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Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking

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A R T I C L E I N F O

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A B S T R A C T

Application of neuroscience methods to analyze and understand human behavior related to markets and marketing exchange has recently gained research attention. The basic aim is to guide design and presentation of products to optimize them to be as compatible as possible with consumer preferences. This paper investigates physiological decision processes while participants undertook a choice task designed to elicit preferences for a product. The task required participants to choose their preferred crackers described by shape (square, triangle, round), flavor (wheat, dark rye, plain) and topping (salt, poppy, no topping). The two main research objectives were (1) to observe and evaluate the cortical activity of the different brain regions and the interdependencies among the Electroencephalogram (EEG) signals from these regions; and (2) unlike most research in this area that has focused mainly on liking/disliking certain products, we provide a way to quantify the importance of different cracker features that contribute to the product design based on mutual information. We used the commercial Emotiv EPOC wireless EEG headset with 14 channels to collect EEG signals from participants. We also used a Tobii-Studio eye tracker system to relate the EEG data to the specific choice options (crackers). Subjects were shown 57 choice sets; each choice set described three choice options (crackers). The patterns of cortical activity
Q3 were obtained in the five principal frequency bands, Delta (0–4 Hz), Theta (3–7 Hz), Alpha (8–12 Hz), Beta (13–30 Hz), and Gamma (30–40 Hz). There was a clear phase synchronization between the left and right frontal and occipital regions indicating interhemispheric communications during the chosen task for the 18 participants. Results also indicated that there was a clear and significant change ($p < 0.01$) in the EEG power spectral activities taking a place mainly in the frontal (delta, alpha and beta across F3, F4, FC5 and FC6), temporal (alpha, beta, gamma across T7), and occipital (theta, alpha, and beta across O1) regions when participants indicated their preferences for their preferred crackers. Additionally, our mutual information analysis indicated that the various cracker flavors and toppings of the crackers were more important factors affecting the buying decision than the shapes of the crackers.

1. Introduction

Consumer neuroscience is an emerging interdisciplinary field that combines psychology, neuroscience, and economics to study how the brain is physiologically affected by advertising and marketing strategies (Lee, Broderick, & Chamberlain, 2007; Madan, 2010). It links consumer choices and decision-making to marketing research (Camerer, Loewenstein, & Prelec, 2004; Pirouz, 2007; Plassmann, Ramsoy, & Milosavljevic, 2012). Q4 The general assumption is that human brain activity can provide marketers with information not obtainable via conventional marketing research methods (e.g., interviews, questionnaires, focus groups) (Ariely & Berns, 2010). This is mainly driven by the fact that people cannot (or do not want to) fully explain their preferences when explicitly asked; as human behavior can be (and is) driven by processes operating below the level of conscious awareness (Calvert & Brammer, 2012). In such cases, the effectiveness of the different marketing strategies may be evaluated by monitoring brain activity resulting from consumers observing different advertisements and products (Astolfi et al., 2009; Ohme, Reykowska, Wiener, & Choromanska, 2009). The change in the human brain signal, denoted as Electroencephalogram (EEG), and its main spectral bands of Delta (0–4 Hz),

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Theta (3–7 Hz), Alpha (8–12 Hz), Beta (13–30 Hz), and Gamma (30–40 Hz) is observed to examine consumers' cognitive or affective processes in response to prefabricated marketing stimuli (Aurup, 2011; Bourdaud, Chavarriaga, Galan, & Millan, 2008; Custdio, 2010; Kawasaki & Yamaguchi, 2012; Khushabaa et al., 2012; Mostafa, 2012; Ohme, Reykowska, Wiener, & Choromanska, 2010). The main goals in such neuromarketing research are first to detect the small changes in commercial stimuli that may prove to have substantial impacts on marketing efficacy (Ohme et al., 2009). Secondly, it also aims to explain how changes in the depiction or presentation of marketing information affect the ways in which the brain reacts (changes in the brain signals). It is assumed that the later provides information about the process of preference-formation/choice (Kenning & Plassmann, 2008).

A number of studies investigated the changes in brain activity while participants observed TV commercials by tracking the cortical activity and changes in functional connectivity in normal subjects (e.g. Ohme et al. (2010), Astolfi et al. (2008), Custdio, 2010 and Vecchiato, Kong, Maglione, & Wei, 2012). These studies found that the amount of cortical spectral activity from the frontal areas and parietal areas was higher for TV commercials that were-remembered, compared with the activity elicited by TV commercials that were forgotten (Ohme et al., 2010; Astolfi et al., 2008). Alpha band activity was also observed in the occipital regions and theta activity in the midline and frontal cortical regions for the well remembered advertisements (Custdio, 2010). Costa, Rognoni, and Galati (2006) investigated the patterns of interdependency between different brain regions as volunteers looked at emotional and non-emotional film stimuli. They concluded that sadness yielded a pattern involving a large exchange of information among frontal channels while happiness involved a wider synchronization among frontal and occipital sites. Nie, Wang, Shi, and Lu (2011) proposed an approach to identify the relation between EEG signals and human emotions while watching movies; they found more importance for alpha, beta and gamma than delta and theta bands.

In general, 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 EEG spectral changes in a simple choice (decision) context designed to measure specific features (i.e., shape, topping, and flavor) of the choice options (crackers) that individuals like/dislike when choosing from 57 choice sets of three different crackers. We used a discrete choice experiment (DCE) to measure individuals' preferences because DCEs simulate typical choice tasks like choosing from a store shelf or a menu; participants in DCEs can indicate what they prefer, but they often find it more difficult to articulate why this is the case. DCEs require participants to make a series of choices (in our context they were presented with 57 unique choice sets) and indicate their most and their least favorite options. DCEs do not require them to rate, rank or articulate why they chose the particular options. This allows us to avoid some of the more restrictive assumptions about how individuals compare competing alternatives (e.g. criticisms of ranking and rating tasks) and issues related to constructed reasoning (e.g. criticisms of retrospective reporting/thinking aloud tasks).We also investigate changes in EEG spectral activity in response not only to the presence of three choice options (presented one at a time), but our analysis recognizes that each choice option (cracker) is described by three specific features (shape, topping, flavor). The participants evaluate the three cracker features to come with an overall evaluation of each cracker. Their choices (favorite and least favorite cracker) provide a discrete indicator measure of each participant's cracker preferences that can be decomposed into separate preferences for each cracker feature. The EEG measurement also allows us to examine associated changes in the EEG spectral activity associated with each cracker feature. Thus, as a first step toward understanding the role of EEG as a measure of emotional and cognitive response in decision making, this paper provides a preliminary study on the dynamics of EEG measurement during elicitation of preferences.

