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How to measure video-ads effectiveness: A multi-tools neuromarketing case study

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Abstract: Advances in state-of-the-art technologies and the rise of interdisciplinary sciences have transformed multiple aspects of human life. In recent years, among various disciplines, neuroscience and artificial intelligence (AI) have had the most profound impact on marketing, giving rise to emerging fields such as neuromarketing and intelligent marketing. Although numerous studies have been conducted in different areas of neuromarketing, two major shortcomings remain. First, due to limited interdisciplinary expertise among marketing professionals, most studies have been led by neuroscience researchers, with a predominant focus on neuroscience concepts. Second, because video analysis is inherently more complex than image analysis, relatively few studies have examined the effectiveness of video marketing within a neuromarketing framework. This exploratory-applied study, adopting a marketing-oriented perspective, proposes a practical method for assessing the effectiveness of video marketing using neuromarketing tools. While offering valuable practical insights for marketing researchers, it addresses the central question: *Can video marketing be reliably evaluated through neuromarketing techniques?* Primary data were collected using established neuroscience methods with EEG, fNIRS, and eye-tracking devices, and analyzed through artificial intelligence models in MATLAB. The findings demonstrate that neuromarketing tools can reliably measure the effectiveness of video advertisements before launching campaigns, thereby reducing unnecessary media expenditure and optimizing return on investment.

Keywords: *neuromarketing, video marketing, EEG, fNIRS, eye tracking, functional brain communications*

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1. INTRODUCTION

Mason Currey, in his well-known book *Daily Rituals: How Artists Work*, quotes the eminent psychologist William James (1842–1910): "The important thing is to make our nervous system our ally instead of our enemy, and the more we can let things happen automatically, the more we can use our higher powers to do real work" (Currey, 2013, p. 72). Over a century ago, James accurately recognized the unconscious mind's influence on decision-making, earning him recognition as a pioneer in cognitive and neural sciences. The functioning of the unconscious mind can be contrasted with conscious recognition (Zielonka, Szymanek, Dzik, Jakieła & Białek, 2024) and, in some contexts, regarded as complementary (Shiv & Fedorikhin, 1999). Despite the often complex classifications of mental functions, a specialized domain within neuroscience, the analysis of unconscious brain responses to stimuli, known as neuromarketing (Knutson, Rick, Wimmer, Prelec & Loewenstein, 2007), has recently gained prominence in marketing (Morin, 2011), particularly in areas such as product design (Morton, 2022), pricing strategy (Karmarkar, Shiv & Knutson, 2015), distribution channel planning (Ferraro, 2020), promotion, and advertising (De-Frutos-Arranz & Blásco-López, 2022; Kumar, 2015; Cheredniakova, Lobodenko & Lychagina, 2021). Neuromarketing, through the application of neuroscience tools and techniques (Ramsøy, 2019; Strieder, 2022), enables marketers to quantify aspects of consumer response that were previously assessed only qualitatively (Venkatraman, 2019; Venkatraman et al., 2015). Traditionally, Likert scales have been used to measure attitudes toward advertisements, offering a graded range between two thresholds (Guerrero, Colomer, Guàrdia, Xicola & Clotet, 2000). However, this method has notable limitations: it requires large samples for validation (Norman, 2010), often measures effectiveness only after campaign execution, thereby increasing the risk of ineffective video marketing (Thero, 2019), and is susceptible to respondent bias influenced by various factors (Sawatzky et al., 2024; Clemons, 2008). Neuroscience-based marketing tools not only address these limitations (Vozzi et al., 2021; Mauri, Rodighiero, Bazzan, Benedetto, Caldato & Armeno, 2018) but, when combined with artificial intelligence, can produce more valid and innovative models for understanding consumer behavior (Kusá & Beličková, 2023). Before 2020, during the rapid expansion of practical AI applications (Ali, Murray, Momin, Dwivedi & Malik, 2024), it was scarcely conceivable to design individualized behavioral models for specific marketing contexts.

