds ath those locations of 2.3 kW at home, 11 kW at work, and 22 kW at groceries and other locations.

For Treatment 2, the number of trips where respondents would have to recharge was calculated based on respondents answers on the number of weekly and long-distance trips that exceeded the electric cars battery range less 10 percent as a safety margin. For the car chosen for the survey, this results in all trips exceeding 195 miles or 314 km. Weekly trips were then multiplied with the average number of work weeks in the UK (46.4). The number of trips without having to recharge was then calculated by subtracting the number of trips where respondents would have to recharge from the the total number of weekly (multiplied with 46.4) and long-distance trips.

The calculation of total cost of ownership for treatment 3 was conducted using respondents' total yearly mileage indicated in the driving diary combined with average service, maintenance and repair costs and depreciation cost per vehicle mile traveled for the UK derived from [43] and cost of refueling or recharging over four years. For refueling, we used the UK average petrol price in the UK in 2022 of 147p per liter. For recharging, we differentiated households by home-ownership. Homeowners were assigned a price of 34p per kWh which is equal to the average UK household electricity price in 2022 according to the Zapmap Price Index [44] for the mileage derived from their weekly driving diary. Non-homeowners were assigned the average price for public charging in the UK in 2022 of 51p per kWh [44] for mileage from their weekly driving diary. For the annual mileage resulting from the long-distance driving diary, both types of households were assigned per kWh which was the average price at rapid charging stations in the UK in 2022 [44].

Respondents were randomly assigned to the treatments. Hence, treatment allocations provide exogenous variation in the information that respondents were provided prior to stating their preference.

3.2 Data

Our final sample consists of 3181 individuals, of which 856 were in the control group, 651 in Treatment 1, 788 in Treatment 2, and 886 in Treatment 3. Table 1, shows descriptive statistics for our final experimental sample. In comparison to national statistics [45], participants in our sample were roughly of the same age as the UK population (39 vs. 40 years). However, our sample has a higher share of individuals identifying as female (57 percent vs. 51 percent) and average income is significantly above the UK average of GBP 32'300. Since only car owners were permitted to participate in the survey, a higher average income was to be expected.

In the same Table 1, we present an assessment of the randomization quality by examining the balance of essential covariates across the four groups within our dataset. Of course, since the allocation of participants between treated and untreated groups is random, any observed differences in group variables likely occurred by chance. However, because some participants of Treatment 1 were excluded for technical reasons, we believe that this balance analysis is necessary[2]. The table includes means

[2]Before any analyses we excluded participants in Treatment 1 (range compatibility) for which the personalized calculation was not calculated correctly. In more detail, there was an error in the formula for range

and standard deviations for some important socioeconomic characteristics (gender, age, income, homeowner, household size, Urban or Rural households, car age, and EV owner), alongside computed T-tests that compare means between the control and respective treatment groups, determining the significance of mean differences. Generally, our findings reveal that the means of individual variables across treatment groups closely resemble those of the control group. The only exception is the age variable which is statistically different at conventional significance levels (5%) between the group of treatment 2 and the control group. Nevertheless, the values of the F-test fail to reject the joint significance of all socioeconomic characteristics considered in the description of the groups. Therefore, it can be concluded that the important socioeconomic characteristics of the treatment and control groups are similar.

Table 1: Balance of basic attributes across the control and treatment groups.

	Control group	Treatment 1		Treatment 2		Treatment 3	
	N = 856 Mean (Std. Dev.)	N = 651 Mean (Std. Dev.)	T-test	N = 788 Mean (Std. Dev.)	T-test	N = 886 Mean (Std. Dev.)	T-test
Female	0.579	0.576	(0.113)	0.573	(0.255)	0.555	(0.995)
	(0.494)	(0.494)		(0.495)		(0.497)	
Age	38.300	39.637	(-2.215*)	39.425	(-1.994*)	38.760	(-0.849)
	(11.436)	(11.737)		(11.402)		(11.132)	
Avg. Income	58596.70	56451.78	(1.405)	60117.59	(-1.035)	57381.03	(0.857)
	(28423.45)	(28934.46)		(29581.2)		(29400.19)	
Homeowner	0.654	0.643	(0.426)	0.679	(-1.062)	0.640	(0.622)
	(0.016)	(0.019)		(0.017)		(0.016)	
Household Size	2.694	2.763	(-1.312)	2.760	(-1.319)	2.719	(-0.507)
	(1.010)	(1.030)		(1.024)		(1.049)	
Urban	0.229	0.230	(-0.066)	0.209	(0.958)	0.256	(-1.325)
	(0.420)	(0.421)		(0.407)		(0.437)	
Car Age	8.377	8.550	(-0.627)	8.209	(0.676)	8.303	(0.298)
	(0.181)	(0.209)		(0.170)		(0.168)	
EV Owner	0.081	0.084	(-0.270)	0.091	(-0.777)	0.094	(-1.048)
	(0.009)	(0.011)		(0.010)		(0.010)	
p-value of F-test of joint significance		(0.0919)		(0.5346)		(0.3393)	

