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Event-Related Potentials of Consumer Preferences

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Abstract

The application of neuroscience methods to analyze and understand preference formation and decision making in marketing tasks has recently gained research attention. The key contribution of this paper is to complement the advancement of traditional consumer research through the investigation of the event-related potentials (ERPs) associated with preferences elicited during a discrete choice experiment (DCE). Five subjects participated in the experiment as they chose their preferred computer background image from a set of images with different colors and patterns. Emotiv EPOC, a commercial wireless Electroencephalogram (EEG) headset with 14 channels, was utilized to collect EEG signals from the subjects while making one hundred and fifty choice observations. The collected EEG signals were filtered and cleaned from artifacts before being epoched into segments of 1000 msec each for ERP analysis. When observing the average of EEG epochs, collected while the subjects chose their preferred background images, there was a clear P300-ERP component with its largest power shown at the left frontal channel (F3 from the international 10-20 system). A significant difference was revealed between the average ERP potential on F3 during the epochs that coincided with the images containing the preferred objects against that coinciding with the images that did not contain the objects of interest (with $p < 0.01$). A clear N400-ERP component on the parietal lobe sensor at P7 was also revealed to be significantly related to the difference in absolute preference (with $p < 0.02$). Our experimental results also showed that there was a negative relationship between the speed of the decision and the difference in preference for the objects in the decision.

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Keywords: Consumer neuroscience, Decision making, Electroencephalogram

1. INTRODUCTION

Consumer neuroscience is an emerging discipline utilizing methods and theories employed originally in brain research for investigating marketing problems and consumer decision-making research[1]. One of the notable findings from the decision making literature is that preferences are constructed in response to a decision task rather than stored in memory and called upon when needed[2]. Numerous theories exist regarding how consumers form these preferences, however, literature largely agrees that preference construction involves several, potentially interacting, processes[2,3].

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A recent proposal is that preference construction can be loosely classified into two parts[4], Systems 1 being generally concerned with the more intuitive and automatic decision making, while Systems 2 being related to the more conscious and considered decision making. Reviews of present studies demonstrate that the mechanisms driving System 2 decision can take many forms, with the consumer being able to actively assess alternatives in numerous ways[5,6,7]. Studies concerning the mechanisms underlying System 1 decisions seem somewhat more elusive. As systems 1 decisions are latent and automated in the mind, observation of them can only be achieved through direct neurological measurement rather than through more common self-reported psychological measurement and modeling[4].

Previous research into functional measures of consumer preferences utilized the human brain activity, denoted as Electroencephalogram (EEG), as a valuable tool to provide marketers with information not obtainable via conventional marketing research methods (e.g., interviews, questionnaires, and focus groups)[8]. The change in the human brain signal and its main spectral bands of Delta (0-4 Hz), Theta (3-7 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (30-40 Hz) has been observed to examine consumers' cognitive or affective processes in response to prefabricated marketing stimuli[9,10,11,12,13]. A number of insights also suggested that the Event-Related Potential (ERP) component of EEG is likely to capture system 1 decision making[14,15,16]. An ERP is in general a measurable change in electrical activity across the scalp arising from a neurological process that corresponds to a sensory, cognitive or behavioral event[17]. There are numerous types of ERPs, each being characterized along two dimensions: the polarity of the change in electrical activity (positive or negative deflection from some stasis level) and the latency of the deflection from when the event occurred. Each type of ERP has been associated with a specific group of neurological processes and are used to measure the activation of those processes[16,17].

Only a limited number of studies have collected both neural (cognitive and emotion) data and preference data, as this is a newly emerging field of research. Unlike most prior work focusing on the effect of different advertisements on human brain activity, this paper focuses on analyzing the ERP changes in a simple choice (decision) context, designed to measure specific features (i.e., colors and patterns) of the choice options (background images) that individuals like/dislike when choosing from different choice sets each consisting of two images. Additionally, the work in this paper is based on using portable brain computer interface known as the Emotiv EPOC, a high resolution, multi-channel, system which has been designed for practical research applications.