Today, with the convergence of brain measurement technologies and AI, such modeling has become feasible (Okeleke, Ajiga, Folorunsho & Ezeigweneme, 2024). Beyond the tools themselves, the marketing environment has also evolved (Subramanian, 2017). Competition increasingly occurs in virtual rather than physical spaces (Nayyar, 2025), and forecasts suggest that the share of marketing budgets allocated to social media will continue to grow (Bondarenko, Kovalchuk, Rodionov, Miroshnik, Kitchenko & Franchuk, 2021). Social media marketing relies heavily on video content (Arantes, Figueiredo & Almeida, 2018), though the extent of this reliance varies across industries.

Despite its potential, the measurement of video marketing effectiveness at the intersection of neuroscience technologies, artificial intelligence, and social media remains underexplored, largely due to its novelty and complexity. For this reason, although a limited number of studies have attempted to examine the measurement and prediction of video marketing effectiveness, the true novelty of this paper lies in its employment of a unique combination of three neuroscience methods, electroencephalography (EEG), eye-tracking, and functional near-infrared spectroscopy (fNIRS), coupled with machine learning techniques as analytical tools to achieve a deeper and more quantitative understanding of video content effectiveness. This research seeks to answer the question: Can the effectiveness of video advertisements be measured prior to launching advertising campaigns and introducing them to the public, and before incurring significant marketing costs?

2. LITERATURE REVIEW

Video marketing, delivered through video advertisements, is increasingly recognized as one of the most effective and impactful tools in the modern marketing arsenal (Boman & Raijonkari, 2017). Researchers have examined numerous factors influencing its effectiveness. Among these, advertisement duration is widely regarded as a critical determinant (Krishnan & Sitaraman, 2013) and has been extensively studied, with many findings supporting the superior impact of shorter advertisements (Meng, Kou, Duan & Bie, 2024). However, considerable debate remains over the precise threshold distinguishing short from long videos (Wang, Wu, Rau & Gao, 2020). A particularly powerful synergy has emerged between video advertising and social media, which serves as a pervasive distribution platform (Lim, Ri, Egan & Biocca, 2015). Social media not only facilitates engaging ad consumption but also introduces a valuable feature: interactivity (García-Perdomo, 2024). The ability to enable two-way communication between audiences and interactive video advertisements has been shown in numerous studies to enhance advertising effectiveness (Moran, Muzellec & Johnson, 2020). Beyond these factors, a variety of additional elements influence video marketing outcomes. These can be broadly categorized into: (1) **content-related features** - such as sound and visual effects (Yang, Wang, Wang, Jiang & Li, 2025), appropriate color schemes (Zhu, 2024), background music (Lupa-Wójcik, 2022), compelling titles (Welch, Cho & Chang, 2010), and storytelling (Zatwarnicka-Madura & Nowacki, 2018); and (2) **platform-related features** - including interactive functionalities (Sundar, Kim & Gambino, 2017), alignment of content type with the target audience (Baker, 1997), ease of platform use, and the ability to display performance metrics such as likes and other engagement indicators. While some features may overlap categories, this classification provides a useful framework. Before the advent of neuromarketing techniques, a major challenge in video marketing was the lack of precise measurement tools (Boman & Raijonkari, 2017; Sakas, Giannakopoulos, Terzi, Kamperos & Kanellos, 2024).

Historically, effectiveness was assessed using platform-provided metrics such as views, likes, shares, and comments, both positive and negative (Pavlou & Stewart, 2000; Usmani, Ali, Imtiaz & Khan, 2019). While informative, these indicators have two major limitations: (1) they depend on post-campaign execution, meaning inefficiencies are detected too late for corrective action, potentially leading to substantial budget losses; and (2) they require very large sample sizes for accuracy (Eisend, 2015), making them time-consuming and costly. The integration of neuromarketing tools, such as electroencephalography, functional magnetic resonance imaging, and near-infrared spectroscopy, into video marketing offers a precise means of quantifying variables previously assessed only qualitatively (Harris, Ciorciari & Gountas, 2018; Alvino, Pavone, Abhishta & Robben, 2020). Although prior research has examined parameters such as visual and auditory stimuli, surprising or innovative elements (Yassin, 2023), and optimal video duration, no previous study has both predicted and measured the effectiveness of advertising videos through a comprehensive analysis of brain response differences to diverse advertisements. Addressing this gap forms the basis of the present research.