The structure of this paper is as follows: Section 2 describes the data collection procedure including a description of both the eye tracker and Emotiv EPOC EEG headset based experiments. Section 3 describes the preprocessing and feature extraction steps, and the use of mutual information to identify associations between preferences and EEG. Section 4 presents the experimental results; and finally, conclusions are provided in Section 5.

2. Data collection

The data collection process employed two sets of equipment; the first was a brain signal monitoring system represented by the Emotiv EPOC EEG wireless headset with 14 channels (<www.emotiv.com>); and the second is an eye-tracker system from Tobii technology (<www.tobii.com>), as shown in Fig. 1 and described in the following sections.

2.1. Emotiv EPOC-based EEG data collection

The Emotiv EPOC is a high resolution, neuro-signal acquisition and processing wireless headset that monitors 14 channels of EEG data and has a gyroscope measure for 2 dimensional control. The electrodes are located at the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the International 10–20 system forming 7 sets of symmetric channels as shown in Figs. 2 and 3. Two electrodes located just above the participants ears (CMS/DRL) are used as references (one for the left and the other for the right hemisphere of the head). The EPOC internally samples at a frequency of 2048 Hz, which then gets down-sampled to 128 Hz sampling frequency per channel, and sends the data to a computer via Bluetooth. It utilizes a proprietary USB dongle to communicate using the 2.4 GHz 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 (Anderson et al., 2011; Bobrov et al., 2011; Campbell et al., 2010; Stopczynski,

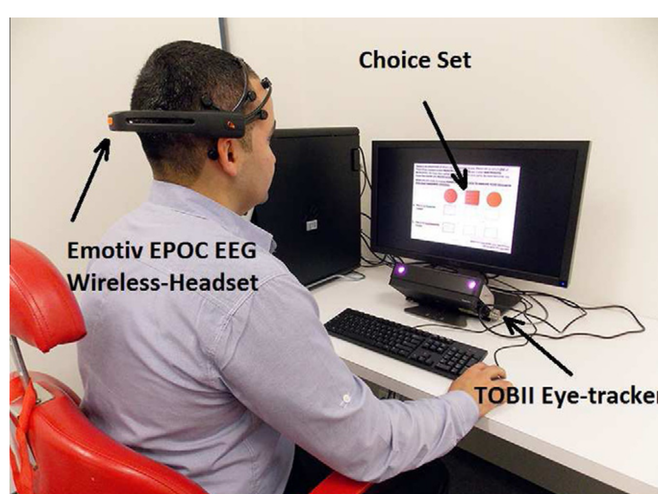

Fig. 1. The experimental setup utilized in this paper.

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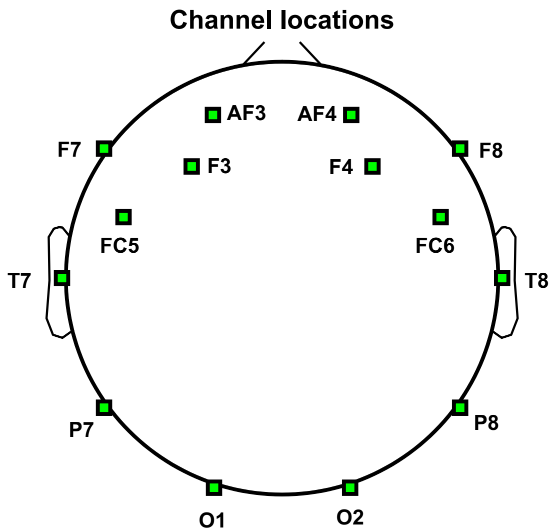

Fig. 2. Emotiv EPOCs electrode positioning.

Fig. 3. Emotiv EPOC headset on a subject showing left, right, and back views.

Larsen, Stahlhut, Petersen, & Hansen, 2011). The effectiveness of the EPOC headset as a real-time brain EEG scanner was demonstrated in a number of recent publications,[1] including a demonstration at the well-known neural information processing conference.[2] Both of the EPOC and eye tracker were forced to start at the same time by means of synchronization software written in Visual Basic to start both modules together. After the data collection step, all collected data were transferred to Matlab for further processing, as described in the next sections.

2.2. Extracting and analyzing eye tracking data

The experiments were conducted using the Tobii X60 eye tracker (<www.tobii.com>); a stand-alone eye tracking unit designed for eye tracking studies of real-world flat surfaces or scenes such as physical objects, projections and video screens. This eye tracker has an accuracy of 0.5° which averages to 15 pixels of error with a drift factor of less than 0.3° and a sampling rate of 60 Hz. Tobii Studio 1.3 was employed as it offers an easy-to-use solution to extract and analyze eye tracking data. The package facilitates efficient multi-person and multi-trial studies. The software combines the collection and analysis of eye gaze data with numerous other data sources, including keystrokes, external devices, video recordings and web browser activities. The X60 monitor mount accessory provides fixed geometry for the eye tracker and screen, allowing the setup to be adjusted for each participant without impacting data quality. Thus, the eye tracking system was calibrated on each subject to provide the best results.

A sequence of 57 choice sets was developed. Each described three crackers that varied in shape, flavor and topping. The context was choosing crackers for a party that the participants would host. Three shapes (round, triangle and square), three flavors (wheat, dark rye and plain) and three toppings (salt, poppy seed and plain) were used to create the objects as shown in Fig. 4. The three cracker features were varied using a full factorial design producing 27 unique crackers. We then used a balanced incomplete block design to assign the 27 different crackers to 57 choice sets. Each of the 57 choice sets contained three crackers; the design also controls for order of appearance, which ensures that each of the 27 crackers appears in every order. The design also insures that each of the 27 crackers appears equally often across the 57 sets, and co-appears with every other cracker equally often. Each of the 57 choice sets was shown on the screen one-at-a-time. Each set consisted of a black screen with the 3 crackers aligned on the left, middle, and right positions as per the example in Fig. 5. The participant's task was to click on the cracker he/she felt that they liked the most, and click on the cracker that they liked the least (to serve at a party they would host). Observing most and least preferred choices in each set provides a complete preference ranking of the three crackers, and allows extrapolation to non-tested choice sets. Throughout the task, the Tobii eye tracker system monitored their eye gaze.

