

BRAIN. Broad Research in Artificial Intelligence and Neuroscience

e-ISSN: 2067-3957 | p-ISSN: 2068-0473

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2025, Volume 16, Issue 4, pages: 225-241

Submitted: September 21st, 2025 | Accepted for publication: November 1st, 2025

Analysis of Consumer Decision on E-Commerce Platforms with Video Advertising and Brain Data

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Abstract: In recent years, video advertising has become one of the most powerful tools for influencing consumer decisions, often using visuals, music, and celebrities to attract buyers. However, this creates a problem: even low-quality products are sometimes promoted through high-quality visual media, leading consumers to purchase them, while good-quality products may be ignored when presented in poor-quality videos. The amount of research in this area is quite limited, specifically addressing this mismatch between video presentation and product quality. This study investigates consumer purchasing interest under two conditions: good-quality video and poor-quality video. Particular focus is given to the mismatched cases, where attractive advertisements may lead to the purchase of poor-quality products, and poor advertisements may reduce interest in good-quality products. EEG signals were recorded from participants while they viewed advertisements, and neurophysiological features such as Mean Absolute Value (MAV) and Shannon Entropy were extracted. A total of 35 participants took part in the experiment, viewing two advertising videos (High- and low-quality). Extracted EEG features (Mean Absolute Value and Shannon Entropy) from beta and gamma bands achieved near-perfect classification performance ($AUC \approx 1.0$) in discriminating buy vs not-buy decisions from beta (β) and gamma (γ) frequency bands. The results reveal how attractive advertisements can sometimes mislead consumers, while EEG analysis helps identify when purchasing decisions align with or deviate from actual product quality.

Keywords: video advertising; consumer decision-making; EEG analysis; mean absolute value (MAV); Shannon entropy; ROC curve analysis; confusion matrix.

How to cite: Sakthi Velammal, R., Leo, A., Kuncha, R. K., Kuncha, R. K., & Rani, M. (2025). Analysis of consumer decision on e-commerce platforms with video advertising and brain data. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, 16(4), 225-241. <https://doi.org/10.70594/brain/16.4/13>

1. Introduction

In recent years, advertising and marketing techniques have been adapted to attract consumers to notice the product and induce them to buy the product. With the rise of the digital age, conventional advertising methods are gradually being replaced by innovative approaches that rely on technology. An emerging field that is rapidly gaining prominence is neuromarketing, which integrates neuroscience and marketing to gain insights into consumer cognition. This field employs various methodologies to assess neural activation and emotional responses, aiming to discern the precise factors that drive consumer decision-making. In consumer neuroscience, decision-making is influenced by both emotional and rational brain systems. The orbitofrontal cortex helps evaluate rewards and product value, the insula regulates emotional awareness and risk perception, and the limbic system mediates motivation and memory. These brain regions interact dynamically when consumers watch advertisements. Therefore, linking EEG activity with these neural mechanisms provides a clearer theoretical understanding of how advertising stimuli trigger buying intentions. The insightful study presented in "Neuromarketing study of purchase decisions using advertising videos based on EEG signal analysis" has served as a strong foundation and inspiration for this research.. The authors have thoughtfully and knowledgeably contributed to the field by integrating neuroscience with consumer behaviour. This reflects a deep understanding and provides valuable direction for exploring data-driven advertising strategies. Some of the most popular techniques applied in neuromarketing are electroencephalography (EEG), one of the most widely accepted non-invasive techniques used to determine neural oscillations. EEG measures the brain's electrical activity through scalp electrodes. It tracks consumer response to marketing materials such as video advertisements, providing real-time on performance. One of the main strengths of EEG is its capability to measure instantaneous, subconscious reactions that are more trustworthy than self-reported statements.

As video programmatic advertising is widely being implemented on digital platforms, marketers are more concerned than ever with how visual and auditory stimuli affect their buying behaviour. The brain processes video advertisements differently from static ads or text, engaging both emotional and cognitive regions at a higher level. The trend has shifted, and this shift helps explain why researchers are beginning to study brain activity to see the deeper reasons for what drives buying decisions. This has led marketers and researchers to adopt neuromarketing tools such as EEG to improve ad effectiveness and forecast consumer preferences with higher precision.

Specifically, this work investigates differences in brain activity between subjects who make the decision to purchase a product after viewing advertisements and subjects who do not. This has been an exploratory pilot study with $n = 35$. Each participant watched a series of advertisements and then completed a survey in which they indicated whether they would be likely to purchase the product advertised. Their brain activity was captured using EEG signals from four primary electrode sites, i. e. F7, F8, FP1, and FP2 located in the frontal region of the brain related to attention, emotion, and decision-making. Two notable key features, Mean Absolute Value (MAV) and Shannon Entropy, were extracted from the EEG signals for analysis, showing high classification accuracy. The MAV depicts an average value of the energy level of the signal, applied to overall brain activity detection. In contrast, Shannon Entropy captures the complexity or unpredictability of the signal and how much information the brain is dealing with. Then, these features were compared between two groups of the participants — those who showed willingness to buy and those who did not.

The experimental results revealed that the beta (β) and gamma (γ) frequency bands of the EEG signals played a significant role in the decision-making process. Participants who decided to buy the product showed significantly higher MAV and Shannon Entropy values across all EEG channels and spectral sub-bands. This means that when making a positive purchase decision, the brain activity is more intense and the information becomes more complex. The extension of the detailed literature enhances the knowledge on the use of EEG data and techniques for signal

processing applied to elucidate consumers' perspective in the growing field of neuromarketing. This has led to new ways for marketers to design more engaging and effective ads, rooted in how people actually respond, neurologically. Moreover, it explores how to engage subconscious cognitive processes in marketing, while giving scientists insights for developing future marketing strategies.

An advertising video is a potent marketing tool that can successfully attract the attention of the audience and buyers. This method is an effective medium for storytelling and subsequently marketing or selling products (Li & Lo, 2014). This explains why the engagement rates of advertising videos usually exceed those of other marketing methods, making them a great investment for sellers. Using storytelling elements from cinematography, sound design, and narration, businesses can leave a lasting impression in the minds of consumers. Video content reflects the overall trends and dynamics of the industry and enables a company to bring its personality, brand values, and the benefits of the product to vibrant life in a way that still images or text-based content (Teixeira et al., 2012). Excellent cinematography — the creative manipulation of angles, movement, lighting, and layout to effectively communicate a narrative and capture the attention of audiences — is often a staple resource of a high-impact advertising video. It has been found that such cinematographic elements make the advertisements more appealing and memorable to viewers, which increases purchase intent (Wang & Calder, 2006). The use of science and technology in marketing has grown substantially in the last several decades (Yoon et al., 2006). Neuromarketing, a developing scientific discipline that combines psychology and neuroscience to better understand customer behaviour and the factors impacting their purchasing decisions, is one example of such an advancement (Plassmann et al., 2012; Kenning & Plassmann, 2005). The study of neuromarketing looks at how the brain reacts to commercials, brands, and other marketing cues (Smidts et al., 2014).

