Using EEG to understand how our brain elaborate information in stated choice experiments: Easy versus hard tasks in the choice of vehicles.

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INTRODUCTION

A persistent problem in using Stated Choice (SC) methods is that respondents often adopt decision processes that deviate from the assumption that individuals evaluate all the attributes presented in a compensatory way. As recently summarized by Cherchi and Hensher (2015), when respondents are "presented with a complex task, it is likely that they show disengagement, adopting simplifying strategies to reduce the mental effort required solving the problem. On the other hand, simplified survey tasks can be seemingly perceived as unrealistic by the respondents, leading to problems with respondents' engagement, or respondents choosing based on other attributes not included in the design". A body of literature has tried to incorporate different decision heuristics in the demand models, but this has often led to indistinguishable effects (see González-Valdés and Ortúzar, 2018). A growing literature on SC experiments has then focused on the problem of the decision process. Evidence, mainly based on model estimation results, shows that the attribute processing strategies adopted by respondents depends not only on the number of attributes and their levels but also on the importance and relevance of the attributes presented.

In an attempt to better understand how individuals make decisions, many researchers have recently used eye tracking technology to identify which visual information respondents pay attention to when making decisions (e.g., Balcombe et al., 2014, Krucien et al., 2014; Cherchi and Raja, 2016; Uggeldahl et al., 2016; Meißner et al., 2016; Cherchi, 2018; Yang et al., 2015). This is a promising area of research, but at the moment, these papers mostly look at different effects of visual attention on the decision process. However, the critical assumption of eye movements do not always hold as people can attend and process visual information that they are not currently fixating on. Moreover making complex decisions involves executive functions such as working memory, inhibition and cognitive flexibility (Diamond, 2013) that are not captured by eye-movement data by themselves. A better understanding of these functions may be revealed using electroencephalography (EEG). This technique measures electrical potentials from the scalp with very high temporal resolution. The potentials reflect activation of different brain structures, which are known to be involved in executive functions, such as regions of the frontal or parietal cortex (Voigt et al., 2019). EEG measures in transport studies have been used mainly to study driving behaviour using driving simulators (e.g., Roman et al., 2001; Hernández et al., 2018; Park et al., 2018), and in some cases to study location functions and happiness in real environment to study (Mavros et al., 2016; Tilley et al., 2017). EEG has also been used to predict consumer choices and preferences (Avinash et al., 2018; Hakim & Levy, 2019; Golnar-Nik et al., 2019; Khushaba et al., 2012). In the current study, we aim to provide preliminary evidence that complex consumer choices depends on cognitive processes and executive functions (Diamond, 2013) that may not be fully captured by current SC approaches. To address this gap, here we combine the standard SC experiment with EEG recordings while manipulating the cognitive demands of the task. Our study is applied to the choice context of a car purchase between a petrol and an electric vehicle.

We then modelled people's choice behaviours in easy and hard decisions, and compared this analysis of their choice behaviour to their EEG responses in these two conditions. Based on previous work, we predict that hard decisions would lead to higher cognitive demands and larger EEG responses in electrodes on the frontal part of the scalp (Avinash et al., 2018; Hakim & Levy, 2019; Golnar-Nik et al., 2019; Khushaba et al., 2012). These demands can lead to choices inconsistent with the compensatory assumptions.

DATA COLLECTION METHODOLOGY

Our SC experiment consisted of a binary choice between an electric vehicle (EV) and an internal combustion vehicle (ICV) with the addition of a "neither of them" option. Five attributes were chosen to characterise the alternatives presented. These were purchase price, driving costs, driving performance (range), environmental effects (CO_2 emissions) and the EV market share. The first four attributes represent the most significant attributes in the choice of EVs, according to the vast literature on EV. The last attribute, the EV market share, is not common in EV studies nor in SC experiments. It is taken from Cherchi (2017) and is a measure of descriptive norms, i.e., the influence that the action (or choice) of other people has on the individual's choice. Information about the recharging station in UK was provided before starting the SC experiment, along with a link to the UK official webpage on the available network. Respondents were also carefully selected to guarantee that the information provided were realistic for them.