During the choice experiments, when an option was selected by a participant, the corresponding shape, flavor and topping levels of the cracker were automatically recorded. As an example, in Fig. 5

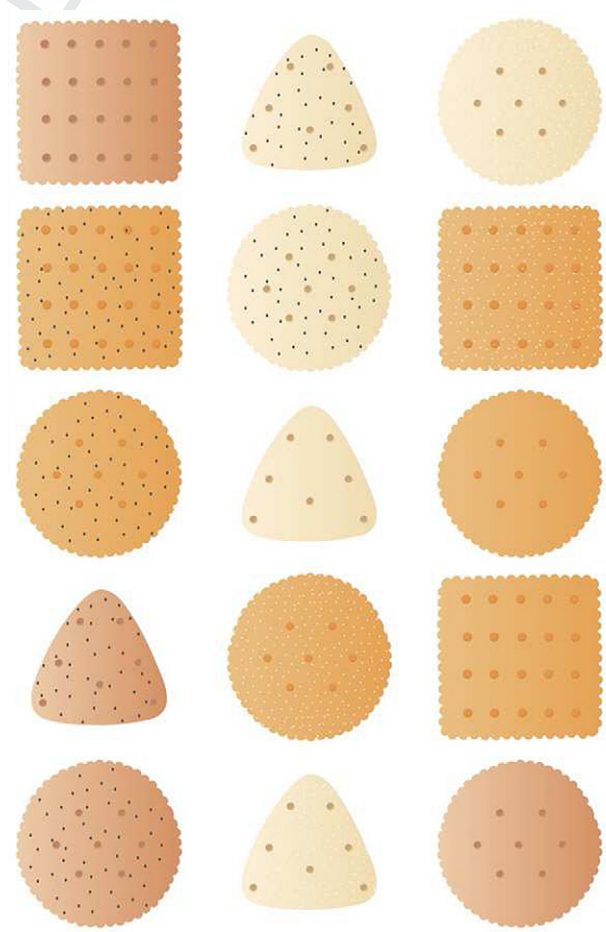

Fig. 4. Illustration of the developed choice set objects which vary shape, flavor and topping.

[1] A list of recent publications on Emotiv EPOC is available at <http://www.emotiv.com/researchers/>.

[2] http://milab.imm.dtu.dk/nips2011demo

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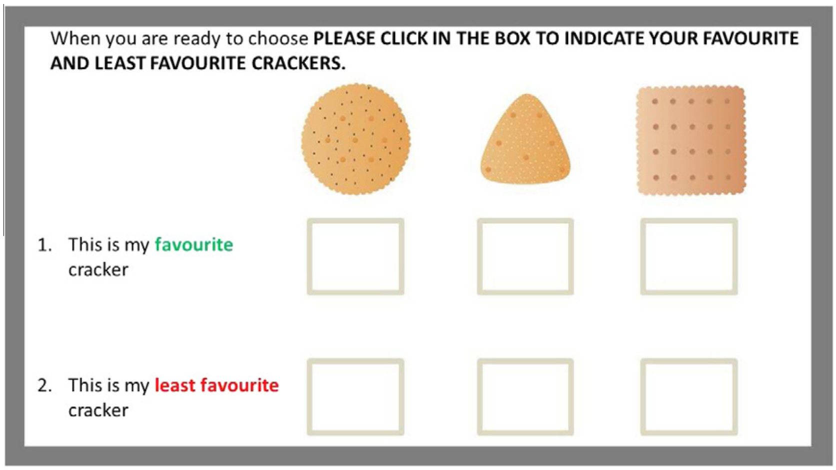

Fig. 5. An example of one choice set of three crackers with different shapes, flavors, and toppings.

participants "see" three shapes, namely round, triangle, and square. If a participant selects the square cracker as his/her most favorite the variable corresponding to square is assigned a value of 3 (round = 1 and triangle = 2). Flavor and topping levels were coded the same way. Thus, across all 57 choice sets and participants each of the three variables (cracker characteristics) were assigned a distinct code that corresponded to the levels chosen as most or least preferred. The resulting characteristics variables are used (described in later sections) to compute the amount of change in EEG spectral activities using the mutual information measure of dependency.

2.3. participants

Eighteen participants (including males and females), were recruited for the study. All participants were aged between 25 and 65 years (average age 38 years). Some participants were right-handed, and some were left-handed; nine wore medical glasses. The experimental procedure was approved by the human research ethics committee in the University. The eye tracker was re-calibrated for each subject to provide accurate measurements for the participant's gaze during the experiments. On average, participants took 7 min to complete the experiment (i.e. reading the instructions and then completing 57 choice sets, selecting their most and least preferred cracker from each choice set of three objects).

3. Data analysis

The data analysis procedure for measuring the correlations between different brain activities at different channel locations with the choice task is shown in Fig. 6 and described in the following sections.

3.1. Cleaning and denoising EEG signals

Detecting and removing artifacts in the EEG data due to muscle activity, eye blinks, electrical noise, etc., is an important problem in EEG signal processing research. We used a combination of Independent Component Analysis (ICA) (Comon, 1994; Hyvarinen, Karhunen, & Oja, 2001) and discrete wavelet transform (DWT) based denoising (Akhtar, Mitsuhashi, & James, 2012; Mallat, 2009) to clean the EEG signals collected by the EPOC headset. The flowchart of the ICA-wavelet procedure we used is shown in Fig. 6. An initial preprocessing starts with a baseline removal, or detrending section due to the included DC offset in the EPOC EEG readings. This is followed by a filtering step that seeks to include only the relevant frequencies in our analysis, remove the effect of 50 Hz noise and eliminate artifacts related to higher frequencies.

Various approaches combining ICA with wavelet denoising have been proposed in the literature proving the efficiency of this combination (Akhtar et al., 2012; Castellanos & Makarov, 2012; Aminghafari, Cheze, & Poggi, 2006; Ren, Yan, Wang, & Hu, 2006; Vazqueza et al., 2012). All these attempts suggested significant enhancements to EEG signals with the application of ICA with wavelet denoising, so we adopted this approach in our work. We make three assumptions in ICA (Akhtar et al., 2012; Castellanos & Makarov, 2012; Chawla, 2011): (i) the collected EPOC data is a spatially stable mixture of the activities of temporarily independent cerebral and artifactual sources, (ii) the superposition of potentials arising from different parts of the brain, scalp, and body is linear at the electrodes with negligible propagation delays from the sources to the electrodes, and (iii) the number of sources is no larger than the number of EEG electrodes (14 in this case). Given a set of observations of random variables $(x_1(t), x_2(t), \ldots, x_n(t))$, where t is the time or sample index, assume they are generated as a linear mixture of independent components $(s_1(t), s_2(t), \ldots, s_n(t))$, with $\mathbf{A}$ being the mixing matrix, and $(v_1(t), v_2(t), \ldots, v_n(t))$ is additive noise, then we write the observations as

$$\begin{pmatrix} x_1(t) \\ x_2(t) \\ \cdot \\ \cdot \\ \cdot \\ x_n(t) \end{pmatrix} = \mathbf{A} \begin{pmatrix} s_1(t) \\ s_2(t) \\ \cdot \\ \cdot \\ \cdot \\ s_n(t) \end{pmatrix} + \begin{pmatrix} v_1(t) \\ v_2(t) \\ \cdot \\ \cdot \\ \cdot \\ v_n(t) \end{pmatrix} \tag{1}$$

or simply as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{v}(t) \tag{2}$$

