

RESEARCH ARTICLE

Analyzing Neural Responses to Video Advertisements: From Visual Attention to Cognitive Load

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Abstract

Understanding consumer engagement is essential for optimizing marketing strategies. This study analyzes neural responses using electroencephalography (EEG) to distinguish interesting and ordinary video advertisements. EEG data from 30 participants (aged 17–40) were recorded across eight channels (F8, F7, T8, T7, P8, P7, O2, O1) and decomposed into five subbands (Delta, Theta, Alpha, Beta, Gamma). Key features, including Power Spectral Density (PSD), Mean Absolute Value (MAV), Hjorth Activity, Zero Crossing Rate (ZCR), and Wavelet Transform, were extracted and analyzed. Results showed that Gamma activity in occipital regions (O1, O2) was higher during interesting advertisements, indicating heightened visual attention, and reduced Beta activity in frontal regions (F7, F8) indicating reduced cognitive load. These findings offer valuable insights for neuromarketing by identifying neural markers of engagement and providing actionable insights for designing effective advertisements.

Keywords: cognitive load, EEG, neuromarketing, video advertisements, visual attention.

I. INTRODUCTION

One of the most engaging forms of promotional content for marketing is utilizing video advertisements. Video advertisements are used to capture consumer attention and evoke emotional responses, influencing purchase decision and brand loyalty [1]. Understanding how consumers respond to these ads is important for marketers to strategies and tailor their content to target audiences. This requires insights not only into their behavioral responses, but also the neural processes that drive consumer engagement [2].

Electroencephalography (EEG) is a powerful tool for understanding consumer responses at neural level. EEG measures electric activity in the brain, offering direct insights into cognitive and emotional states during ad exposure [3]. By analyzing brainwave patterns across various channels and frequency bands, researchers can identify specific neural response correlates to attention, memory, and emotional engagement, which are vital for evaluating advertisement effectiveness [4]. Using EEG in neuromarketing provides an objective understanding for assessing consumer behavior, helping marketers to refine their strategies based on neural data [5].

Neuromarketing integrates neuroscience into marketing research, addressing key challenges in understanding consumer behavior. Despite that, neuromarketing faces several limitations, including the lack of standardized protocols and underutilization of advanced EEG features such as Power Spectral Density (PSD), Hjorth Parameters, and Zero Crossing Rate (ZCR) [6]. Many studies focused on generalized neural patterns, neglecting the detailed analysis

of specific frequency bands and their relevance to advertisement engagement [7]. This gap underscores the need for research that explores detailed EEG features and their correlation with consumer engagement metrics. Furthermore, previous studies have predominantly concentrated on emotional processing and decision-making separately, with limited integration of these elements in a marketing context [8]. This research seeks to bridge this gap by simultaneously analyzing both emotional responses and decision-making processes through detailed EEG feature analysis, allowing for a more holistic understanding of consumer engagement.

Despite the advancements in neuromarketing research, there remains a significant gap in the detailed analysis of EEG features and their correlation with specific consumer engagement metrics. Many existing studies focus primarily on general brainwave patterns without exploring the nuanced contributions of individual frequency bands or their interplay with various channels [9]. This limitation hinders a comprehensive understanding of how different subbands, such as Gamma and Beta, relate to attention and cognitive load during ad exposure. Additionally, the lack of standardized methodologies for EEG data processing and feature extraction further complicates comparisons across studies. Our research aims to fill this gap by employing a robust preprocessing pipeline and detailed feature extraction to provide deeper insights into the relationship between EEG signals and consumer engagement.

In our previous research, our team analyzed neural responses on emotional processing. We identified variations in brain signals when viewing sad and happy videos, with emotion recognition being more noticeable in Hjorth activity features compared to other Hjorth parameters [10].