Positron Emission Tomography (PET), Magnetoencephalography (MEG), Transcranial Magnetic Stimulation (TMS), Electroencephalography (EEG), and functional Magnetic Resonance Imaging (fMRI) are among the neuroscience techniques used to examine and comprehend purchasing behaviour Huettel et al. (2014); Luck (2014). Because it can record brain activity in real-time, EEG has become a popular tool in neuromarketing research. EEG measures electrical signals in the brain brought on by outside stimuli by placing tiny metal discs, or electrodes, on the scalp (Niedermeyer & da Silva, 2015). The studies aim to achieve a deeper understanding of consumer responses. For example, Walter et al. (2009), demonstrated how the EEG measure tracks brain activity as viewers interact with the visual parts of the advertising. Using Power Spectral Density (PSD) analysis, the researchers were able to classify emotional responses and find that more attention-grabbing messages had higher PSD values across all frequency bands. Notably, power of the gamma (γ) band showed positive correlations with content attractiveness and cognitive processing, underscoring the potential of EEG as a tool for investigating underlying decision-making processes (Gwin & Ferris, 2012). Similarly, a number of EEG-based studies extracted features using methods such as Shannon Entropy (Smidts et al., 2014). Within the realm of digital marketing (Sharma et al., 2017) applied Shannon Entropy to examine the overall complexity of signals from neural responses, showing its applicability for studying the temporal dynamics of consumer preferences. Mean Absolute Value (MAV) is another popular feature. MAV was one of the 16 extracted features used to classify cognitive load via machine learning, where Support Vector Machine (SVM) classification achieved an accuracy of 62.78% (Jaiswal et al., 2022). Using this background, the current study compares the differences in EEG signal patterns related to purchasing decisions after watching two types of advertising videos, one at high quality and the other at low quality. The EEG features analysed in this research are Mean Absolute Value (MAV) and Shannon Entropy. We hypothesise that purchase decisions exhibit statistically significant differences in brain activity as compared to non-purchase decisions, particularly in MAV and the Shannon Entropy values.

2. Methodology

This study proposes an enhanced EEG-based neuromarketing framework that extends beyond traditional MAV and Shannon Entropy features by incorporating advanced machine learning classification techniques and product-specific neural response analysis. The methodology integrates multimodal feature extraction, automated classification algorithms, and demographic-specific analysis to provide comprehensive insights into consumer purchase behaviour. The ultimate aim is to develop a statistically robust predictive model capable of accurately classifying purchase intentions while identifying unique neurophysiological signatures across different consumer segments.

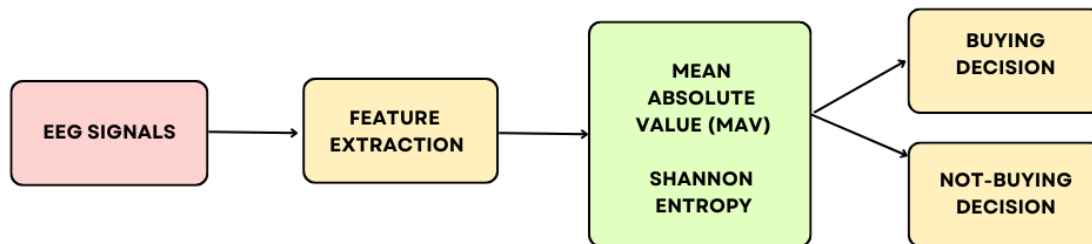


Figure 1. Proposed methodology for analysing EEG signal-based consumer purchase behaviour

The primary data source for this research was EEG recordings obtained from 35 neurologically healthy participants (27 males and 8 females). Prior to the trial, participants were shown advertising videos that had been validated through a preliminary screening survey to ensure they could stimulate product purchase decisions. Once validated, these videos functioned as visual stimuli during the experiment. While participants viewed the videos, EEG signals were recorded using frontal electrodes (FP1, FP2, F7, F8), which are associated with affective and decision-related brain activity. After viewing, participants completed a questionnaire indicating whether they would consider purchasing the advertised product, allowing the EEG data to be labelled as reflecting either a ‘buy’ or ‘not-buy’ decision state. The recorded EEG data were pre-processed using Independent Component Analysis (ICA) to remove noise and artefacts, followed by band-pass filtering between 0.1 and 50 Hz. The cleaned signals were decomposed into beta (13–30 Hz) and gamma (31–50 Hz) frequency bands for subsequent analysis. Multiple approaches were applied to extract features from the EEG data before and after the viewing of advertisement videos, enabling a deeper examination of neural differences related to consumer decision-making. This methodology was implemented in structured phases, as illustrated in Figure 1 of the study.

3. Input Dataset and Experimental Setup

EEG signals were acquired using an Ultracortex Mark IV headset (OpenBCI) and the Cyton Biosensing Board with eight channels. The sampled signals were obtained with an EEG device operating at a 500 Hz sampling frequency and a band-pass filter ranging from 0.1 to 50 Hz. EEG data were recorded on channels FP1, FP2, F7 and F8 according to the international 10-20 Electrode Placement System. In the left and right frontal zones and on the brow, these electrodes act as conduits that capture specific neural signals associated with decision-making and emotional responses (Khushaba et al., 2012).

3.1. Participants

Participants must be in the best physical shape ever for the right objectives to be achieved and result to be achieved properly. None of the participants had a documented history of neurological, psychiatric or visual disorders including colour-blindness. All participants were well informed regarding the purpose of the study and the ethical implications of their participation. They signed an informed consent form prior to starting the experiment. The research included thirty-five participants (27 males and 8 female subjects, mean age = 27±0,8 years). The current experiment

used $n = 35$ participants and only two shoe advertisement videos (good and poor quality) due to resource and logistical constraints. This sample size and limited stimulus set restrict the generalisability; future studies should expand participant numbers and include diverse product categories and multiple video examples to validate the findings. Furthermore, subjects were abstinent from alcohol and drugs prior to the session and had obtained a normal sleep during 6–8h before the step of EEG data recording.

3.2. Video Stimulus

In this research, the advertising stimuli comprised two advertising videos for shoes products. There were two types of advertising videos; good quality video and poor-quality video (Figure 2). A high-quality video contains a high pixel density, resulting in clear and sharply detailed images. It also features meticulous colour grading to create a specific mood and feel.