2. Methods

2.1. Experimental Design

The measurement in this research employed a Discrete Choice Experiment (DCE) to elicit choices while participants were attached to an EEG headset as shown in Fig.1. The DCE asked participants to choose a new pattern for their computer background from pairs presented to them in sequence. This task of choosing a pattern for a background was used as it would not require any economic reasoning or rational assessment, thus only system 1 would have been activated. In this case, the lack of reasoning arises from the absence of any price, purchase process, installation, or other information. Only the background itself is available for consideration, with each background being an amorphous pattern that will elicit some level of visual appeal and aesthetic. This task does not preclude the activation of system 2, as the two systems cannot be completely isolated from each other, but this task would most heavily draw on system 1 processes.

The various computer background alternatives were designed by manipulating pattern and color compositions. Two pattern types of solid color and organic shapes were used. The three colors of yellow, red and blue were used. The patterns and colors were organized into background alternatives using a full factorial that generated every possible combination of pattern and color, thus forming six background alternatives. The background alternatives were then organized into pairs using a permutation design. This permutation design showed every possible pair wise combination in every possible order. Thus the experiment comprised 30 choices among pairs of backgrounds. One hundred and fifty choice observations were drawn from five participants. The participants were students at a major Higher Education Institution (ethical approval was acquired from the same institution). All participants were screened to be right handed, and none needed to wear glasses during the experiment. The computer on which participants completed the DCE task recorded the screen at an average frame rate of 60 Hz. This allowed the decision times to be synchronized with the EEG signals to an accuracy of 17 msec.

Fig. 1. Photograph showing the experimental setup using the Emotiv EPOC headset.

2.2. EEG Data Collection

The neurological data for the experiment was collected with the Emotiv EPOC, a wireless multichannel EEG system. It is comprised of 14 channels located at the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 according to the international 10-20 system. Two additional reference electrodes are located behind the ears on the EPOC system. The 14 EEG channels were recorded at a 128 Hz sampling frequency. The headset utilizes a proprietary USB dongle to communicate using the 2.4GHz band. Prior to use, all felt pads on top of the sensors have to be moistened with a saline solution. The Emotiv Software Development Kit (SDK) provides a packet count functionality to ensure no data is lost, a writable marker trace to ease single trial segmentation tasks, and real-time sensor contact display to ensure quality of measurements[18,19].

2.3. EEG Signal Processing

One of the most important steps in EEG signal processing systems is to detect and remove artifacts caused by muscle activity, eye blinks, and electrical noise. The analysis of the EEG signals started with a preprocessing step to remove the baseline induced by the DC offset included in the EPOC EEG readings, as shown in Fig.2. Following this step was a filtering step in which an IIR filter, Chebyshev Type-II of minimum order (as designed by Matlab automated filter parameter generation application) was utilized to band-pass filter the EEG signal to 0.5Hz - to- 40Hz.

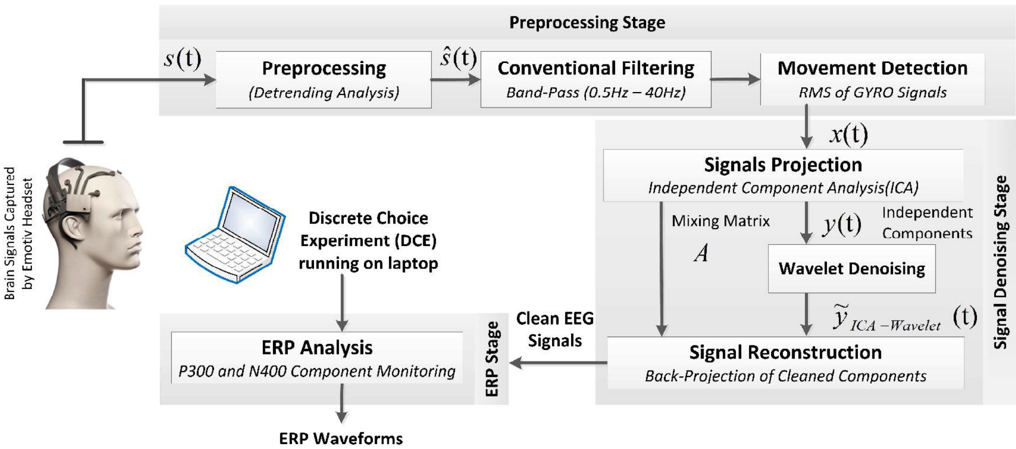

Fig. 2. Block diagram of the EEG processing system for ERP detection.