Furthermore, the frontal regions of the human brain (Fp1, Fp2, F7, and F8) can be utilized to classify positive and negative emotions [11]. Our research also demonstrated that the feature values associated with happy emotions were greater than those of sad emotions [12]. We also succeeded in revealing differences between buy decisions and not-buy decisions by analyzing the Mean Absolute Value and Shannon Entropy features in F7, F8, Fp1, and Fp2 channels [13]. Observation of channels T3, T4, O1, and O2 revealed that the PSD is elevated when participants are exposed to attractive packaging in contrast to unattractive packaging [14].

The primary objective of this research is to analyze EEG signals recorded during participants watched video advertisements which then categorizes as interesting or ordinary level of engagement according to their observation. The research examines 8 EEG channels (F8, F7, T8, T7, P8, P7, O2, and O1) and their subbands (Delta, Theta, Alpha, Beta, Gamma) to identify neural markers that differentiate interesting and ordinary ones. Specifically, this research investigates the role of Gamma activity in occipital regions (O1, O2) and Beta activity in frontal regions (F7, F8) as indicators of visual attention and cognitive load. The study uses feature extraction techniques such as PSD, Hjorth Parameters, and entropy measures, to capture both time-domain and frequency-domain characteristics of EEG signals.

This research contributes to the field of neuromarketing by providing an analysis of neural engagement during ad exposure to consumers. This research highlights the relevance of specific channel-subband combinations such as O1 Gamma and F7 Beta, to understand consumer responses. Furthermore, the research also introduces a robust preprocessing pipeline and feature extraction methodology that can be adopted in future studies. This study provides a scalable approach for evaluating advertisement effectiveness, helping marketers in creating content that appeals to their audience. The findings possess wider significance for consumer neuroscience, facilitating interdisciplinary study at the convergence of neuroscience, psychology, and marketing [15].

II. METHOD

A. Experimental Design

The experiment was carefully structured to analyze neural activity during the viewing of video advertisements using EEG signals. The study involved 30 participants aged 17 to 40, were selected based on their ability to make independent purchase decisions, ensuring cognitive and emotional relevance to the study, all of whom were healthy, non-depressed, and not sleep-deprived. Both male and female participants were included to ensure gender balance.

The stimuli used in the experiment consisted of 20 video advertisements ranging from 15 to 110 seconds in duration with most are in 30 seconds. These ads were selected to represent varying levels of engagement as perceived by the participants. Advertisements were categorized based on the participant evaluations using a 6-point Likert scale on dimensions such as empathy, persuasion, impact, and communication from EPIC model, with prompts like “I can easily remember the advertisement”, “I remember the message/information conveyed in the advertisement”, “

Advertisements can affect my emotion.”, and “I was interested in watching the advertisement to completion.”. Six ads were chosen to be analyzed as outlined in Figure 1 and classified into two distinct groups, which are Interesting and Ordinary, as outlined in Table 1 from the top 3 and bottom 3 of the total average scale of the questionnaire evaluation. The remaining ads, which evaluated somewhere in the middle, were excluded from further analysis to ensure significant differences between the two categories.

TABLE 1. VIDEO ADS STIMULUS CLASSIFICATION

Interesting	Ordinary
Marjan (marjan)	Nutrisari Jeruk (ns_jeruk)
Head & Shoulders (hs)	Tropicana Slim Patricia Gouw (ts_pat)
Astra Honda (honda)	Tropicana Slim Nana Mirdad (ts_nana)



Fig. 1. Video Ads Stimulus

After viewing each video, a questionnaire administered collecting participants subjective evaluations, providing insights into memory, impact, attention, empathy, emotion, and engagement. To ensure neural data stability, a 3-minute resting-state baseline EEG recording was obtained before the experiment, and a recovery EEG session was conducted between ads. The neural states of participants are restored during these recovery sessions, reducing the impact of carryover effects from previous stimuli. In an effort to further alleviate the effects of fatigue, the EEG data collection was added by a half-hour break following the presentation of ten advertisements.

Figure 2 shows the design of the experiment, where each participants were instructed to fill the biodata questionnaire and then recorded a baseline EEG prior to the video advertisement stimuli. The baseline is a reading of EEG on resting state where a blank screen was shown and the participants were suggested to relax. The data collection was done in an quite isolated room to sheer away unwanted distraction such as unnecessary voices and distracting sighting.