Table 1: Characteristics of the videos used

Video	Appearance frames per second	Appearance width*height	Duration second
1	24	640-360	47
2	30	640-360	88
3	24	640-360	61
4	25	640-360	61
5	25	1920-1080	50
6	25	1920-1080	20
7	25	640-352	48
8	25	1280-720	30
9	30	1280-720	90
10	25	640-360	31

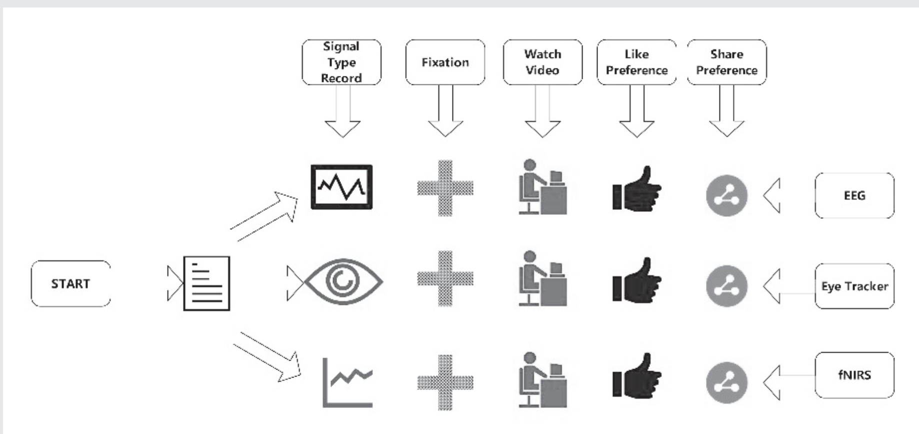
Source: Authors

3. RESEARCH METHODOLOGY

This study aims to address the question: Can video marketing—traditionally evaluated solely through social media engagement metrics such as likes, shares, and comments—be measured and quantified through the analysis of brain activity while viewers watch video advertisements? The primary objective is to introduce novel applications of neuroscience in marketing, essentially, neuromarketing for marketers. While numerous prior studies have documented the distinct and diverse functions of various brain regions, this research moves beyond a reductionist, activity-specific perspective. Instead, it adopts the paradigm that the brain, as an integrated system, may exhibit distinct and meaningful patterns of activity when exposed to attractive versus non-attractive advertising videos. Addressing the research question involves two key challenges: (1) determining how to differentiate between attractive and non-attractive advertisements, and (2) identifying the appropriate tools for measuring viewers' brain activity. To address the first challenge, a two-phase methodology was implemented. In Phase 1, 24 marketing and advertising specialists were asked to identify at least one attractive and one non-attractive video, under the condition that they would be willing to like and share the attractive video on their preferred social media platforms, but would neither like nor share the non-attractive video. In Phase 2, these specialists categorized the collected videos into two groups: attractive and non-attractive. Based on a strong consensus, over 90% agreement, seven videos were classified as the most attractive and three as the least attractive, and these were selected for testing. The advertising videos used in this research are available at *video-marketing.blogsky.com*, and their characteristics are presented in Table 1.

In response to the second challenge, we used three common tools in cognitive sciences for measuring brain activity asynchronously but with identical tasks. The measurement and signal recording stages were conducted according to the pipeline shown in Figure 1.

Figure 1: Signal measurement pipeline



Source: Authors

The cognitive tasks, designed and executed using PsychoPy version 2024.1.1, were presented on all three measurement tools via a 21-inch monitor (1080 × 1920 pixels) with a 60 Hz refresh rate, positioned 70 cm from the participants' eyes. The sample size for this study was determined independently for each tool. Before the start of the experiment, participants were trained to indicate their inclination to like and share after viewing each of the 10 advertising videos (presented in random order) by pressing the corresponding buttons. To establish a baseline for brain activity in a neutral state, a neutral gray image was displayed for 90 seconds at the beginning of the task. Additionally, to control for potential cognitive halo effects from preceding videos, a neutral gray image was shown for 5 seconds before each video. During these intervals, participants were instructed to maintain a calm focus on the center of the screen.