The Gyroscope signals included in the EPOC were then utilized to detect and remove the movement sections by observing their root mean square values, followed by a combination of Independent Component Analysis (ICA) and Discrete Wavelet-Transform (DWT) based thresholding as described in Khushaba *et al.* [19]. This approach performs a DWT-based denoising step on the yielded independent components and then projects the cleaned components back to the original domain for ERP analysis. For more details about the ICA-wavelet procedure, the reader is encouraged to refer to [19].

3. Experimental Results

Prior to evaluating the relationships between the EEG and preference data, it is important to confirm that the choice task elicited suitable preference data from participants. Table. 1 presents the choice frequencies from the DCE, the indicator for preference, for each of the background alternatives, and for all subjects (S1 to S5). Choice frequencies clearly vary across the alternatives indicating preference is not uniform. There is also clear heterogeneity, suggesting no dominant alternatives were present. Subjects were thus free to express their personal preferences. Heterogeneity in preference was highly desirable in this case, as it removes any bias in the neurological measurement that may be attributed to the presence of a dominant option in the experiment.

In terms of the ERP analysis, for each subject, there were timestamps that marked the beginning and end of the period during which each of the 30 possible combination of background images was displayed. For each of these periods, the EEG data that belongs to the first 1000 msec while the subjects were eliciting their preferences on the background images was segmented for later processing. The EEG epochs that belong to the background images containing the most preferred objects (color and pattern) for all subjects were then grouped together (averaged), while also grouping together the EEG epochs that belong to the background images containing the non-preferred objects. When plotting the ERPs related to the most preferred objects across all channels, and averaged across all subjects, a significant positive potential around 300 msec, i.e., P300 component, was revealed with a maximum value on F3 as shown in Fig.3, using the EEGLAB toolbox available at `sccn.ucsd.edu/eeglab/`. This component was elicited when the subjects reacted to their preferred objects, and it was distributed over the left frontal and right parietal and temporal regions, a finding which is in agreement with previous research [20,21]. However, unlike previous research, our experiments required the subjects to indicate their actual preferences on multiple objects and choose among alternatives, while wearing a commercial EEG headset. The process of preference formation is depicted to activate starting from the temporal, parietal, and occipital lobes during the first 50 msec while progressing to a strong P300 component on the frontal left F3 channel for preferred objects.

In order to validate these findings, we have utilized the well-known student t-test to check the significant differences between the ERPs associated with the preferred objects against that of the ERPs associated with the non-preferred objects on each of the channels, on average across all subjects. The t-test results indicated significant differences between the ERPs of preferred vs. non-preferred objects on all of F7, F3, FC5, P7, O1, P8, T8, FC6, F8, and AF4 (with $p < 0.01$ for all tests, except P7 with $p < 0.02$), while also revealing no significant difference between the two sets of ERPs on AF3, T7, O2, and F4 with $p > 0.05$ for all tests. As the P300 component had its largest power on F3 then we plotted the ERPs of preferred vs. non-preferred objects on F3 as shown in Fig.4. This figure also contains the N400 ERP of preferred vs.non-preferred objects that had its smallest power on P7 ($p < 0.02$). These plots clearly distinguishes the ERPs associated with the preferred objects vs those associated with the non-preferred

Table 1. Preference data summary

			Choice Frequencies				
Background	Color	Pattern	S1	S2	S3	S4	S5
1	blue	solid	2	6	2	1	4
2	yellow	solid	0	4	4	5	2
3	red	solid	4	4	0	8	0
4	blue	shapes	8	10	9	2	8
5	yellow	shapes	6	0	9	7	10
6	red	shapes	10	6	6	7	6