Note: The table reports the means and standard deviations (in parentheses) for some of the main sampling variables across the four groups, as well as the T-statistics for testing the difference in means between the control group and the respective treatment groups for these variables. The F-test fails to reject the joint significance of all observable characteristics included. Hence, we conclude characteristics of the treatment and control groups are similar, and the two groups are balanced.
*, ** and *** respectively denote significance at 10%, 5% and 1% levels.

compatibility, instead of multiplication of the battery size with 0.9, there was a division with 0.9. This resulted in trips between 195 and 241 miles were not included in the calculated amount of trips required to stop. We excluded all participants who had the following error, and as reported below ran the balance tests to ensure this did not impact the randomization.

4 Methodology and results

4.1 Perceptual biases: Perceived and actual compatibility of BEV

In the first part of the survey, participants estimated in random order perceived range, charging, and total cost of ownership (TCO) compatibility. In more detail, for perceived range compatibility, they estimated which proportion of their annual car trips in 2022 they could complete with a given BEV battery range, while for perceived charging compatibility, they estimated how many times per week they would need to recharge the car. For both, range and charging compatibility, eight battery-range levels were selected to cover most available battery ranges from 70 to 420 miles (increasing in steps of 50 miles). For perceived TCO compatibility they estimated the total price of BEV (ID.3) and ICEV (Golf) over a four-year period [3]. In the second part of the survey, participants reported their driving and parking behavior during the previous year (2022) by filling in the driving and parking diary (see Methods for more details). The actual range compatibility of BEV battery ranges with drivers' needs was computed as the ratio of the number of car trips that could have been completed with a given battery range divided by the total of reported car trips. The actual charging compatibility of BEV battery ranges with drivers' needs was computed based on the reported weekly driving diary divided by battery size, and the actual TCO compatibility of BEV and CE was calculated by summing road tax, depreciation, fuel, and SMR (service, maintenance, and repairs) costs based on their yearly mileage.

Figure 4 shows the perceived and actual compatibility of BEV battery ranges with car owners' mobility needs. Participants underestimate the range compatibility, overestimate the charging needs, and underestimate the total cost and the difference between EV and CE.

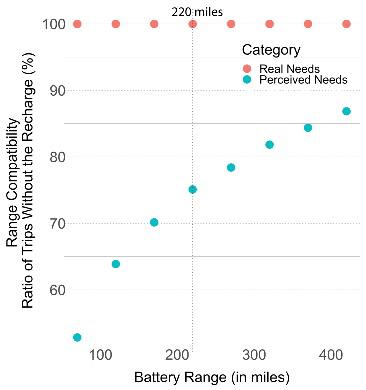
4.2 Treatment effects

In this section, we present the empirical results of the experiment. This analysis aims to estimate the impact of the various treatments on households' decisions regarding the stated choice of an electric car or a similar combustion engine alternative.

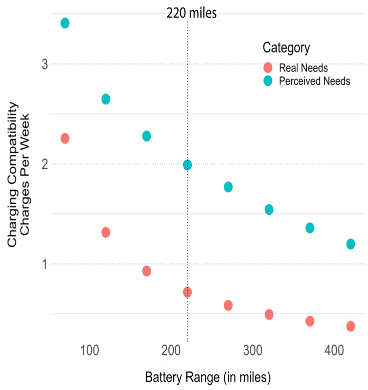
Table 2 presents statistics on the proportion of respondents in each group (control, and treatments 1, 2 and 3) who stated that they would choose the BEV over a similar combustion engine alternative. While the percentage in the control group was about 40.07%, it was 48% in the group for Charging Treatment, 48% for Range Treatment, and the share was 54% for respondents in the TCO group. The proportion of respondents choosing BEV in each treatment group are significantly different compared to the control group (Charging and Range treatment at the 5% level and TCO treatment at the 1% level). These findings suggest that, compared to the control group, the treatments are likely to have had a positive effect on the likelihood of respondents stating that they would choose an BEV.