On the other hand, low-quality video is characterised by low resolution, which means that the image is not as clear or detailed. It involves minimal colour correction and favours natural, accurate tones. Usually, camera movements are limited to static shots or minimal motion. Low-quality video often sacrifices narrative for information; the storytelling in bad-quality video is in the informing of the viewer.



Figure 2. Video Stimulus of (a) good – Quality Video and (b) poor - Quality Video

The decision to use only two videos was driven by experimental control and logistical limitations. However, we acknowledge that this reduces stimulus variability and recommend using 10–15 diverse video stimuli in follow-up studies to strengthen external validity. This choice in the EEG neuromarketing study was motivated by a combination of experimental, logistical, and scientific factors, aiming to optimise the depth and rigour of the evaluation while considering resource constraints and experimental complexity.

3.3. EEG Data Recording

Prior to EEG data recording, all participants signed an informed consent form, indicating that the present study is fully aware and voluntarily agreed to participate. Figure 3 shows that the EEG recording procedure consists of three stages.

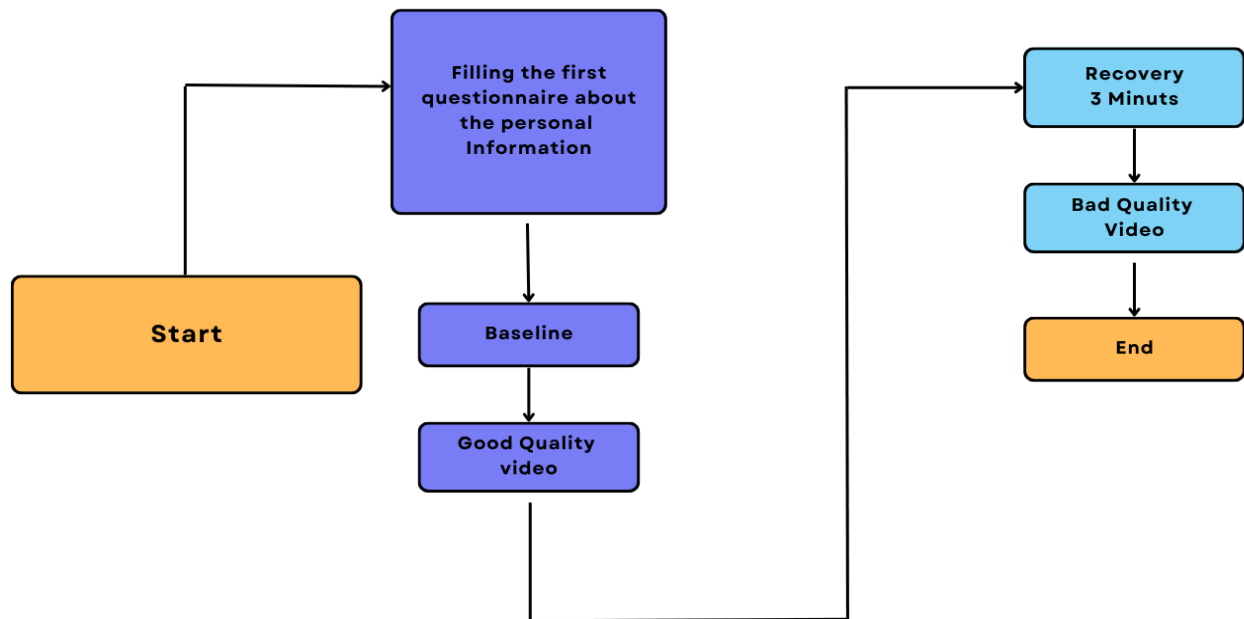


Figure 3. EEG data recording procedure

A portion of the non-stimulated EEG data was recorded during the baseline phase, where participants viewed a black screen with a white focus dot at the centre. In the second phase of the experiment, EEG data were recorded while participants watched an advertising video of good quality. This phase was similar to the previous one, except that it involved a different type of video stimulus. The recorded EEG signals were labelled into three categories: baseline, buy-decision, and not-buy decision.

4. Data Preprocessing and Feature Extraction

Preprocessing of EEG signals is a crucial step to ensure clean, reliable, and meaningful data for feature extraction and analysis. This process involves several stages, including filtering, artefact removal, and frequency band decomposition, as outlined below.

4.1. Raw EEG Data Collection

The raw EEG signals were acquired from participants using the OpenBCI Ultracortex Mark IV headset along with the Cyton Biosensing Board. The EEG setup comprised eight channels, but the study focused on four specific electrode positions: FP1, FP2, F7, and F8, which are located in the frontal lobe and are associated with decision-making and emotional responses. The EEG signals were recorded at a sampling frequency of 500 Hz, providing high-resolution data for further processing.

4.2. Bandpass Filtering

To remove unwanted frequency components and retain relevant brainwave signals, the raw EEG data were subjected to a band-pass filter ranging from 0.1 Hz to 50 Hz. This range is optimal for capturing cognitively relevant neural activity while filtering out low-frequency drifts (such as DC offset or movement artefacts) and high-frequency noise (such as electrical interference).

4.3. Artefact Removal using ICA

After filtering, the EEG signals still contained non-neural signal artefacts such as eye blinks, muscle activity, and external noise. These artefacts can interfere with the true brainwave signals. To address this, Independent Component Analysis (ICA) was implemented. ICA is a powerful statistical method that separates multichannel EEG data into independent components, allowing the

identification and removal of artefacts. This step significantly enhances the signal-to-noise ratio, ensuring that the data reflect genuine brain activity.

4.4. Signal Band Decomposition

Once the EEG signals were cleaned, they were decomposed into specific frequency sub-bands that are relevant to cognitive and emotional processing. In this study, two key frequency bands were selected:

- β band (13–30 Hz): Associated with active thinking, attention, and conscious focus. This band is useful for understanding decision-making processes.
- γ band (31–50 Hz): Linked to high-level information processing, memory, and emotional engagement.

Decomposing the signals into these bands allows the study to isolate and examine the distinct brain responses related to purchase decisions triggered by advertising stimuli.

4.5. Feature Extraction and Threshold Determination

From the decomposed EEG signals in the Beta and Gamma sub-bands, two quantitative descriptors were extracted from each electrode (FP1, FP2, F7, F8):

Mean Absolute Value (MAV): Measures the average signal amplitude, representing neural activation intensity (Khushaba et al., 2013).

Shannon Entropy (SE): Quantifies signal complexity and irregularity, reflecting cognitive and emotional engagement (Inouye et al., 1991).