Independent component analysis consists of estimating both the matrix $\mathbf{A}$ and the $s_i(t)$, when we only observe the $x_i(t)$. After the application of ICA, the resulting $\widehat{\mathbf{s}}_{ICA}(t)$ (ICA's version of $\mathbf{s}(t)$) are usually manually inspected to identify the independent components corresponding to artifacts, where such components are replaced by zeros to construct a new ICA data (Akhtar et al., 2012; Aminghafari et al., 2006; Castellanos & Makarov, 2012; Ren et al., 2006; Vazqueza et al., 2012). In our approach, we denoise each of the acquired components by applying the DWT rather than replac-

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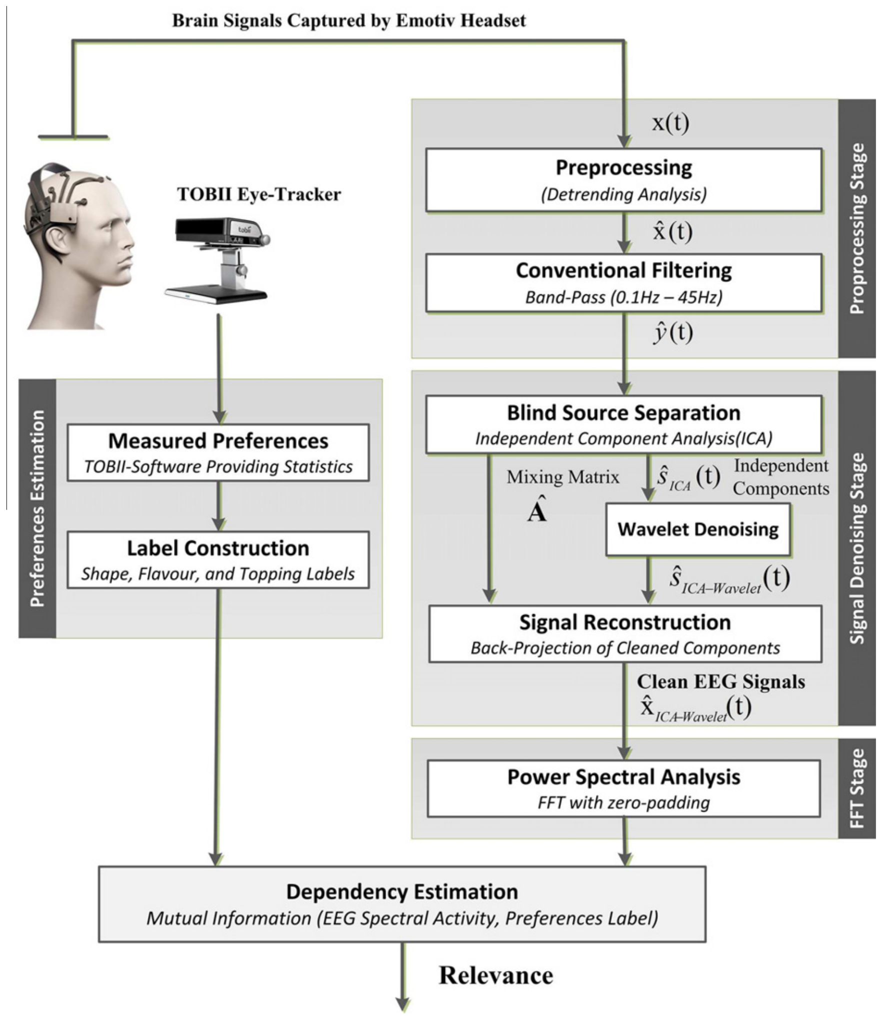

Fig. 6. Block diagram of the data analysis part.

ing the whole component with zero. For a signal $s_i(t)$ composed of m samples, DWT is applied with a scale factor of 2^j and is given as

$$w_k^j = 2^{-j/2}\sum_{t=0}^{m-1} s_i(t)\psi\left(\frac{t}{2^j}-k\right) \tag{3}$$

where the scale factor j is related to the frequency, the parameter k is related to the time at which a frequency component occurs, w_k^j is the wavelet coefficient of $s_i(t)$ at scale index j and time index k, and $\psi(n)$ is an orthogonal basis. We used the fifth-order Daubechies compactly supported wavelet with 5 decomposition levels, as it proved to yield good practical results. We then implemented a hard-thresholding step on the wavelet coefficients in which only those coefficients with values less than a specific threshold T were maintained, with all other coefficients replaced by zeros. The value of T was selected empirically as the median of the signal plus 3 times its standard deviation. We then used the inverse wavelet transform to acquire the denoised version of the ICA components $\widehat{\mathbf{s}}_{ICA-wavelet}(t)$. After the wavelet denoising step, we obtained the clean EEG signals by multiplying the denoised ICA components by the mixing matrix $\mathbf{A}$ as

$$\hat{\mathbf{x}}_{ICA-wavelet}(t) = A\widehat{\mathbf{s}}_{ICA-wavelet}(t) \tag{4}$$

A key advantage of the above approach is that no manual intervention is required to select the noisy components to remove from ICA before projecting back because the purpose of the wavelet denoising is to remove the associated noise from the components automatically before projecting back to the data.

3.2. EEG-power spectrum analysis

We analyzed changes in spectral power and phase to characterize perturbations in the oscillatory dynamics of ongoing EEG. During the choice modeling task, each participant had to observe 57 choice sets of three crackers that differed in shapes, flavors and toppings. It should be noted that each participant spent different amounts of time "looking" at each of the 57 choice sets. The time spent by each participant was calculated from the data provided by the eye-tracker and we calculated the total time across all participants by averaging the individuals' time as shown in Fig. 7. The average time across all participants decreased at a decreasing rate in terms of time spent "looking" at each of the 57 choice sets as participants became more and more familiar with the cracker options by the end of the experiment. For power spectral analysis, only EEG segments corresponding to the time during which the participants were actually indicating their preferences in each choice set were analyzed. That is, EEG segments corresponding to time segments during which participants were moving their hands to click on the mouse and time after making their choices were not included in the analysis.