The levels of all the attributes were pivoted around the actual values of purchasing prices, driving costs, ranges and emissions of the UK car market, as well as the current market penetration of EVs. Following some pilot testing, for the EV market share we decided to include both the total number of new EV registration in 2019 in the UK and the percentage of new EV registered compared to the total number of cars registered in the same year. This differed from our previous work (Cherchi, 2017).

The SC experiment was customised based on the car size that respondents intended to buy within the next 5 or 10 years or the last car purchased in the household. In order to ensure that the prices range displayed in the SC experiment was realistic, respondents were also asked to indicate the range of prices for their next or past purchase. Three ranges were defined, corresponding to a small, medium or large car. Some screening information was collected to guarantee realism. In particular, respondents needed to have a drive licence, and they had to live in an area where it is realistic to install a recharging station at home.

One strong assumption in the SC research, based on economics principles, is that respondents evaluate all the attributes presented, weigh them, and compute an overall benefit for each alternative they are given. Their stated choice is then predicted to be based on these benefits. According to these models, choice behaviours would not depend on the cognitive demands of the task. However, from a cognitive point of view, the stages in the decision process can be very demanding for complex choices such as choosing a type of car because there are many different attributes to weigh when trying to decide which type to purchase. We therefore first manipulated the difficulty of the choice scenarios to manipulate cognitive demands. An orthogonal design was built, accounting only for main effects, for a total of 16 choice scenarios. Using priors available from previous studies, simulated scenarios were built in a way to ensure that roughly in 8 scenarios the probabilities to choose EV and ICV were within 39% and 59% (we defined these cases as "hard" scenarios). and in the other 8 scenarios were higher that 59% or lower than 39% (we defined these cases as "easy" scenarios).

The survey was first implemented online in SurveyEngine. Other than the SC experiment, the survey included several questions about the number and type of cars available in the household, the specific car most used by the respondent, the purpose this car was most used for, and the kilometres driven daily as well as socio-economic characteristics. Finally, a set of attitudinal questions was asked, measuring attitudes toward environment and injunctive norms. The statements were taken from Cherchi (2017). A sample of 118 participants was randomly selected from members of a panel, trying also to match the gender, age and education balance.

EEG Study

After completing the online survey Twenty participants from the larger sample were invited to participate in the EEG follow-up experiment. Participants completed the same SC experiment in the laboratory while we recorded EEG responses. Participants complete two blocks of the SC task, with a break between blocks. The 16 scenarios for each participant's preferred car size were presented in a random order on each block for a total of 32 trials. This ensured that there were a sufficient number of trials in each condition for a high signal-to-noise ratio in the EEG data. Approximately half the participants received information about the EV on the left column and half on the right (matched to how the information was presented to that participant on the online survey). They sat approximately 50 cm from the computer monitor. On each trial, they were shown a white fixation cross on a grey background for 1 sec, followed by a 0.5 sec grey screen, followed by a choice scenario for 35 sec. The scenario was then replaced by a blank grey screen for 1 sec, followed by a grey response screen with the three possible responses indicated in white text ("electric", "neither", "petrol"). Participants responded by pressing the arrow key corresponding to their choice on the numeric keypad with the right hand. There was a 2-sec grey screen following the response before the next trial began. The experiment was synchronised to the EEG recording by sending an event marker on the onset of each choice scenario. The event marker coded the condition (easy or hard).

DATA ANALYSIS AND RESULTS

The EEG data were analysed off-line using EEGLAB (version 2019; Delorme & Makeig, 2004). For each participant, the data were resampled to 250 Hz (to speed up analyses), band-passed filtered with frequency cut-offs of 0.3 and 30 Hz, and segmented into 25-sec easy and hard epochs relative to the onset of the choice scenario (32 epochs total). Next, an independent component analysis (ICA) was run on the epoched data separately for each condition, and components related to eye blinks, eye movements and muscle artefacts were manually rejected.