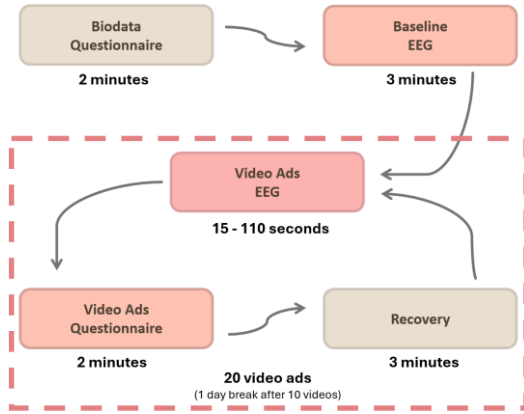
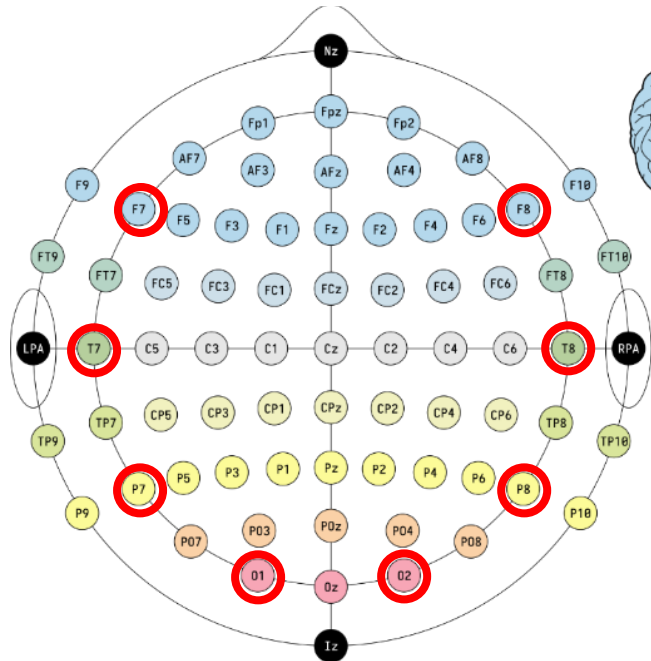


Fig. 2. Flow design for data collection

B. Data Acquisition

EEG signals were recorded using the Ultracortex Mark IV with Cyton 8 headset by OpenBCI, chosen for its portability and reliability in capturing neural activity. Eight channels were chosen on F7, F8, T7, T8, P7, P8, O1, and O2, corresponding to regions associated with attentional, emotional, and cognitive processing. Data were sampled at 250 Hz, and the recordings were saved in Excel format via the iMotions software. This setup ensured comprehensive data collection across the scalp, encompassing regions of interest for neuromarketing [16]. Figure 3 illustrates the channel's position situated around the participant's head, with the selected channels strategically distributed to capture specific neural activity associated with different cognitive and emotional processes. F7 and F8 are positioned in the frontal regions, known for their involvement in higher-order functions such as attention and decision-making. T7 and T8, located in the temporal regions, are linked to memory and auditory processing. P7 and P8 in the parietal regions are associated with sensory integration and spatial awareness. Lastly, O1 and O2, situated in the occipital region, are crucial for processing visual information, which is particularly relevant when evaluating video advertisements.



which are variance and kurtosis with thresholds set on the 95th percentile, while peak-to-peak amplitudes exceeding 150 μV were also excluded. This ensures robust detection and removal of artifacts while avoiding overcorrection of clean EEG data.

The final step, neural signals were decomposed into five subbands which are Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz), and Gamma (30–49 Hz). Subband decomposition allows for isolating frequency-specific neural activities linked to distinct cognitive and emotional states. Gamma band activity, for instance, has been associated with heightened cognitive processing, while Alpha and Theta bands relate to relaxation and emotional responses, respectively [23]. This subband approach ensures a detailed analysis of neural responses to advertisements, capturing a comprehensive spectrum of brainwave dynamics.