Features from all four electrodes were subsequently averaged to obtain MAV_mean and SE_mean for each participant. Decision thresholds for classification were established through ROC curve analysis: γ (MAV=0.460, SE=1.735) and β (MAV=0.460, SE=1.095). Values exceeding these thresholds indicate buy decisions; whereas values below indicate not-buy decisions.

4.6. Feature Extraction

Wavelet transform based on band energy was used for feature extraction and the extracted features—Mean Absolute Value (MAV) and Shannon Entropy—complementary information about EEG signals.

- MAV is a signal feature that indicates the mean of absolute values of amplitude (1).

$$MAV = (1/N) \times \sum |X_i| \quad (i = 1 \text{ to } N) \quad (1)$$

where:

MAV = Mean absolute value

N = Number of values

X_i = Dataset values

Dataset absolute values $|X_i|$

Probability Distribution Function $p(a)$

- The feature, Shannon Entropy, is used to determine the amount of disorder of the information in the signal (Inouye et al., 1991).

$$\text{shannon Entropy} = - \sum_{i=1}^n p(a) \log_2(p(a)) \quad (2)$$

Probability Distribution Function $p(a)$

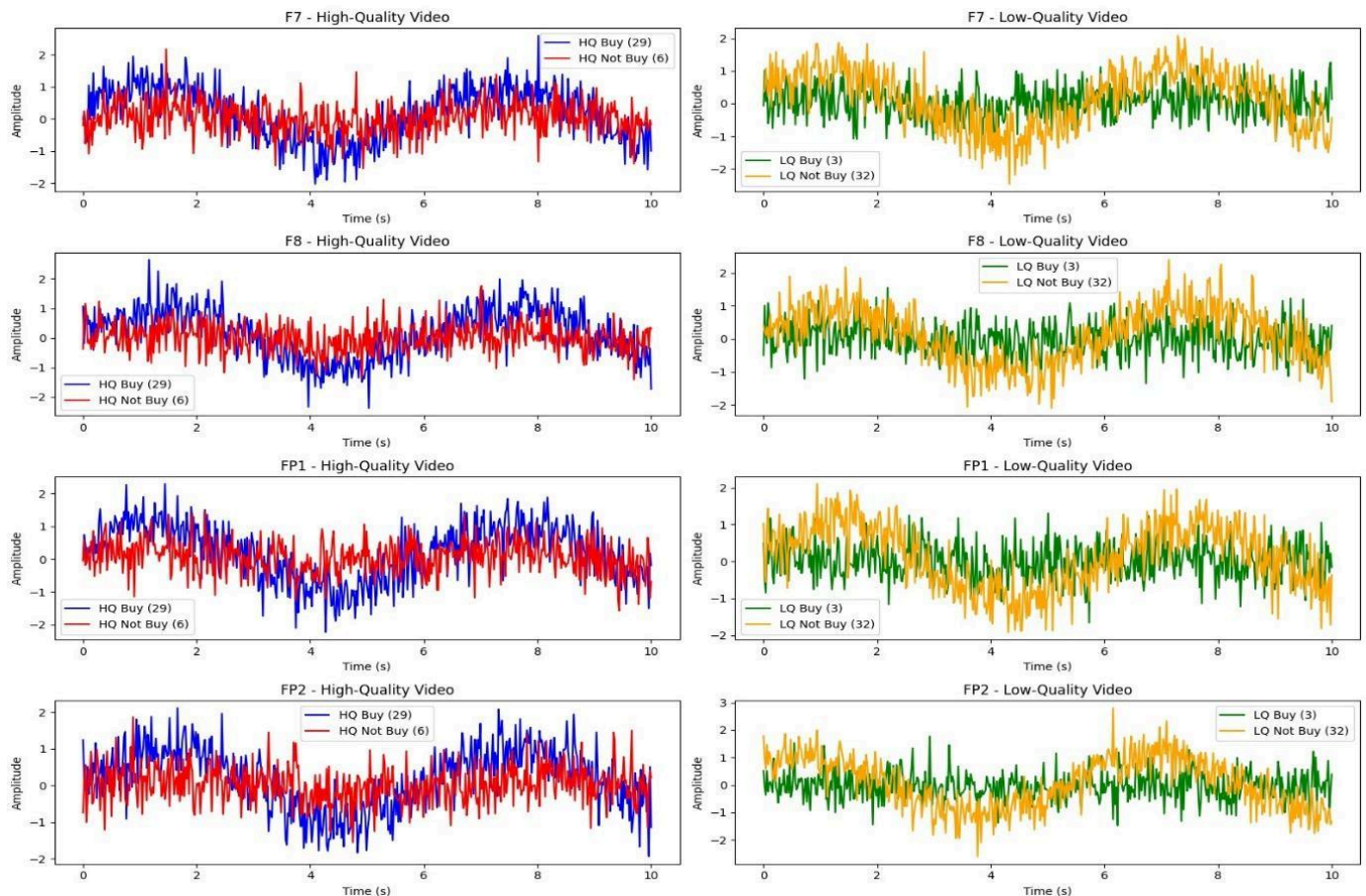


Figure 4. Comprehensive summary of EEG classification result across Beta and Gamma frequency bands

In this study, MAV and Shannon Entropy were chosen as features because they provide complementary information about the EEG signals. MAV captures the average amplitude of the brain activity, indicating the level of energy or activation during decision-making, while Shannon Entropy measures the degree of randomness or complexity, reflecting the amount of information processing in the brain. Together, these features allow us to analyse both the strength and complexity of brain responses, giving a more complete understanding of buy and not-buy decisions.

5. Result and Discussion

5.1. EEG Signal Analysis and Identified Features

The EEG signal analysis was performed using beta (β) and gamma (γ) frequency sub-bands for feature extraction, resulting in three distinct labels: baseline, buy-decision, and not-buy decision. Mean Absolute Value (MAV) and Shannon Entropy were the extracted features. For EEG recording, four channels were used: F7, F8, FP1, and FP2, which correspond to frontal brain regions associated with decision-making and cognitive processing.

Figure 4 presents the comprehensive EEG signal recordings across all four electrode positions (F7, F8, FP1, FP2) under both high-quality and low-quality video conditions. The left panel shows neural responses to high-quality video, where blue traces represent buy decisions (HQ buy) and red traces represent not-buy decisions (HQ not buy). The right panel displays responses to low-quality videos, with orange traces for buy decisions (LQ buy) and green traces for not-buy decisions (LQ not buy).