Moving-average spectral analysis of the preferences related EEG data was then accomplished using epochs of EEG data of various

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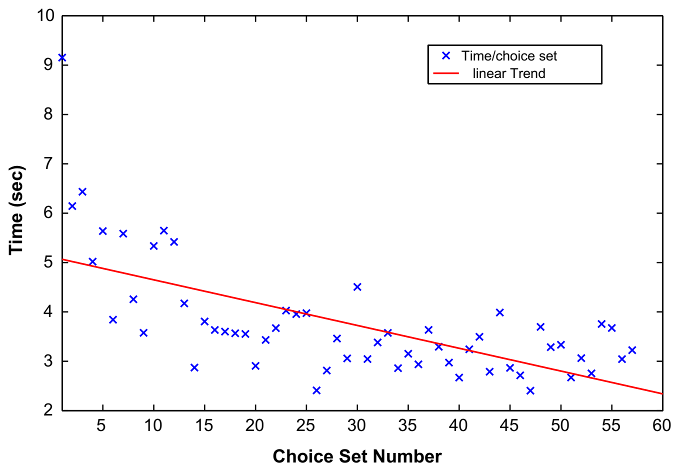

Fig. 7. Average time spent by the participants to elicit their preferences on each of the 57 choice sets.

lengths as shown in Fig. 8. Each EEG epoch corresponding to each of the 57 choice sets was analyzed using a 128-point window with 64-point overlap (i.e., 1sec windows stepped in 1/2 s). When an EEG-frame comprised less than 128-points, the corresponding EEG-frame was extended to 128 points by zero-padding to calculate its power spectrum by using a 256-point fast Fourier transform (FFT), resulting in power-spectrum density estimation with a frequency resolution near 0.5 Hz. Then, an average power spectrum of all the sub-epochs within each epoch was calculated in each of the well-known EEG rhythms of δ, θ, α, β, and γ. Previous studies showed that EEG spectral amplitudes change more linearly in a logarithmic scale than a linear scale (Lin et al., 2006). Thus, we normalized the averaged power spectrum of each epoch to a logarithmic scale to linearize these multiplicative effects. We then extracted the power spectrum features as the mean of power in all of the δ, θ, α, β, and γ bands in addition to the mean of the total power spectrum.

We also investigated patterns of interdependency between different brain regions as participants looked at the different cracker characteristics. Because we already use the magnitude of the FFT of the EEG signals to detect the interdependence between the change in power and preferences, we also employ the phase of the FFT to directly quantity frequency-specific synchronization (i.e., transient phase-locking) between two EEG signals. Direct evidence supporting phase synchronization during emotional response to positive and negative film stimuli already exists (Costa et al., 2006). However, we were unable to find additional studies that evaluated EEG phase synchrony while participants actually indicated like/dislike decisions for a product. We used the phase locking value (PLV) as a measure of synchrony, which is defined at time t as the average value (Costa et al., 2006; Lachaux, Rodriguez, Martinerie, & Varela, 1999)

$$PLV = \frac{1}{N}\left|\sum_{n=1}^{N} \exp(j\phi(t,n))\right| \tag{5}$$

where $\phi(t,n)$ is the phase difference $\phi_1(t,n) - \phi_2(t,n)$ of the EEG signals from two brain regions, representing the inter-trial variability of this phase. Our approach to detecting synchrony in a precise frequency range between two recording sites (i.e., the PLV value) is to calculate this quantity for each of the δ, θ, α, β, and γ bands to detect what brain regions and which EEG bands are mostly getting phase synchronization, while the above approach detects interdependencies between the power in each of these bands at each channel with preferences for the shapes, flavors and toppings of the crackers.

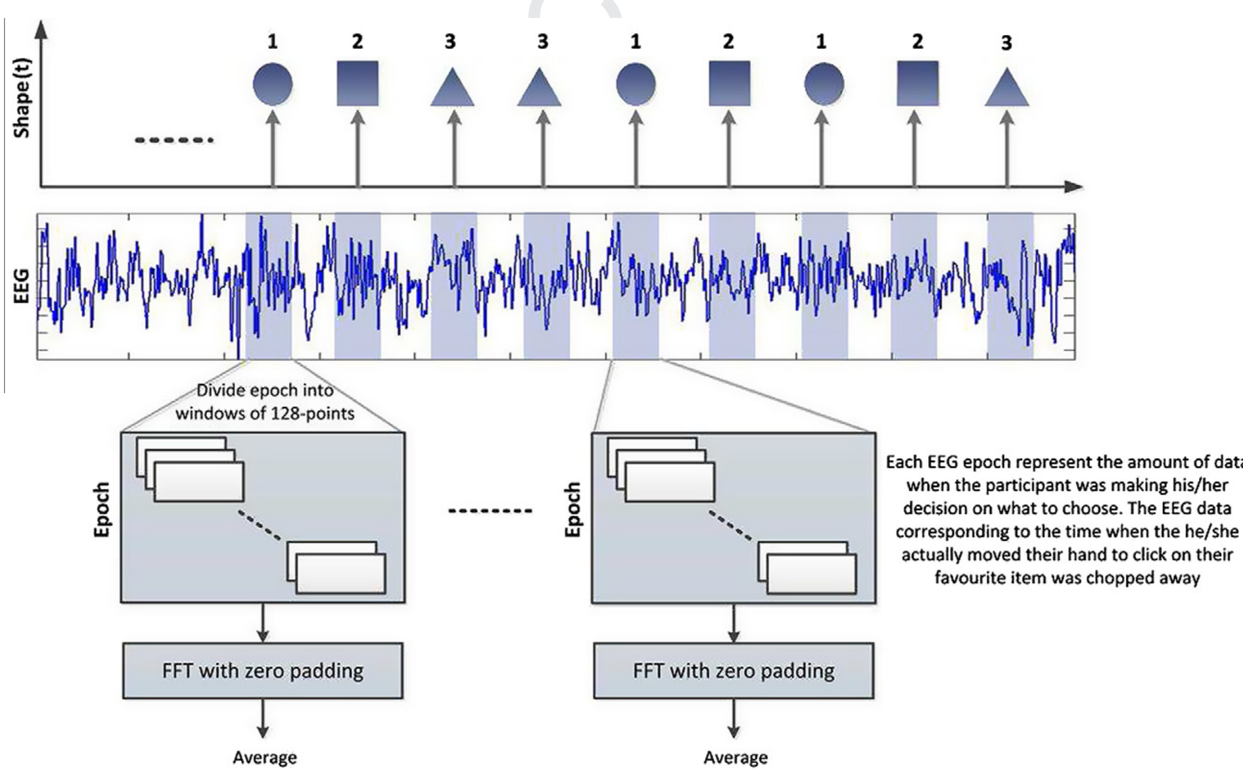

Fig. 8. Signal processing procedures of the spectral feature extraction with an output represented by a paired data set including the spectral power and the corresponding choice factor elements with shape chosen as an example (square, triangle, or round).