D. Feature Extraction

Feature extraction is the core of this study, aiming to translate neural signals into quantifiable metrics for analysis. Time-domain features such as mean absolute value (MAV), standard deviation, and peak-to-peak amplitude captured the amplitude and variability of neural signals, offering insights into the intensity of brain activity during engagement [24]. Frequency-domain features, including power spectral density (PSD), wavelet transform, and Fourier transform, provided a frequency-specific understanding of neural oscillations, reflecting attentional and emotional processes caused by the advertisements [25]. Entropy-based metrics such as Shannon entropy, spectral entropy, and sample entropy quantified the complexity and randomness of neural responses, correlating with cognitive flexibility and engagement levels [26]. Additionally, Hjorth parameters and fractal dimensions (e.g., Petrosian and Higuchi) highlighted the dynamic nature of neural signals, further enriching the analysis [27]. Each feature was computed for the five subbands and all eight channels, yielding a multidimensional dataset that facilitated nuanced comparisons between interesting and ordinary advertisements.

E. Classification

To validate the discriminative power of the extracted features, a Random Forest classifier was employed. Although classification was not the primary focus of the study, it served as a complementary tool to evaluate feature relevance and neural activity patterns. The accuracy result can support the hypothesis that neural engagement levels vary distinctly across advertisement categories, with Gamma band activity indicating heightened cognitive processing for interesting content, and Beta band reductions signaling lesser cognitive load for ordinary advertisements [8].

III. RESULT AND DISCUSSION

The study results are presented in the form of the average PSD, MAV, standard deviation, Hjorth activity, peak-to-peak, zero-crossing rate, and wavelet transform comparison of EEG signals between interesting and ordinary video advertisement engagement levels. Data is presented for each channel subband pair which are O1 Gamma and O2 Gamma for visual attention and F7 Beta, F8 Beta for cognitive load.

A. Frontal Region

Beta activity in F7 and F8 was considerably lower for interesting advertising, indicating a decrease in cognitive burden. This discovery indicates that captivating information enhances the efficiency of neural resource distribution, implying reduced cognitive effort for processing. Metrics including PSD, MAV, and Standard Deviation in the beta-band exhibited notable decreases for interesting commercials. Ordinary advertisements, deprived of engaging content, provoked increased beta activity in the frontal areas, suggesting heightened cognitive effort. The noted reduction in beta-band activity for engaging content indicates a cognitive state marked by ease and automation, which optimizes neural efficiency and task engagement, hence confirming the difference in cognitive load across varying levels of engagement. Figure 5 indicates that for the Wavelet Transform difference of the F7 Beta and F8 Beta between ordinary and interesting advertisement.

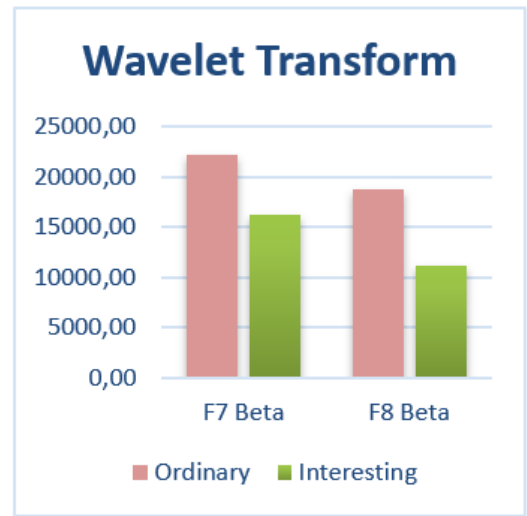


Fig. 5. Mean Wavelet Transform in the F7 and F8 Beta.