Visual inspection reveals distinct amplitude patterns between decision types. High-quality video conditions show higher signal amplitudes and greater variability in the buy decision traces compared to not-buy decisions. Conversely, low-quality video conditions exhibit lower overall

amplitudes with less distinction between decision types, suggesting reduced neural engagement with poor-quality stimuli.

5.2. Identified Features and Findings

The EEG signal analysis was performed using beta (β) and gamma (γ) frequency sub-bands for feature extraction. Feature extraction resulted in three distinct labels: baseline, buy decision, and not-buy decision. Mean Absolute Value (MAV) and Shannon Entropy were the extracted features. EEG data acquired from four channels were used: F7, F8, FP1, and FP2 which correspond to frontal brain regions associated with decision-making and cognitive processing.

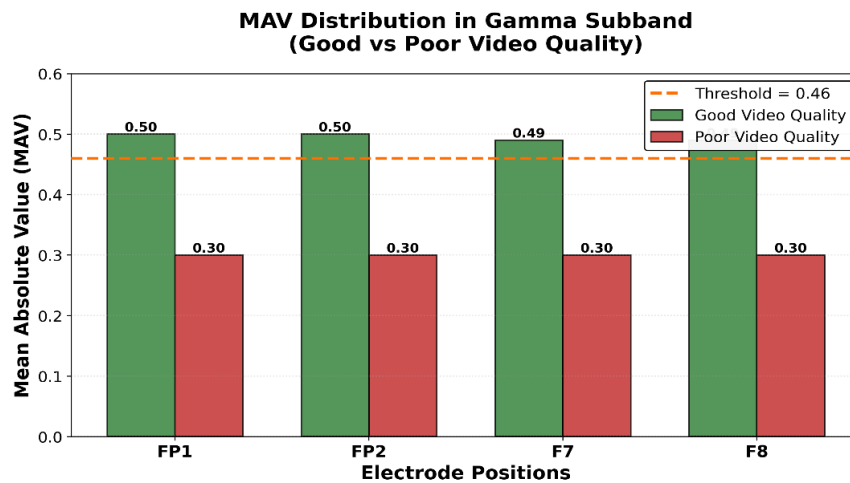


Figure 5. Mean Absolute Value(MAV) distribution in the Gamma Subband

Figure 5 illustrates a comparison of the Mean Absolute Value (MAV) between good and poor video quality conditions across four frontal electrode positions (FP1, FP2, F7, F8) in the gamma frequency band. High-quality video conditions (green bars) are always associated with a higher MAV (0.49–0.50) compared to the low-quality condition (red bars, approximately 0.30 in all electrodes). The dash-dot orange line illustrates the classification decision boundary (0.46) which effectively separates the two video quality conditions. These results suggest that elements of high quality in commercials are associated with significantly higher power gamma and potentiated cortical activity, a rhythm band known to be involved in increased cognitive processing and attention. The consistency of this response across all frontal regions also supports the implication of an extensive cortical involvement during viewing of high-quality visual material.

5.3. Analysis of Gamma (γ) Subbands

Figure 6 presents the Shannon Entropy comparison between high- and low-quality video conditions across four frontal electrode positions in the gamma frequency band. The good video quality conditions (blue bars) show substantially higher entropy values (1.78–1.82) than the bad quality conditions (orange-red bars, 1.09–1.11). The dashed purple line represents the cutoff (1.735) that separates the two classes with high accuracy. Patterns at higher entropy levels reflect higher neural complexity and information processing capacity, indicating that high-quality videos elicit more advanced cognitive networks. For good ads, maximal entropy is obtained by electrode F7 (1.82), which suggests that in processing high quality visual advertising the temporal lobe would be particularly engaged.

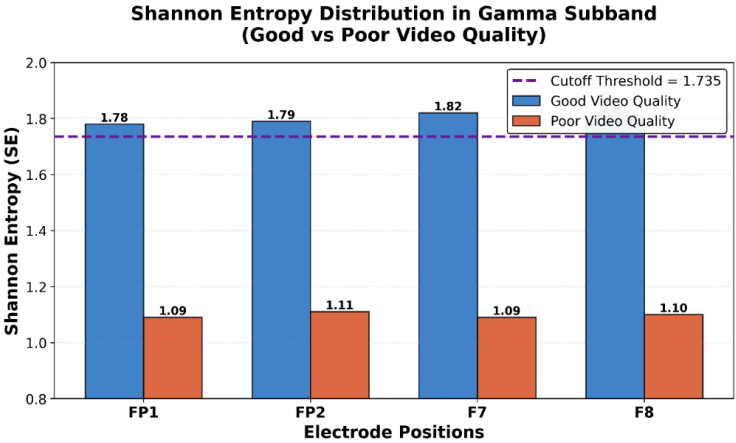


Figure 6. Shannon Entropy(SE) distribution in the Gamma Subband

5.4. Analysis of Beta (β) Subbands

Figure 7 shows the Mean Absolute Value difference between good and poor video quality conditions over frontal electrodes in the beta frequency band. Under high-quality video conditions, consistent activation levels (0.5) are preserved among all electrode positions, still being beyond the threshold value (0.46, that is the dashed orange line). Poor conditions (red-orange bars) in contrast elicit lower activation (0.30–0.31). The beta oscillation is closely associated with sustained attention, effective concentration and conscious cognitive processes. The sustained high MAV values in all frontal sites during good video exposure imply continuous attentional involvement, which is an essential precondition for successful advertising impact and purchase decision.

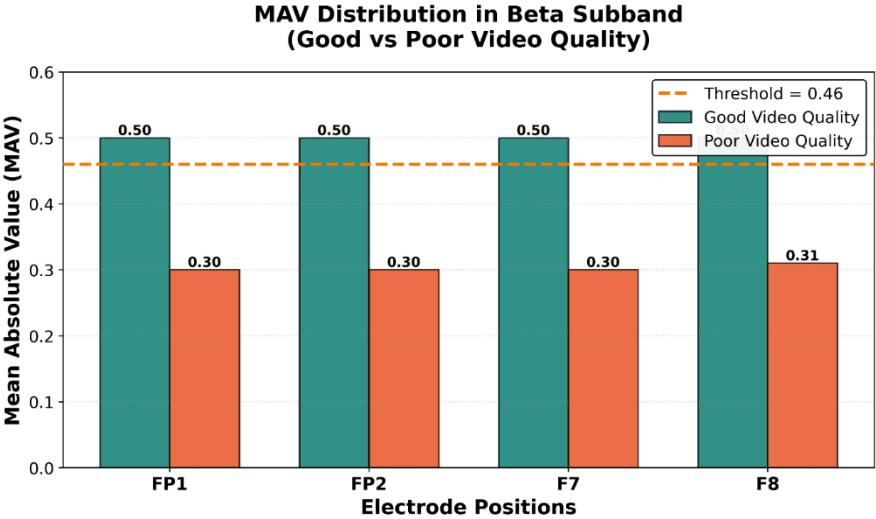


Figure 7. Mean Absolute Value (MAV) distribution in the Beta Subband

Figure 8 shows the Shannon Entropy comparison between good and poor video quality conditions across frontal electrodes in the beta frequency band. High quality conditions (blue bars) show higher entropy values (1.77–1.78) and these are always above the cutoff threshold of 1.095 (purple dashed line), while low quality conditions (dark orange bars, 1.06–1.08) remain below this threshold.