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3.3. Mutual information analysis

In probability theory and information theory, the mutual information between two random variables is the amount by which the knowledge provided by one variable decreases the uncertainty about the other variable (Klir, 2006). It can also be defined as a quantity that measures the mutual dependence of the two random variables (Cover & Thomas, 2006). Shannon's information theory (Shannon & Weaver, 1949) provides a suitable way to quantify the above concepts. In our case, a number of features (or variables) describing the change in the EEG power spectrum of δ, θ, α, β, and γ were extracted from each of the available 14 EEG sensors from the EPOC headset. We try to discover the most relevant brain regions associated with the choice task by estimating the mutual dependence between the extracted features from each sensors and the corresponding class label of preferences as indicated by each user (in terms of shape, flavor, and topping). In this case, if we can identify the sensor from which the extracted features highly depend on preferences for cracker characteristics variables (coded cracker characteristics associated with the most and least preferred choices) we also can identify which brain region for which the EEG signal was most relevant to the choice task.

If we define the probabilities for the different classes (classes refer to the different options within each choice factor, for example square (1), triangle (2), and round (3) for shape) as $P(c)$; $c = 1, \ldots, N_c$, then the initial uncertainty in the output class is measured by the *entropy*:

$$H(C) = -\sum_{c=1}^{N_c} P(c) \log P(c) \tag{6}$$

the average uncertainty after knowing the feature vector f, where f might be any of the δ, θ, α, β, and γ features, (with N_f components) is the conditional entropy:

$$H(C|F) = -\sum_{f=1}^{N_f} P(f) \left(\sum_{c=1}^{N_c} P(c|f) \log P(c|f) \right) \tag{7}$$

where $P(c|f)$ is the conditional probability for class c given the input vector f. In general, the conditional entropy will be less than or equal to the initial entropy (being equal if and only if one has independence between features and output cracker characteristics coded values). The definition of mutual information between variables c and f, denoted as $I(C;F)$ is the amount of reduction in the uncertainty about the class c as provided by the feature vector f (Battiti, 1994):

$$I(C;F) = H(C) - H(C|F) \tag{8}$$

which also can be simplified to

$$I(C;F) = I(F;C) = \sum_{c,f} P(c,f) \log \frac{P(c,f)}{P(c)P(f)} \tag{9}$$

where P (c,f) is the joint probability distribution function of C and F, and $P(c)$ and $P(f)$ are the marginal probability distribution functions of C and F respectively. We used the ratio of $I(C;F)/H(F)$, with $H(F)$ being the entropy of the feature f itself, to denote the normalized mutual information between the extracted feature and the class.

4. Experiment results

In the first part of the experiments, we used the PLV measure to detect phase synchronization while participants indicated their preferences for the different cracker characteristics. Each pair of electrodes from the left and the right hemispheres were analyzed together to study symmetry between these regions and their relation to the preference elicitation task. As previously noted, we did this along each of the δ, θ, α, β, and γ bands with the computed PLVs shown in Fig. 9.

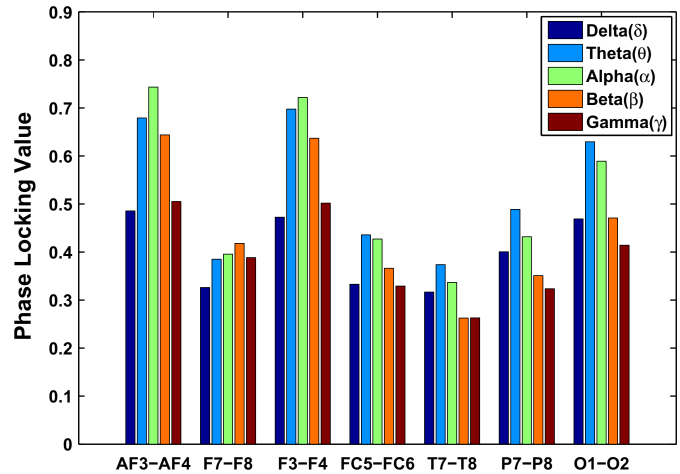
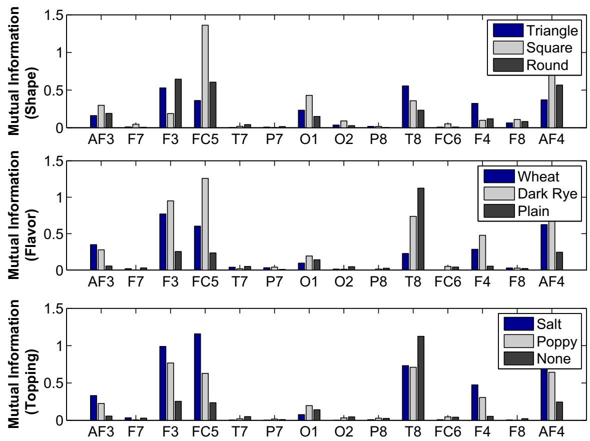


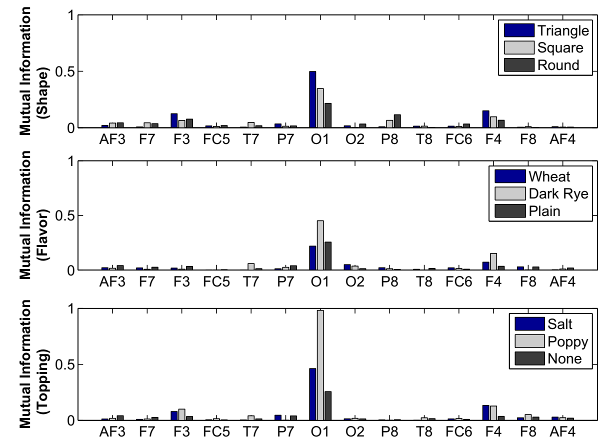
Fig. 9. Phase locking values between all of the δ, θ, α, β, and γ bands at each symmetric pair of electrodes..