A fast Fourier transform (FFT) was used to compute the power spectral density (PSD) for each electrode and epoch on the pre-processed and cleaned EEG data. The PSD reflects the power at each frequency between 0.3 and 30 Hz. The median PSD was calculated across epochs separately for each condition to allow for comparisons between easy and hard choice scenarios. Following previous studies (Avinash et al., 2018; Hakim & Levy, 2019; Golnar-Nik et al., 2019; Khushaba et al., 2012), we focused on frontal, central and parietal clusters of electrodes in the left and right hemispheres. For each cluster, we averaged the power across the electrodes in that region. The power data were submitted to analyses of variance (ANOVAs) with the factors: cluster, frequency band and condition. For all statistical analyses, an alpha = .05 was used as the significance level and partial-eta-squared as a measure of effect size (0.06 to 0.14 considered medium effect size, and > .14 considered large effect size).

Figure 2 shows the mean EEG power (averaged across participants) for each frequency band, cluster and condition. Most of the power in all clusters is concentrated in the slow delta band, and power was highest in frontal clusters. We submitted the power data to a separate ANOVA for each frequency with cluster (frontal, central, parietal; averaged across hemisphere) and condition (easy, hard) as repeated measures. There was a large main effect of cluster for all frequency bands (delta: $F(2,38) = 17.83$, $p < .001$, partial-eta-squared = .48; theta: $F(2,38) = 21.57$, $p < .001$, partial-eta-squared = .53; alpha: $F(2,38) = 24.93$, $p < .001$, partial-eta-squared = .57; beta: $F(2,38) = 43.50$, $p < .001$, partial-eta-squared = .70). The condition factor was marginally significant for the slower delta bands, and it was significant for the faster alpha and beta bands. Previous studies suggested that power in frontal theta band could be used to predict consumer decisions and preferences, as frontal brain regions are thought to be involved in complex decision making (Avinash et al., 2018; Hakim & Levy, 2019; Golnar-Nik et al., 2019; Khushaba et al., 2012). In line with these studies, there was some indication that power differences between trial types were more enhanced for frontal compared to the other electrode clusters for the theta bands.

Our preliminary results suggest that more difficult decisions can recruit higher oscillation frequencies (e.g., beta) which may play a role in helping people bind information. Previous work showed that theta power in frontal electrodes play an important role in reflecting consumers' preferences for a product (e.g., Golnir-Nik et al., 2019). Although not significant in the current study, we found a similar trend that frontal theta power can reflect consumers' preferences when they had more than one alternative to choose from, which require them to weigh the attributes across both alternatives. Further investigation is needed as some of the findings approached significance and effect sizes were in the medium to large range (partial-eta-squared > 0.06). Furthermore, electrical potentials measured at any one position on the scalp reflect summed activities across several cortical regions so the cortical sources of EEG signals cannot be resolved exactly. These sources can be estimated from EEG signals but future studies can use a similar SC experiment with functional magnetic resonance imaging to more accurately localise the specific brain regions involved.

Analyses of the discrete choices

We first compared the distribution of the choices from the sample online and the sample who did the SC experiment in the lab with the EEG. First we note that the distribution of the choices in the online sample reflect the distribution assumed in the SC experiment. The choices split almost equally between the EV and ICV, for all car classes, when the tasks were hard, while there is a marked preference for EV for small and medium cars (and for ICV for large car) when the tasks were easy. Interestingly, this is not the case when respondents performed the same experiment in the lab with EEG. In particular, results are opposite for the easy tasks, small cars, where respondents prefer ICV more than EV cars. The case with hard tasks, however, is the one that shows the most striking difference, with respondents clearly preferring ICV for small cars and EV for large cars. We note that this effect is the same if we consider only the first 8 choice scenarios presented, or all 32 scenarios. We can safely rule out the assumption of fatigue, learning or practise effect in the analysis of these results (recall that in the online survey, each respondent evaluate 8 choice scenarios, while in the lab experiment 32). Finally, we note the number of time the alternative "none" was chosen in the lab experiment is significantly lower than in the online experiment.

We then compared individual preferences estimated using the stated choice data collected online (table 1). The first column (labelled "full experiment") reports the results from the entire dataset, while the other two columns report the results specification estimated using only the tasks classified as "easy" and as "hard". The model structure used in this paper is a mixed logit model typically used to model choices among a set of discrete and mutually exclusive alternatives. Mixed logit models are grounded on the concept of rationality that assumes that individuals possess a mental order of preferences that allow them to have perfect information about all the available options and the possible consequences of their actions. Mixed logit models rely on the concept of utility, i.e. a unique index that summarises the level of satisfaction received from the eventual choice of each alternative, implicitly assumes the concept of trade-off among attributes, i.e. that a bad attribute can be compensated by a good attributes.