An important practical consideration in neuromarketing research is determining the sample size required to ensure reliable measurement of advertising processing. In current practice, sample sizes between 20 and 30 participants are common in neuromarketing ad-testing studies, although the exact number depends on the specific variables being measured. Furthermore, the optimal sample size may also vary according to the study's purpose. For example, a sample of approximately 30 participants, each viewing one commercial, may be sufficient to reliably estimate the average performance of an advertisement (van Diepen, Boksem & Smidts, 2024). One reason neuromarketing studies often employ smaller sample sizes than conventional marketing research is the substantial increase in the volume of data collected per second (i.e., sampling frequency). For instance, given the sampling rates of tools such as EEG, fNIRS, and eye-trackers, and assuming a 616-second test duration, approximately 308,000, 1,200, and 60,000 data points per participant were collected, respectively. This high data density significantly enhances the applicability of neuromarketing tools, particularly for deep learning computations, which require large datasets. Moreover, in this study, each participant was exposed to 10 video advertisements. Considering the number of participants, this resulted in 220, 140, and 310 recorded video-ad samples for EEG, fNIRS, and eye-tracking, respectively. Such data volumes are well-suited for machine learning–based analyses. The choice of sampling frequency in neuromarketing instruments depends on multiple factors, including the research objective, device accuracy, required measurement precision, and the availability of computational resources capable of processing large-scale, complex datasets. In the present study, sampling frequencies were selected based on the precision of the available measurement instruments and informed by findings from prior research.

3.1. Electroencephalography (EEG)

To measure cortical electrical activity, an electroencephalography (EEG) device was employed (Müller-Putz, Riedl & Wriessnegger, 2015). The sample for this phase comprised male and female students from Shiraz University of Applied Sciences (Iran), recruited through an initial screening process conducted via social media. Eligibility criteria required that participants have no history of substance addiction, psychological disorders, or pregnancy (n = 22; males = 12; mean age = 32; variance = 9). The experimental procedure commenced only after participants had reviewed and signed the informed consent form. Before the main task, an initial test trial was administered to familiarize them with the procedure. The performance data for participants in this phase are presented in Table 2.

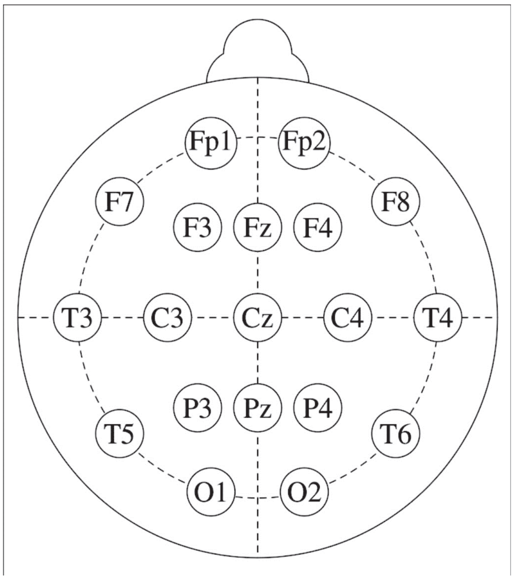
A 19-channel electroencephalography (EEG) device manufactured by Mitsar was used, employing the international 10–20 electrode placement system. Silver electrodes with a silver chloride coating were utilized, with a sampling frequency of 500 Hz. The average signals from both ears served as reference points, and the Fpz electrode was designated as the ground. The electrode nomenclature and arrangement are illustrated in Figure 2.

Table 2: Sample performance in the EEG test

Gender	No.	No. of like -	No. of like +	Like sum	No. of share-	No. of share+	Share sum
Female	10	49	44	93	34	59	93
Male	12	50	52	102	29	73	102
Sum		99	96	195	124	72	195

Source: Authors

Figure 2: Electrode naming in EEG



Source: Authors

3.2. Eye Tracking

To measure eye behavior in response to stimuli, an Optera-brand eye tracker (Massaro et al., 2012) with a sampling frequency of 120 Hz and 9-point calibration was employed. The sample for this phase comprised male and female students from Shiraz University of Applied Sciences (Iran), recruited through an initial screening conducted via social media. Eligibility criteria required that participants have no history of substance addiction, psychological disorders, or pregnancy (n = 31; males = 15; mean age = 28.11; variance = 4.93). The experimental procedure commenced only after participants had reviewed and signed the informed consent form. Before the main task, an initial test trial was administered to familiarize them with the procedure. The performance data for participants in this phase are presented in Table 3.