The PLV results suggest a few important findings, including that the frontal channels (AF3–AF4 and F3–F4) and occipital channel (O1–O2) were the most synchronized channels, which in turn indicates the importance of cognitive processing taking place at these brain regions. Costa et al. (2006) attributed such large phase synchronization values to the dynamic cooperation between cortical areas which highlights the role of information exchange during emotional responses. In contrast, we applied this idea to an actual decision making task designed to elicit preferences to indicate the actual phase synchronization. This finding supports the idea that there was wide inter-hemispheric communication during this experiment. The results presented in this paper also clearly show the importance of all of the θ, α, and β that reflected the highest PLV at the aforementioned frontal and occipital regions. These EEG bands and the corresponding regions with the highest PLV values was found to be very relevant for tasks involved with emotional processing of preferred vs. non preferred marketing stimuli when these regions were studied separately in prior work (Aurup, 2011; Custdio, 2010). The PLV was also calculated at each frequency band for all the couples of possible electrodes, rather than just the symmetric ones. In this case the set of frontal channels represented by AF3, F3, F4, and AF4 showed the highest PLVs among each other at all of the θ, α, and β bands. On the other hand, the occipital channels (O1 and O2) showed its highest PLVs with the parietal channels (P7 and P8) instead of the frontal channels as indicated by Costa et al. Costa et al. (2006), a difference which could be due to the nature of the task itself (preference judgments for crackers in our case rather than watching emotional video scenes in Costa et al. (2006)). Thus, our results further support the idea that synchronization provides an interesting and useful tool for studying and understanding variation in brain activity occurring during an actual decision making task related to subjective preferences for several characteristics (features) of a product or service. However, we extend this prior work by also looking at how the power of the EEG signals change with preferences.

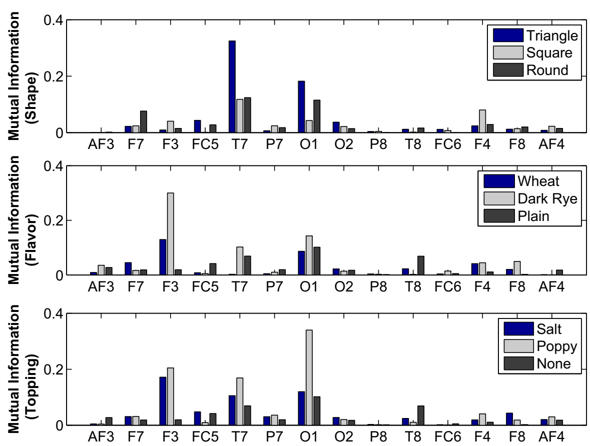
In the second part of the experiments, we assessed individual preferences for each cracker characteristic (shapes, flavors and toppings). Recall that the eye tracker provides information about what was selected as the most and least preferred cracker in each choice set. This information allows us to decompose the chosen option into preference values for each characteristic level (three levels each of shape, flavor and toppings). For example, we decomposed



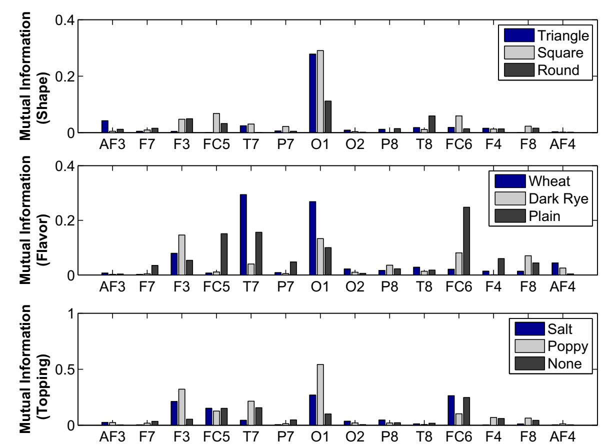
(a) MI(Delta,Preferences)



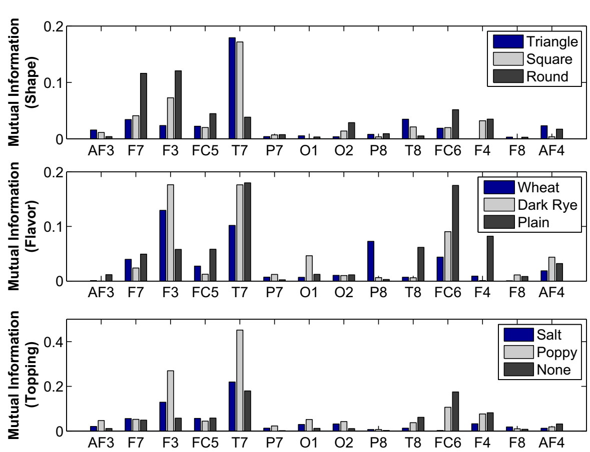
(b) MI(Theta,Preferences)



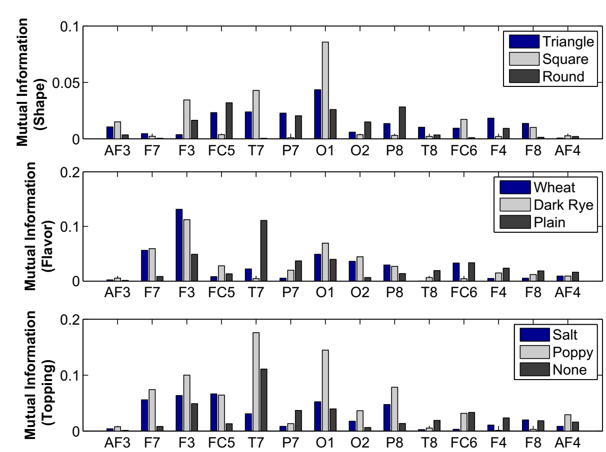
(c) MI(Alpha,Preferences)



(d) MI(Beta,Preferences)



(e) MI(Gamma,Preferences)



(f) MI(Total-Power-Spectrum,Preferences)

Fig. 10. Mutual information between the extracted features from the δ, θ, α, β, and γ bands and total spectrum with the class labels of shapes, flavors, and toppings.

the chosen shape into three binary vectors, one to indicate that a square shape was chosen (indicated by 1's) versus all other cases where square was not selected (indicated by 0's), and similarly for rectangle and rounded shapes. This produces three vector representations of shape preferences typically known as dummy codes. We used the same coding logic to represent flavors and toppings for a total of nine vectors of preferences.

It is worth noting for this experiment that each of the extracted EEG features provided one summary measure for each of the 57 choice sets with the suggested mutual information measure further summarizing the results along these 57 choice sets for each person. Ideally, we would like the EEG information to be provided for each of the three crackers in each choice set, but the data sampling is insufficient to get reliable measures from this experiment.

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Thus, the proper way to interpret our results for the cracker feature levels is that these represent deviations from the choice sets measures associated with the levels across all 57 choice sets. Technically, these reflect differences among the features of the crackers in each choice set. Thus, the analysis identifies how the change in the attributes of the crackers magnifies/attenuates the EEG power, which is in turn captured by the amount of estimated mutual information. In simple words, high mutual information value between the EEG features and the preferences labels means that the corresponding cracker attribute had high impact on magnifying/attenuating the EEG power in a specific band. The mutual information between the extracted δ, θ, α, β, and γ bands' power features and the constructed choice labels vectors was then computed and graphed as shown in Fig. 10.