We can see that all coefficients have the expected sign, in agreement with the microeconomic theory. As expected, the purchase price is the most relevant attribute in the choice of the vehicle, followed by the range. In line with the literature on discrete choice models, panel effect is highly significant and reveals also the presence of significant random heterogeneity in the preference for EV and ICV.

The model estimation highlighted differences in participants' choice behaviours between the easy and hard tasks. In the model estimated with only the easy tasks, purchase price and range became slightly more significant, and in particular the preference for the range double, while CO_2 emission became slightly less significant and the descriptive norms takes a wrong sign (though not significant). Thus, it seemed that respondents were still engaged for easy decisions, but they had a tendency to focus more on few key attributes. The model estimated with only the hard tasks, on the other hand, revealed a clear deviation from the predicted compensatory behaviour. None of the attribute, not even the purchase price and the range, is significant at 95%. More analyses are required to identify if there are simplifying strategies behind these choices. At the moment, it seems that the decision process is almost random.

Overall the model estimation results suggest that participants were not equally using the same attribute values in the easy and hard tasks, and so additional factors may be involved. In line with this interpretation, our preliminary EEG results suggest that people may use executive functions differently for easy and hard decisions. That is, hard tasks, which we constructed to require more cognitive demands, may engage more executive functions as reflected by increased frontal power and increased binding and manipulation of information as reflected by increased power in the beta frequency band.

Table 3 Model estimation results

	Full experiment	**Easy tasks**	**Hard tasks**

	Value	Robust t-test.	Value	Robust t-test.	Value	Robust t-test.
ASC (EV)	0.286	0.29	2.120	1.37	1.390	0.90
ASC (ICV)	-9.36	-2.48	-3.110	-1.08	-2.690	-1.13
SIGMA (EV)	5.78	4.04	5.380	2.89	3.330	2.54
SIGMA (ICV)	2.53	6.92	2.840	5.56	2.710	6.01
RHO2 (ICV)	6.22	4.59	5.640	3.22	4.050	3.95
Characteristics of the vehicles						
Purchase price [10,000 *GBP*]	-4.38	-4.76	-3.650	-3.83	-1.460	-1.71
Fuel costs [*pence/mile*]	-0.134	-0.34	-0.388	-0.43	0.544	0.90
CO2 Emissions [*grams/mile*]	-1.01	-1.58	-1.040	-1.05	0.376	0.35
Driving range (EV) [100 *miles*]	3.64	6.47	6.000	5.90	1.260	1.13
Driving range (ICV) [100 *miles*]	2.22	3.72	4.490	4.17	0.499	0.55
Measures of Descriptive Norms						
EV new registration [10,000]	0.0363	0.65	-0.063	-0.78	-0.391	-1.97
Overall statistics						
Number of draws	1000		1000		1000	
Number of observations	944		504		440	
Log-likelihood at the maximum	-623.757		-338.36		-352.50	
Akaike Information Criterion:	1269.513		698.71		7226.99	
Bayesian Information Criterion:	1322.865		745.16		771.95	

CONCLUSIONS

Our preliminary results confirm that hard decisions lead to higher cognitive demands and larger EEG responses in electrodes on the frontal part of the scalp and these demands can lead to choices inconsistent with the compensatory assumptions. In the SC literature, it is recommended that the tasks should not be too easy, otherwise the choice would not be informative in terms of the trade-off between attributes; but not too complex, otherwise respondents may find the task too difficult and so their choices may not be based on trading-off the attributes. Both our behavioural and neural findings support this recommendation.

It is important to note that the definition of hard and easy tasks carry a certain degrees of arbitrariness. It depends on the actual levels presented and how similar respondents perceived those levels. Finally, it is important to stress that an easy choice does not necessarily imply that one alternative is dominant over the other. We did not have any dominant alternatives in our experimental design.

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