3.3. Near-Infrared Spectroscopy (fNIRS)

The final measurement in this study employed near-infrared spectroscopy (fNIRS) to measure and compare the intensity of oxygenated and deoxygenated blood flow in the prefrontal cortex (Crespi, 2007). Data were collected using the Oxymap version 3 system, operating at a sampling frequency of 10 Hz and wavelengths ranging from 730 to 850 nanometers. The setup consisted of two light sources and six detectors, resulting in a total of six channels, with each detector positioned 2.5 cm from its corresponding light source. All components were housed in a flexible black silicone cover. To minimize noise, the forehead area designated for sensor placement was cleaned with 70% alcohol, and an elastic headband was used to secure the electrodes, fully covering them. Additionally, laboratory lights were switched off for the duration of the task. The arrangement of the light sources and detectors is illustrated in Figure 3.

Figure 3: Light sources and detectors arrangement (source & detector dimension: 2.5 cm)

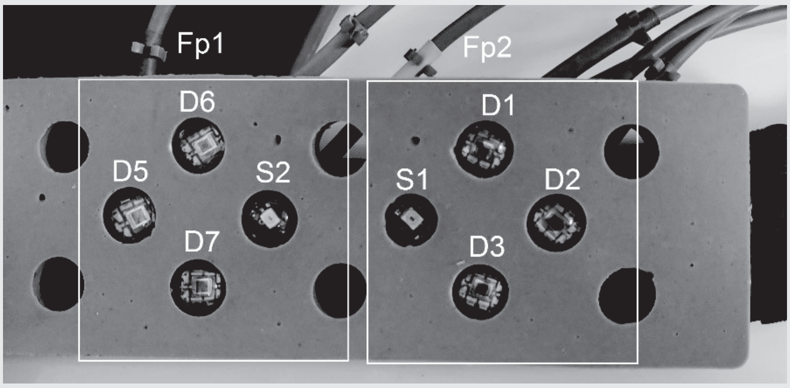


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Table 3: Sample performance in the Eye Tracker test

Gender	Count	No. of like +	No. of like -	Like sum	No. of share+	No. of share-	Share sum
Female	16	85	75	160	95	65	160
Male	15	81	69	150	93	57	160
Sum		166	144	310	188	122	310

Source: Authors

Table 4: Sample performance in the fNIRS test

Gender	Count	No. of like +	No. of like -	Like sum	No. of share+	No. of share-	Share sum
Female	7	40	30	79	33	37	68
Male	7	35	34	69	21	48	69
Sum		75	64	139	54	85	137

Source: Authors

The sample for this phase of the experiment consisted of male and female students from Shiraz University of Applied Sciences (Iran), selected through an initial screening via social media, ensuring they had no history of addiction, psychological disorders, or pregnancy (n=14, male=7, ave.=20.7, var.=1.8), and the initiation of the experimental process was contingent upon acceptance and confirmation of the items presented in the informed consent form before the experiment, and an initial test task was displayed to them. The performance of the samples in this phase of the experiment is shown in Table 4.

4. ANALYSIS AND RESULTS

Data analysis was performed using MATLAB Beta 2023 in conjunction with the EEGLAB 2023 toolbox. For the EEG measurements, raw data were first preprocessed by applying a 0.5–35 Hz bandpass filter. Signal noise was then removed using the Artifact Subspace Reconstruction (ASR) plugin and Independent Component Analysis (ICA). Normalized power values from the alpha, beta, and theta frequency bands, along with the beta-to-alpha ratio, were extracted as features for classification. A five-fold cross-validation procedure with a 10% test split was employed for model evaluation.

The algorithms k-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision trees, and Neural Networks (NN) were selected for this study to capitalize on their complementary strengths. KNN provides a straightforward baseline for instance-based similarity assessment, SVM offers robust classification performance in high-dimensional spaces, and NN is capable of modeling complex nonlinear relationships. The combined application of these algorithms was intended to triangulate results and enhance the analytical robustness of the neuromarketing data analysis. The random chance levels for the dataset are presented in Table 5, and the classification results obtained at this stage are shown in Table 6.