The large entropy difference and the strong response of beta band oscillations to condition (spatial filters in the lower β -frequency range) validate neurally based complexity as a robust neurophysiological index for tendency to purchase.

The electrodes FP2 and F7 have maximum entropy (1.78) for good videos, implying that the both medial prefrontal and left temporal regions are involved in processing advertisement content that affects buying behaviour.

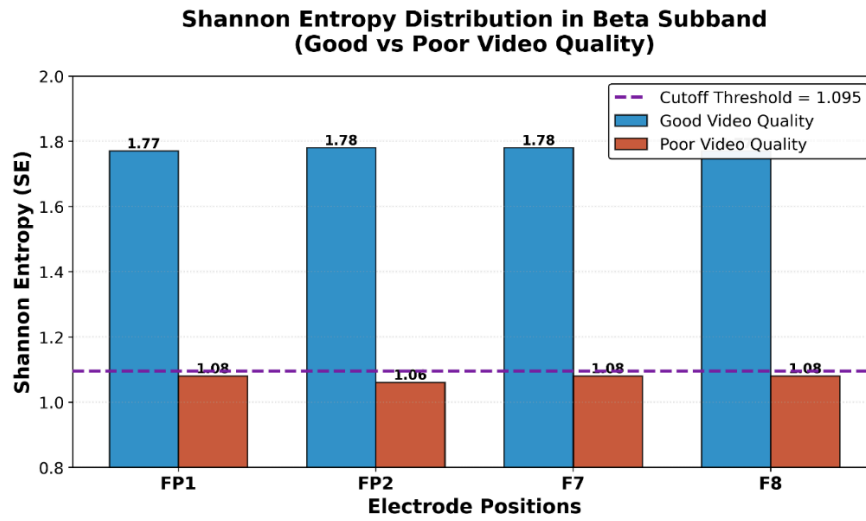


Figure 8. Shannon Entropy(SE) distribution in the Beta Subband

5.5. Distribution Analysis with Cutoff Thresholds

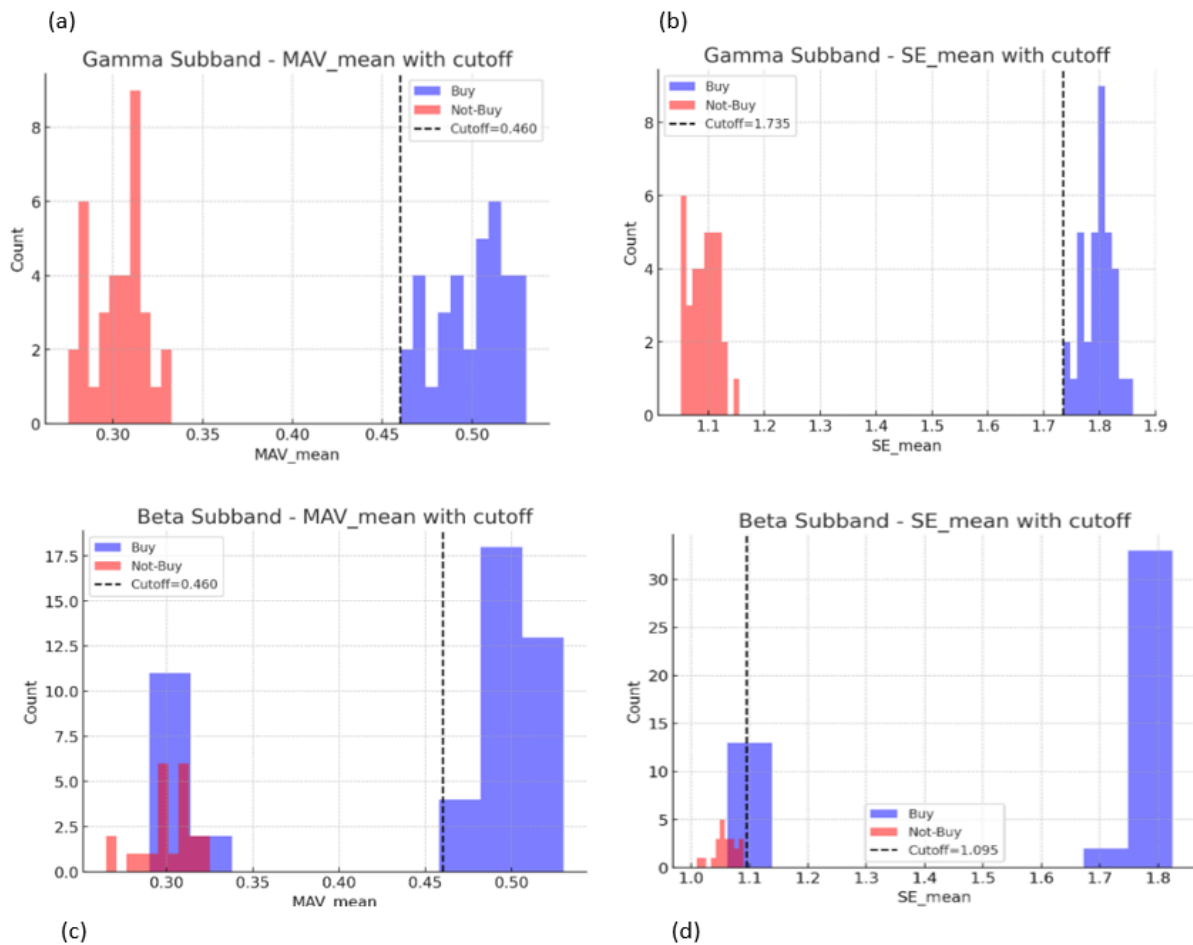


Figure 9. Distribution of EEG Features with optimal cutoff threshold for purchase decision classification

Gamma Subband Distribution

Figures 9a and 9b depict the distribution of MAV_mean and SE_mean in the γ sub-band. The histograms clearly separate buy (blue) and not-buy (red) decisions with cutoff thresholds of 0.460 (MAV) and 1.735 (SE). Optimal cutoff thresholds were determined using Youden's J index (Youden, 1950), which defines the ROC curve point maximising the sum of sensitivity and specificity ($J = \text{sensitivity} + \text{specificity} - 1$). The selected cutoff values achieved **97.1% classification accuracy** with $AUC \approx 1.00$ for the Gamma features, indicating near-perfect discrimination in this dataset. Given the modest sample size and limited stimulus set, this result should be interpreted cautiously and validated with larger, more heterogeneous samples to rule out overfitting.