B. Occipital Region

The research demonstrated that gamma activity in O1 and O2 was considerably higher for interesting advertising in comparison to ordinary ones. This outcome highlights the increased visual attention provoked by captivating commercials, as gamma-band activity in occipital areas is closely linked to attentional focus and sensory processing. Attributes such as PSD, Hjorth Activity, and Wavelet Transform exhibited increased values in the gamma-band during the observation of engaging advertising. The results demonstrate a robust link between visually stimulating content and brain activation in the occipital regions, confirming the importance of gamma oscillations in attentional processes. The increase in gamma-band activity corresponds with the expected brain response to dynamic and visually dense stimuli that effectively maintain visual attention. Figure 6 demonstrates how Hjorth Activity of O1 Gamma and O2 Gamma are different between interesting and ordinary.

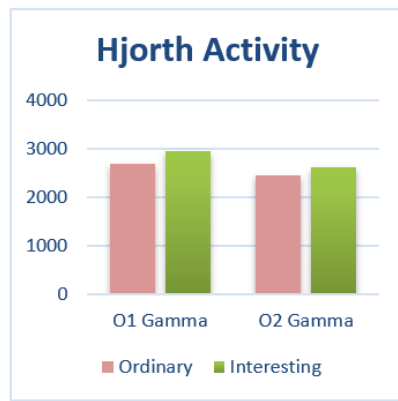


Fig. 6. Mean Hjorth Activity in the O1 and O2 Gamma.

C. Discussion

The differentiation between interesting and ordinary advertisements was most evident in the occipital Gamma and frontal Beta bands. While interesting advertisements elicited increased occipital Gamma activity, ordinary advertisements showed relatively subdued responses. Previous research has demonstrated that gamma activity in occipital regions correlates with enhanced visual attention during visually stimulating tasks. For instance, it was found that gamma-band EEG features shown notable increases for tasks requiring heightened attention and visually stimulating stimuli, particularly in the occipital regions [28]. Furthermore, studies have reported that higher gamma power was observed in the occipital areas during the display of engaging advertising, indicating enhanced visual attention [29].

This finding emphasizes the role of visual engagement in determining the appeal of advertisements. On the other hand, the reduced Beta activity for interesting advertisements suggests that engaging content reduces the cognitive effort required to maintain attention, offering a potential explanation for the enhanced viewer experience. For example, studies indicate that decreased frontal beta power correlates with increased mental effort and increased cognitive stress [30]. Additionally, beta power from frontal electrodes diminishes as task complexity escalates, indicating a greater cognitive load [31]. The combination of these channels, subbands, and extracted features demonstrated their effectiveness, as evidenced by the Random Forest classification achieving an accuracy of 83.09%.

Interestingly, the results challenge the common assumption that all engagement-related features will uniformly increase during interesting advertisements. For example, the reduction in Beta activity highlights the need to consider efficiency, rather than intensity, as a marker of engagement. Figure 7 show that interesting advertisements tend to exhibit relatively lower Beta activity compared to ordinary ones. Figure 8 highlights a different trend for Gamma activity, which reveal relatively higher values for interesting advertisements. The plots illustrate the variability in the distinction between ordinary and interesting within the PSD feature, showcasing how different neural bands and channels respond uniquely to varying levels of engagement. Whilst seemingly randomly dispersed, table 2 also supports how noticeable that it corroborates the observed findings that ordinary engagement requires a greater cognitive effort,

whereas interesting engagement enhances visual focus. This finding aligns with emerging research suggesting that efficient cognitive processing can be just as indicative of engagement as increased neural activation.

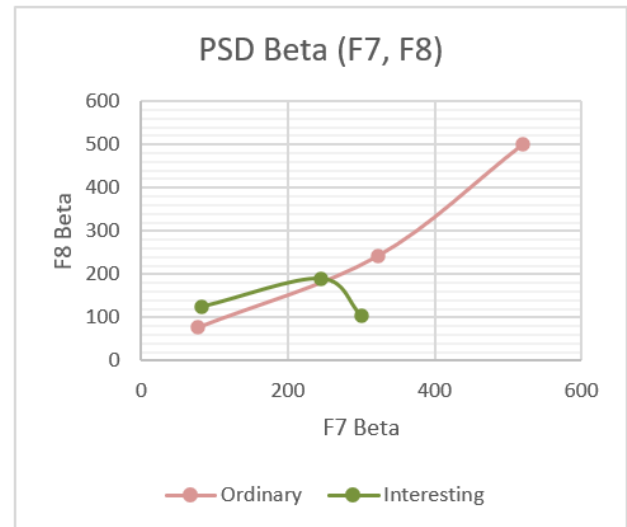


Fig. 7. Scatter plot of PSD between ordinary and interesting video advertisements on frontal beta.