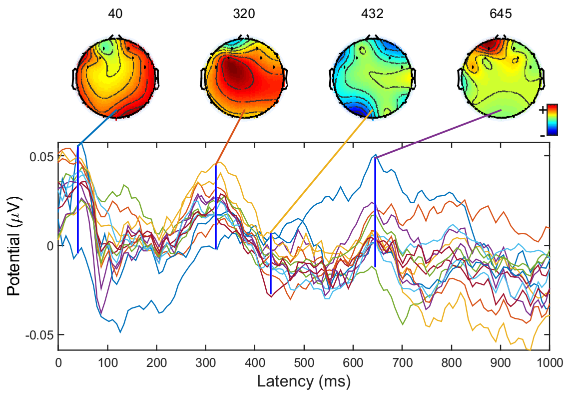

Fig. 3. Average ERPs of most preferred objects across all subjects

objects. The remaining channels that showed significant differences between the ERPs of preferred vs. non-preferred objects had a significant negative component around 100 msec. However, the literature has identified such early waves, or components peaking roughly within the first 100 msec after stimulus as 'sensory' or 'exogenous' as they depend largely on the physical parameters of the stimulus[22]. In contrast, ERPs generated in later parts, i.e., P300 and N400, reflect the manner in which the subject evaluates the stimulus and are termed 'cognitive' or 'endogenous'.

Finally, we have also observed a negative relationship between the speed of the decision, and the difference in preference for the objects in the decision. This finding offers a practical evaluation of the validity of the experiment. If the decision was harder because of decreases in preference differences between the backgrounds, then the choice should have taken longer to make. On average, participants took 4.64 seconds to make a choice for each pair of backgrounds. The correlation between the time taken to make the choice and the absolute difference in choice frequency is negative and highly significant (r = -0.263, $p < 0.01$). This offers a strong support for the findings of our study.

4. DISCUSSION AND CONCLUSIONS

The focus of this research was to examine the neurological basis for system 1 preference formation and decision making. We used ERP potentials related to consumers' preferences elicitation to show, for the first time using Emotiv

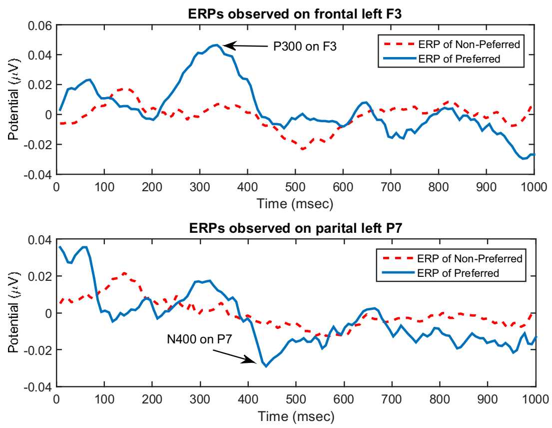

Fig. 4. Average ERPs across all subjects for most preferred vs non-preferred objects.

EPOC, that differential neural activity between preferred and non-preferred items exist mainly around 300 msec on F3 and 400 msec on P7. Based on the present research examining the P300-ERP, we argued that, when measured mainly on frontal channel F3, it captures the ability of the brain to act as a difference engine. The P300 measures the systems 1 preference formation processes of examining the possible bases of difference between objects and then identifying the most different object. In this case, the difference is based on the unique preferences of the person making the decision. Emotiv EPOC-based P300 may potentially be used in marketing research as an endogenous neural indicator of measuring consumer's preferences. The results of our experiment also demonstrate the amplitude of the N400 on P7 is significantly related to the difference in absolute preference, as measured through choice frequency, between the various pairs of computer backgrounds offered. What this indicates, is that as the difference in preference between the alternative increases and the choice becomes more obvious, then the systems 1 neurological processes encompassed in the N400 are activated to a much lesser extent as greater levels of processing are simply not needed. The implications of this research for research examining preference formation are substantial. The decision task used in this research was designed to activate systems 1 more-so than system 2 preference formation. This has allowed us to identify the neurological features underlying systems 1. Future researchers can now more directly observe the impact of experimental manipulations on the activation of such processes.

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