Of course, this simple analysis is valid under the unconditional independence assumption, i.e. there are no unobservable differences between respondents in the

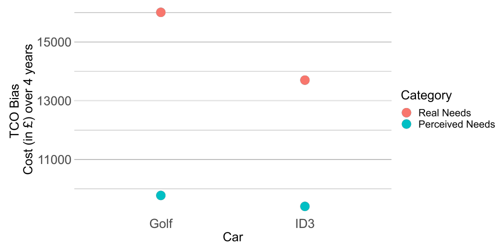
[3] Average car in the UK is changed every 4 years [46].



(a) Range Bias



(b) Charging Bias



(c) TCO Bias

Fig. 4: Perceived and actual compatibility of BEVs with mobility needs for Range, Charging, and TCO. Data are presented as mean values and the vertical line represent a battery range of 220 miles.

Table 2: Treatment Effects: Comparision of means

Group	Control	Treatment 1	Treatment 2	Treatment 3
Proportion opting for EV	40.07	48.08	47.72	54.18
	(0.017)	(0.020)	(0.018)	(0.017)
Observations	856	651	788	886

Note: The table reports the means and standard errors (in parentheses) for the outcome variable (whether the respondents selected the electric BEV) across the four treatments.

treatment and control groups. This assumption is likely to be valid due to the randomization of treatment assignment. As shown in Table 1, the treatment groups and the control groups appear to be balanced over important individual characteristics.

Nevertheless, we decided to apply regression analysis to analyze the possible heterogeneity effects of the treatments. Before presenting this heterogeneity analysis,we first run a probit regression model, conditional on a set of individual and vehicle characteristics [4]. The probit model has the following form:

$$E_i = \alpha_i + \beta D_{i,j} + \delta X_i + \epsilon_i \quad (1)$$

where the dependent variable E_i is a dichotomous variable with a value of 1 when respondent i chooses the electric version of the car, and 0 otherwise. Variable $D_{i,j}$ is an indicator for whether respondent i was treated by Treatment j ($j = 1, 2, 3$), α_i denotes the intercept, and ϵ_i denotes the residual. Variable X_i is a set of characteristics of respondents and of their current vehicle. We are interested in estimating the average treatment effects on the treated, namely the parameter β. These results are provided in Table 3. The first three columns show empirical results obtained by estimating model (1) for one treatment at a time. Column four presents results for the model when all three treatments are considered at the same time.

Table 3: Regression Results.

Model Column	Treatment 1 only (1)	Treatment 2 only (2)	Treatment 3 only (3)	All three treatments (4)
Treatment 1	0.203** (0.066)			0.203** (0.066)
Treatment 2		0.194** (0.062)		0.194** (0.062)
Treatment 3			0.356*** (0.060)	0.356*** (0.060)
Observations	1507	1644	1742	3181

This table reports the coefficients of the models using probit methodology for the estimations. The dependent variable is a dummy variable for whether the respondent stated that he or she would choose a battery electric car. The regression sample includes 3181 observations. $*$, $**$, and $***$ respectively denote significance at 10%, 5%, and 1% levels.

From the results, we find that Treatment 1, Treatment 2, and Treatment 3 had a positive coefficient. That means that, compared to the control group, have increased the likelihood of respondents selecting the electric car. The magnitude of the coefficient of Treatment 1 and Treatment 2 are large and significant at the 1% level and for Treatment 3 at the 0.1% level.

Next, following the probit model estimations, we present the marginal effects for the model that considers all treatments at the same time. Table 4 reports the average marginal effects (at the means of the independent variables) of the three informational treatments on the probability of opting for the electric car, compared to the control group. Each of the three treatments appears to have had a positive effect on the stated choice of the respondents. Treatment 1 (Range treatment) increased the probability of choosing the BEV over the ICEV by 8.0 percentage points, compared to the control group. Similar results are found for Treatment 2 (Charging treatment), with an increase of 8.2 percentage points. Conversely, Treatment 3 (TCO treatment) has a

[4]As robustness check we run the models also using a simple linear probability model. The results obtained with the probit are confirmed

larger increase of 14.1 percentage points. All coefficients are statistically significant and can be interpreted as average treatment effects on the treated.

Table 4: Marginal Effects.

	Treatment 1	Treatment 2	Treatment 3
Average marginal effect	0.080**	0.076**	0.141***
	(0.025)	(0.024)	(0.023)

Note: The table reports the average treatment effects on the treated (the marginal effects corresponding to the coefficients on the treatment dummies in Table 3, calculated at the means of the independent variables) and standard errors (in parentheses). The results correspond to the coefficients from the probit estimation in column 4 of Table 3 that includes all three treatments and uses 3181 observations. $*$, $**$, and $***$ respectively denote significance at 10%, 5%, and 1% levels.