Table 5: Chance level in the EEG test

Classification	Feature	Count	Chance level
Like	Yes	96	49%
	No	99	51%
Share	Yes	132	68%
	No	63	32%

Source: Authors

Eye-tracking systems record multiple parameters of ocular activity during experimental tasks. The specific data collected-often differing between eyes depending on device precision-serve a variety of purposes across research domains. For example, gaze point (Gheorghe Purcărea & Gheorghe, 2023) and saccadic movements (dos Santos, de Oliveira, Rocha & Giraldi, 2015) have been shown to predict certain unconscious viewer states, while fixation metrics have been validated in numerous studies (Gheorghe et al., 2023). In the present study, dynamic video stimuli were used instead of static images. Because the number of fixations at any given moment during video playback can vary

Table 6: Measurement results in the EEG test

Feature	Action	Tree	SVM	kNN	NN	Max
Beta/(alpha+theta) power ratio	Like	75.6	69.2	68.2	67.6	75.6
	Share	77.3	83.5	82.4	76.7	83.5
Alpha power	Like	59.1	65.3	64.8	56.2	65.3
	Share	59.1	67.6	67.6	61.9	67.6
Beta power	Like	49.2	51.3	49.2	51.3	51.3
	Share	66.2	67.7	67.7	61.0	67.7
Theta power	Like	48.9	58.5	56.3	56.8	58.5
	Share	65.3	68.2	67.6	56.2	68.2

Source: Authors

Table 7: Chance level in the Eye Tracker test

Classification	Feature	Count	Chance level
Like	Yes	166	54%
	No	144	46%
Share	Yes	188	60%
	No	122	40%

Source: Authors

Table 8: Measurement results in the Eye Tracker test

Feature	Action	Tree	SVM	kNN	NN	Max
Mean number of eye fixations per unit time	Like	81.9%	78.4%	75.2%	78.7%	81.9%
	Share	72.3%	71.6%	68.7%	64.2%	72.3%

Source: Authors

among participants, a composite measure, defined as the mean number of fixations per unit time for each video, was calculated and used as the primary fixation-based index. The chance level of the data and the corresponding results are presented in Tables 7 and 8.

In the section measuring vital signals using the fNIRS tool, the average signal range for oxygenated and deoxygenated blood (HBO and HBR) for each channel (S1D1, S1D2, S1D3, S2D5, S2D6, S2D7) was introduced as the main feature. Cross-validation 5 5-fold with a 10% test was used for data classification. The random chance levels of the data and the results obtained are shown in Tables 9 and 10.

Signal preprocessing in this phase of the study was conducted using the Wavelet transform across 10 decomposition levels. For the final analysis, the cognitive frequency range was set between 0 and 79 millihertz. To remove the DC component, the coefficients at level 10 were set to zero, and to eliminate high-frequency noise, the coefficients from levels one through five were discarded. These preprocessing steps are illustrated in Figure 4.

5. FINDINGS

A consolidated summary of the results obtained from the three measurement modalities, Electroencephalography (EEG), Eye Tracking, and functional Near-Infrared Spectroscopy (fNIRS), is presented in Table 11.

The EEG tool predicted the effectiveness of video advertisements in eliciting "likes" with an accuracy of 75.6%, and the effectiveness in eliciting the willingness to share with an accuracy of 83.5%, using the beta power–to– (alpha + theta) power ratio as the classification feature. The eye tracker achieved accuracies of 81.9% and 72.3% for predicting likes and shares, respectively, based on the average number of eye fixations per unit time. Finally, the functional near-infrared spectroscopy (fNIRS) tool achieved accuracies of 64.7% for likes and 61.5% for shares. Comparing these accuracies with the respective chance levels shows that the differences for likes were 24.6% (EEG), 27.9% (eye tracker), and 8.7% (fNIRS). For shares, the differences were 15.5% (EEG), 12.3% (eye tracker),

Table 9: Chance level in the fNIRS test

Classification	Feature	Count	Chance level
Like	Yes	75	54%
	No	64	56%
Share	Yes	54	39%
	No	85	61%