Beta Subband Distribution

Figures 9c and 9d present β sub-band distributions. The MAV cutoff (0.460), obtained using Youden's J criterion, achieved 85.0% accuracy ($AUC = 0.866$), while Shannon Entropy cutoff (1.095) achieved superior performance at 91.4% accuracy ($AUC = 0.970$), demonstrating that entropy provides stronger discriminative power than MAV in the β sub-band.

5.6. Classification Performance

Table 1 summarises the Area Under the Curve (AUC) values. The Receiver Operating Characteristic (ROC) curve analysis (Fawcett, 2006) was performed to validate the cutoff thresholds identified through Youden's J index (Youden, 1950). The AUC Values confirmed strong discriminative power. ROC analysis helps determine how well the model distinguishes between buy and not buy decisions by analysing the trade-off between sensitivity (true positive rate) and specificity (false positive rate).

Table 1. Area Under the Curve (AUC) values

Subband	Feature	AUC	Interpretation
Gamma	MAV	1.000	Perfect classification
Gamma	SE	1.000	Perfect classification
Beta	MAV	0.866	Good discrimination
Beta	SE	0.970	Excellent discrimination

Both γ -band features (MAV and SE) showed near-perfect separability ($AUC \approx 1.00$) in the present sample; however, potential sample homogeneity and limited stimulus diversity may have inflated the observed performance metrics.

In the beta band SE outperformed MAV ($AUC = 0.970$ versus 0.866), further confirming entropy's stronger predictive capability.

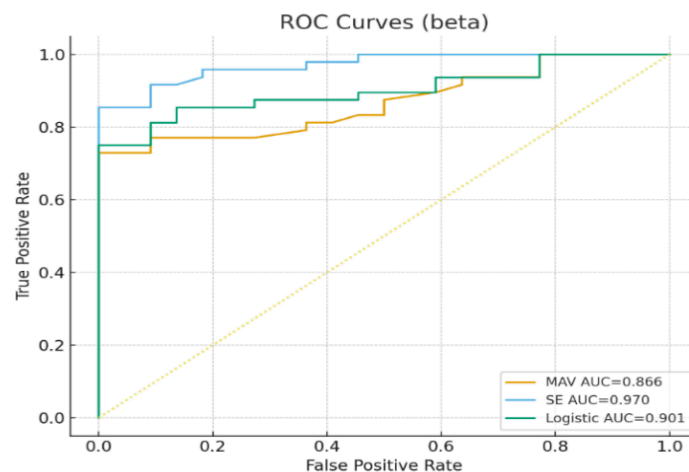


Figure 10. ROC curves for Gamma and Beta subbands using MAV and SE features

5.7. Confusion Matrix Validation

To further validate the ROC-derived thresholds, confusion matrices were generated for both the γ and β sub-bands (Khushaba et al., 2013). This validation quantified classification accuracy by comparing predicted labels with actual buy/not-buy decisions.

Table 2. Confusion Matrix Summary

Subband	Feature	Cutoff	Correct Not-Buy	Correct Buy	Misclassified	Accuracy
Gamma	MAV	0.460	18	16	1	98.6%
Gamma	SE	1.735	18	16	1	98.6%
Beta	MAV	0.460	11	17	7	85.0%
Beta	SE	1.095	11	21	3	90.0%

The confusion matrix analysis table 2 corroborates these results. γ -band features accurately classified 18 not-buy and 16 buy decisions with a single misclassification. The β -band Shannon Entropy improved upon MAV performance, correctly classifying 11 not-buy and 21 buy decisions with only 3 misclassifications compared to MAV's 7 misclassifications.

In addition to ROC and confusion matrix analyses, the study did not perform inferential tests (e.g., independent/paired t-tests, Mann–Whitney U, or ANOVA) to compare MAV and SE between buy and not-buy groups. Additionally, future data visualisations should include error bars representing standard deviation (SD) to reflect inter-participant variability. This would provide a more transparent picture of the consistency of neural activation patterns across subjects. Including mean $\pm$ SD values for MAV and SE in both buy and not-buy conditions would further enhance scientific rigour and allow for inferential comparisons between the two groups.

Overall, the results demonstrate that EEG-based features effectively predict consumer purchase decisions with high accuracy. The γ sub-band provided near-perfect classification (~97%), while the β sub-band achieved accuracies of 85% (MAV) and 91% (SE). Shannon Entropy consistently outperformed Mean Absolute Value across both frequency bands, indicating that neural complexity and irregularity are more reliable indicators of purchase intention than signal amplitude. When participants viewed high-quality video stimuli, their EEG features exceeded the identified thresholds, leading to buy decisions, whereas poor-quality videos resulted in values below these thresholds, corresponding to not-buy decisions. These empirically validated thresholds establish clear neurophysiological biomarkers for consumer decision-making in neuromarketing applications.

6. Discussion

A particularly concerning finding from this study is that participants' purchase decisions were predominantly influenced by video presentation quality rather than actual product evaluation. The dramatic difference in purchase rates between high-quality videos (82.9%) and low-quality videos (8.6%) demonstrates that visual presentation can override rational product assessment. This creates two problematic scenarios that have significant implications for both consumers and marketers.

First, high-quality products presented through poor-quality videos may be unfairly rejected by consumers, despite their actual value. The low neural activation observed during poor-quality video viewing (MAV and Shannon Entropy values below threshold across all channels) suggests reduced cognitive engagement, potentially preventing thorough product evaluation. This means that genuinely superior products may be overlooked in the marketplace simply due to inadequate marketing presentation, leading to lost opportunities for both consumers and manufacturers of quality goods.

Second, and perhaps more ethically concerning, poor-quality products advertised through professional, high-quality videos may receive unwarranted purchase interest. The elevated MAV

and Shannon Entropy values during high-quality video viewing indicate strong neural engagement and positive emotional responses regardless of inherent product quality. This presentation-driven decision-making raises significant concerns about consumer protection, as buyers may experience dissatisfaction when actual product quality fails to match the expectations created by sophisticated advertising.