Analysis of the mutual information between the extracted EEG features (magnitude of the FFT) and preferences revealed that in terms of δ, changes in the mutual information values during stimulation with different cracker characteristics were more apparent in the left frontal region (F3 and FC5) of the brain than the right regions (F4 and FC6). It was also apparent that the right temporal (T8) and anterior frontal (AF4) regions exhibited higher mutual information with the preference characteristics vectors than the corresponding right regions of T7 and AF3. Delta oscillations were identified previously in the literature as a signature of stimulus-elicited activity in the brain's reward circuit (Stefanics et al., 2010; Knyazev, 2007; Wacker, Dillon, & Pizzagalli, 2009). In this experiment participants were stimulating their own reward system (or simply rewarding themselves) by continuously selecting crackers with combinations of characteristics (visual stimulus) that gave them most pleasure. So, the observed cracker characteristics may have acted as reinforcers as their occurrence increases the probability of choosing the most (and least) preferred shape, flavor and topping. This in turn resulted in high δ-relevance to the problem of choosing most and least preferred crackers, while also indicating the significance of the left frontal regions and the right temporal regions to this choice task. We used analysis of variance (ANOVA) to test for significant differences between actual δ band feature values from different EEG channels (significant level is reported at $p < 0.05$). The results indicated significant differences between δ band features from each channel indicated in parentheses in the left (AF3, F3, FC5, T7) and right hemispheres (AF4, F4, FC6, T8). All these tests were associated with a p-values $\leqslant 0.001$.

Theta band power exhibited the highest level of mutual information with the cracker characteristics measures over the left occipital region and to some extent bilaterally over the frontal regions (F4 and F3), as shown in Fig. 10(b). The left occipital theta response has been related in the literature to encoding of visual stimuli (Hald, Bastiaansen, & Hagoort, 2006). We suggest that in this study this is related to processing of semantically coherent or semantically violated sets of cracker characteristics. The strength of preference-related theta-modulation effects was recently studied by Kawasaki and Yamaguchi (2012) who found enhanced θ activity in the right and left occipital electrodes when the participants focused on their preferred colors in the opposite hemifield. In turn, this suggests that changes in θ are correlated with changes in preferences, in which case our results are in-line with those in the literature. Our results for θ also suggest that the different toppings had the largest impact on preferences due to high dependence between the stated preferences and θ power changes on the left occipital region. The change in α band power also agreed with θ on the importance of the left occipital region. However, in addition to the occipital region, α power also showed high mutual dependence between the EEG and stated preferences at the left frontal and left temporal regions as shown in Fig. 10(c). The importance of the frontal and temporal regions also was indicated in several studies, including work in Min et al. (2003) and Potts and Tucker (2001), and the association between θ and α from the left frontal regions and stated preferences was established in several studies (Custdio, 2010; Kawasaki & Yamaguchi, 2012; Nie et al., 2011; Yokomatsu, Ito, Mitsukura, Jianting, & Fukumi, 1720). Alpha mutual information further emphasized the impacts of different flavors and toppings as preferences for these characteristics achieved higher mutual information values on F3 than shape preferences. However, the literature suggests no clear agreement on which frontal channel, F3 or F4, and which bands from these channels, should be more related to the decision making process. That is, some researchers reported that either F3 or F4 could be interchangeably more active across different participants (Aurup, 2011). ANOVA results also indicated significant differences between α band features at F3, T7, and O1, with an achieved p-value $\leqslant 0.001$ for all tests.

On the other hand, β bands' power changes further confirmed the above results as it also was associated with higher mutual information values with the stated preferences. This was shown for the left occipital region, bilateral frontal regions (FC5 and FC6), and the left frontal region (F3). The mutual information values achieved by β further supports our finding that flavor and topping had larger impacts on preferences than shape, as we found higher mutual information values for β with flavor and topping preferences than for shape preferences. Gamma also exhibited high mutual information values with flavor and topping preferences on bilateral frontals and left temporal regions. This may be due to familiarity with the visual stimulus and degree of preference for it modulating the induced EEG activity in the γ band, resulting in higher dependence between γ band power and flavor and topping preferences than shape preferences (Golumbic, Golan, Anaki, & Bentin, 2008). Finally, changes in the total power spectrum also suggested the importance of the frontal, temporal, and occipital regions, while also suggesting more importance for flavor and topping preferences than shapes. ANOVA test results further confirmed the significant differences across the different channels on β as well as on γ power features, with an achieved p-value $\leqslant 0.001$ for all tests.

In the final part of this experiment, it should be noted that a key limitation of this research was a wide variation in the amounts of EEG data available for each person in each choice set. This in turn resulted in having insufficient EEG observations in some choice sets to reliably estimate the effects of the attribute levels on the EEG measures. Future work should try to deal with this issue, and one way to do that would be to present the crackers (or more generally, stimuli with varying features) individually one-at-a-time to insure that there is no confound. A second possibility is to present the items in each choice set one-at-a-time, and then observe the choices in each set collectively.

5. Conclusion

We used a commercially available wireless EEG headset to investigate the brain activities taking place during decision-making. A series of 57 choice sets, each set described by three choice objects, was shown to participants with them asked to select (by mouse clicking) their most and least favorite choice options for a party that they would host. The frequencies of their choices were recorded by eye tracker software from a Tobii X60 eye-tracker system. The eye tracker system was used in this case solely to map the transition between the choice sets and the actual choice of object. When studying the EEG activities related to the choices made by participants several important points emerged. The first is that there was a clear phase synchronization between symmetric frontal and occipital channels with high phase locking values for θ, α. and β. On the other hand, the phase locking value across non-symmetric channels showed higher values among all of the *AF*3,*F*3,*F*4,*AF*4 while occipital channels were highly synchronized with the parietal channels. Secondly, in terms of the change in the EEG power spectrum and the relevance of this change to the stated preferences, the left frontal channel (F3), left temporal (T7), and left occipital (O1) were the most important as they showed high mutual information values with the stated preferences. Our analysis also showed that higher mutual information values were achieved by almost all EEG bands power with the flavor and topping labels in comparison to that of the shape. This in turn suggests that these attributes of the crackers initiated more cognitive processing in a way which caused the power of the different EEG bands to correlate well with the change in the factors making each of the flavor and topping attributes, i.e., wheat, dark rye, plain for flavor and salt, poppy, no topping for topping.

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