4.2.1 Heterogeneous effects

We are interested to identify whether our information treatments are more effective for certain groups of individuals. We are particularly interested to analyze if the treatment effects are different with respect to gender, income, and ownership of an electric car and of a house. In order to compute the conditional average treatment effects on the treated, we estimate a probit model of Table 5, including all three treatment indicators in the same estimation, as well as interaction terms with the relevant variables (i.e. gender, current car type and house ownership). This model takes the following form:

$$\mathrm{E}_i = \alpha_i + \beta \mathrm{D}_{i,j} + \gamma \mathrm{H}_i + \lambda \mathrm{H}_i^* \mathrm{D}_{i,j} + \delta \mathrm{X}_i + \epsilon_i \tag{2}$$

where Hi now denotes a variable over which heterogeneous effects are calculated. The rest of the notation remains unchanged from expression 1. We are interested in estimating the parameter vector β, and thus evaluating whether the coefficients on the interaction terms differ from that on the main effect, given by λ, i.e., whether there are heterogeneous effects over different subgroups of the population.

We estimate a single model for evaluating heterogeneous effects. In more detail, we included the gender of the respondent, the car type of the respondent, and whether they own a house, and included interaction terms of the treatment indicators with these variables.

Table 5 presents the marginal effects effects calculated with respect to the control group. We find the absence of heterogeneous effects with regard to gender, and house ownership, and a small effect of car type on TCO treatment.

5 Discussion and Conclusion

This study examines biases related to Battery Electric Vehicle (BEV) adoption and employs personalized non-monetary information treatments to address them. Focusing on range, charging, and Total Cost of Ownership (TCO) compatibility biases,

Table 5: Heterogeneous Marginal Effects.

Variable	Treatment 1	Treatment 2	Treatment 3
Gender	-0.036	0.022	0.026
	(0.052)	(0.050)	(0.048)
Car Type	0.005	-0.094	0.142*
	(0.084)	(0.084)	(0.079)
House Owner	0.071	-0.011	-0.002
	(0.054)	(0.052)	(0.050)

Note: The table reports heterogeneous marginal effects calculated over variables related to gender, house owner, and car type. These marginal effects are calculated based on a probit estimation similar to that Table1 using 3181 observations, with the main effects as well as interaction effects of the treatment dummies included. These marginal effects (calculated at the means of the independent variables) are to be interpreted as conditional average treatment effects on the treated. $*$, $**$, and $***$ respectively denote significance at 10%, 5%, and 1% levels.

we conducted a survey with 3181 UK car owners. The results reveal existing biases and demonstrate the significant impact of personalized interventions, particularly in enhancing BEV purchase intentions.

Taken together, our results sheds light on the extent of 1) misconceptions of EV compatibility, 2) the effectiveness of non-monetary treatments, and 3) personalized nudging for electrical vehicle adoption. First, we have developed a detailed survey that captures participants' perception of BEV compatibility with their own behaviour an that collects detailed information on their driving and parking behaviour. Our results confirm strong perception biases by respondents both on the expected need for high battery ranges and the number of charging instances per week. Furthermore, respondents underestimate the cost savings potential of electric cars compared to combustion engine vehicles. Second, addressing these three biases with separate information treatments in a randomized controlled trial setting, we found that our treatments significantly increase BEV adoption in a stated choice setting. The treatments for range and charging compatibility increased intentions by 8 percent, while the TCO treatment led to a 14 percent increase compared to the control condition.

This study is one of the first to shed light on the extent of misconceptions of BEV compatibility, the effectiveness of non-monetary treatments, and personalized nudging for electrical vehicle adoption which offer an easy-to-implement and promising avenue to promote BEV adoption and widespread electrification of personal vehicles. Although stated choices in a controlled experimental setup are highly used in the context of the adoption of relatively new energy-efficient technologies, and new products such findings may not necessarily translate to actual choices in real-world settings as these choices entail real financial implications and hypothetical bias [47, 48]. We believe future studies on revealed preferences to validate our findings are therefore needed. We believe such field studies are feasible, as the self-reported, easy-to-implement approach used in the present research allows for straightforward integration of tailored compatibility information into existing online tools by policymakers and industry (car manufacturers, retailers, and car-sharing providers). We believe a promising future research avenue should further explore to what extent such personalized treatments on psychological barriers could complement with other existing incentives, such as financial incentives (purchase subsidies or tax benefits), expanding charging infrastructure, and adjusting traffic regulations. Future studies could also take a look into different car and battery sizes, and investigate whether such treatments indeed promote lower-range BEV adoption. Taken together, we hope addressing major behavioural barriers, such as range, charging, and TCO compatibility together with other incentives will further promote BEV adoption and widespread electrification of personal vehicles and help reduce transportation-related CO_2 emissions.

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