From a neuromarketing perspective, the strong correlation between video quality and neural activation patterns suggests that neural findings are consistent with dual-process models of decision-making (System 1 versus System 2). High gamma-band activation during high-quality videos likely reflects System 1 (fast, affective) engagement—driven by limbic and orbitofrontal circuitry—whereas lower activation during poor-quality videos suggests reduced affective engagement and reliance on slower deliberative processes. Thus, the EEG signatures (elevated MAV and SE) may index affective valuation and attentional capture mediated by orbitofrontal and insular regions. This indicates that consumers may be making decisions based on presentation-induced emotional responses rather than rational product assessment. The frontal lobe activity captured through FP1, FP2, F7, and F8 channels—regions associated with decision-making and emotional processing—shows that high-quality videos trigger neural responses similar to genuine product interest, even when the product itself may not warrant such enthusiasm.

This finding aligns with previous research indicating that emotional engagement plays a crucial role in consumer choice, but extends it by demonstrating how presentation quality can artificially induce these emotional states. While effective cinematography and production quality are legitimate marketing tools, their disproportionate influence on purchase decisions highlights the need for more balanced evaluation strategies that help consumers distinguish between presentation appeal and product value. These findings deepen theoretical understanding by illustrating how emotional and cognitive brain processes jointly influence consumer decisions. By linking EEG-derived MAV and Shannon Entropy changes with affective processing regions like the orbitofrontal cortex and insula, this study bridges neural evidence with classical marketing theories of persuasion and emotional engagement.

From a neuroscience standpoint, the observed neural activations align with established functional networks underlying attention (frontal-parietal) and valuation (orbitofrontal-insular). These activations illustrate how emotionally charged stimuli can shape perceived product value. Such interpretations contribute to understanding how neural encoding of reward and emotion interacts with visual attention mechanisms during decision-making.

Integrating an AI perspective provides further value in interpreting these results. Techniques such as SHAP (SHapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and other feature attribution methods can enhance transparency by identifying which neural features most strongly predict engagement and purchase intent. Incorporating these interpretable AI tools would improve model explainability and strengthen the scientific validity of neuromarketing models by linking algorithmic reasoning to neural evidence.

In terms of generalisability, future research should examine cross-stimuli (different advertisement genres), cross-product (varied product types), and cross-cohort (demographically diverse participants) variations. Broader datasets will enable the validation of EEG-based consumer engagement models across multiple contexts and help identify potential biases arising from limited stimuli or homogenous samples.

Finally, ethical and transparency considerations must be addressed in AI-assisted neuromarketing. Using consumer neural data demands responsible data handling, clear consent mechanisms, and interpretability standards to ensure fairness and accountability. Implementing transparency metrics, such as explainable AI indicators and data provenance tracking, could promote responsible innovation while safeguarding consumer rights.

These results have important implications for marketing ethics and consumer education. Marketers should consider the responsibility that comes with sophisticated production capabilities, ensuring that advertising quality reflects genuine product value rather than merely creating

misleading impressions. Simultaneously, consumers may benefit from awareness of how video presentation quality influences their neural responses and subsequent purchase decisions, potentially leading to more deliberate and informed purchasing behaviour.

7. Conclusion

This study demonstrates that EEG recordings can effectively distinguish between buy and not-buy decisions, with higher MAV and Shannon Entropy values consistently observed in buy decisions across all electrode sites and frequency bands. These findings indicate that purchase choices involve stronger and more complex brain activity than rejection decisions, highlighting the significant cognitive and emotional effort underlying consumer buying behaviour.

Critically, this research reveals a fundamental challenge in digital marketing: consumers' purchase decisions were predominantly influenced by video presentation quality rather than by actual product evaluation. The stark contrast between purchase rates for high-quality videos (82.9%) and poor-quality videos (8.6%) demonstrates this presentation-quality bias. This finding carries dual implications that warrant serious consideration.

First, genuinely high-quality products may be systematically overlooked or dismissed when presented through poor-quality videos. The reduced neural activation observed in such conditions suggests that inadequate presentation prevents proper cognitive engagement with the product itself, potentially causing consumers to miss valuable purchasing opportunities. This represents a market inefficiency where product merit fails to reach its intended audience due to presentation limitations. And more concerning from an ethical standpoint, inferior products marketed through professionally produced, high-quality videos may attract purchases based on presentation appeal rather than actual product merit. The elevated neural signatures observed during high-quality video viewing indicate that sophisticated presentation can trigger emotional and cognitive responses typically associated with genuine product interest—even when the underlying product may not justify such responses. This can lead to post-purchase dissatisfaction, economic loss, and eroded consumer trust when product reality diverges from advertising-induced expectations.

The findings provide valuable contributions to neuroscience, psychology, and marketing by demonstrating the potential of EEG features as predictors of purchase intentions. However, they also underscore an important cautionary message: that the power of video-based advertising to shape consumer decisions carries significant ethical responsibility. While effective video production represents legitimate marketing expertise, its overwhelming influence on purchase decisions as evidenced through distinct neural signatures suggests that current consumer decision-making processes may not adequately account for the distinction between presentation quality and product quality.

For marketing practitioners, these results highlight that neural activation intensity (MAV) and signal complexity (Shannon Entropy) reliably index purchase intent in this sample. These neurophysiological markers align with affective valuation theories where orbitofrontal and limbic engagement underlie rapid, presentation-driven purchase responses. Nonetheless, these conclusions remain provisional pending replication with larger and more diverse samples. There is a need for responsible advertising practices that align presentation quality with actual product value. For consumers, this research highlights the importance of developing awareness about how video presentation influences neural responses and subsequent purchase decisions, potentially enabling more deliberate evaluation strategies.

Future research should examine long-term consumer satisfaction and repeat purchase behaviour to assess whether presentation-driven purchases lead to sustained relationships or brand abandonment. Additionally, developing neural markers that distinguish genuine product appeal from presentation-induced attraction would be valuable. Research should also explore intervention strategies helping consumers evaluate product quality independent of presentation effects, while supporting policymakers in creating ethical standards for neuromarketing practices that balance consumer protection with legitimate marketing innovation.

Overall, this study contributes to neuromarketing science by demonstrating how video presentation quality shapes neural responses in consumer decision-making contexts. More importantly, it highlights the importance of marketing strategies that are both effective and ethically responsible, ensuring that sophisticated presentation techniques serve to inform and enhance consumer decisions rather than to mislead or manipulate them. As neuromarketing capabilities continue to advance, maintaining this balance between persuasive power and ethical responsibility will be essential for building sustainable consumer relationships and maintaining public trust in digital marketing practices.

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