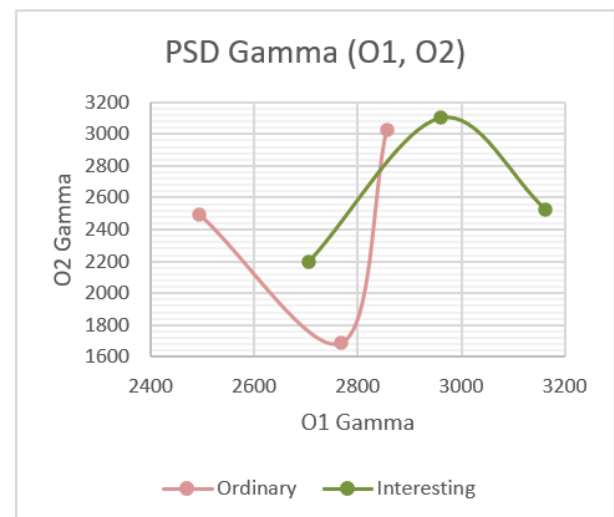


Fig. 8. Scatter plot of PSD between ordinary and interesting video advertisements on frontal beta and occipital gamma.

The findings strongly align with the primary objective of this research: to analyze neural activity differences between interesting and ordinary advertisements. By leveraging specific EEG features and channel-subband combinations, this study successfully identified neural markers of engagement, providing actionable insights for neuromarketing. The results demonstrate that interesting advertisements activate distinct neural pathways, characterized by enhanced visual processing and reduced cognitive load, thereby validating the hypotheses guiding this research.

TABLE 2. FEATURE METRICS FOR EEG SIGNALS IN ORDINARY AND INTERESTING EADS

Feature	Ordinary				Interesting			
	F7 Beta	F8 Beta	O1 Gamma	O2 Gamma	F7 Beta	F8 Beta	O1 Gamma	O2 Gamma
PSD	307,94	278,11	2699,48	2444,15	209,42	140,70	2942,62	2616,33
MAV	7,58	7,89	33,26	31,14	6,90	6,44	36,98	34,09
Standard Deviation	8,95	9,38	35,24	33,24	8,41	7,84	39,29	36,36
Hjorth Activity	308,30	277,91	2697,89	2442,75	206,96	139,29	2944,25	2616,35
Peak to Peak	32,47	35,31	88,77	85,28	33,18	31,20	99,26	93,31
Zero Crossing Rate	45,89	45,43	92,31	92,09	45,66	45,37	93,60	93,53
Wavelet Transform	22122,79	18714,74	169964,27	148136,67	16212,47	11080,28	188404,69	161930,30

IV. CONCLUSION

This research explored the use of electroencephalography (EEG) signals to analyze neural engagement with video advertisements, focusing on distinguishing interesting and ordinary levels of consumer engagement. By examining eight EEG channels and their subbands, the study identified key neural features and channel-subband combinations indicative of engagement. Gamma activity in occipital regions (O1, O2) emerged as a noteworthy marker for interesting advertisements, reflecting heightened visual attention, while Beta activity in frontal regions (F7, F8) decreased, indicating reduced cognitive effort during engaging content. These findings challenge conventional assumptions about engagement and emphasize the importance of both enhanced attention and reduced cognitive load.

The research offers actionable insights for neuromarketing, providing a scalable framework for evaluating advertisement effectiveness and optimizing content strategies. Future work should expand the sample size, integrate statistical validation, and explore multimodal approaches to deepen the understanding of consumer behavior responding to video advertisement as marketing tools.

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