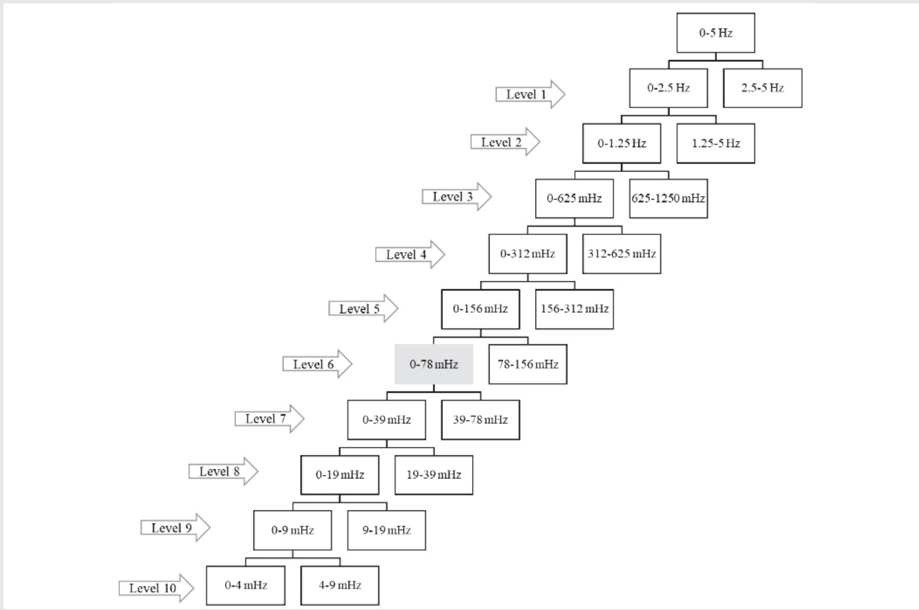
Source: Authors

Table 10: Measurement results in the fNIRS test

Feature	Action	Tree	SVM	kNN	NN	Max
Mean amplitude of blood flow signal	Like	56.8%	64.7%	68%	53.2%	68%
	Share	54%	61.2%	61.2%	51.8%	61.2%

Source: Authors

Figure 4: Noise removal using the Wavelet method



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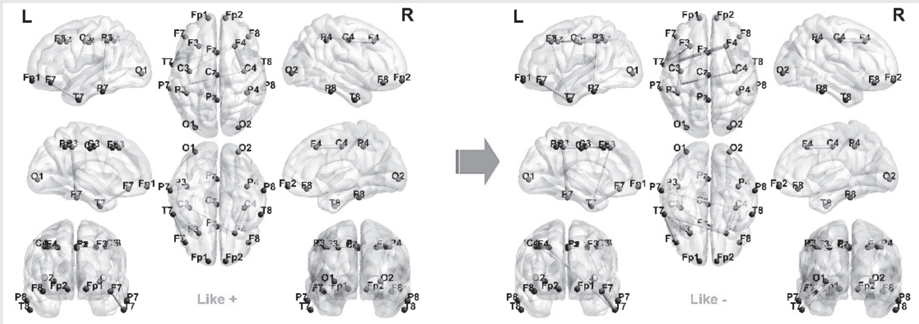
and 1.5% (fNIRS). Notably, the largest improvement over chance in predicting likes was achieved by the eye tracker (81.9%), whereas for shares, the EEG tool yielded the highest accuracy (83.5%). Analysis of EEG signal data also revealed an important finding in neuroscience: functional connectivity, which reflects the degree of coordinated activity between different brain regions during cognitive tasks. Functional connectivity was assessed by computing pairwise correlations between signals from all electrodes ($19^2 = 361$ connections), removing half due to redundancy, and excluding the main diagonal (unity values). Significant connectivity correlations ($p < 0.001$, $Q < 0.7$) indicated a clear pattern: the brain exhibited greater interhemispheric connectivity when participants decided not to like or share advertising videos, suggesting increased neural coordination during these decisions. This difference is illustrated in Figures 5 and 6.

Table 11: Summary of measurements in the EEG, Eye Tracker, and fNIRS tests

Modality	Variable	Classifier	Peak accuracy	Maximum chance level	Classification
EEG	Like	Theta power	58.50%	51%	SVM
	Share		68.20%	68%	SVM
	Like	Alpha power	65.30%	51%	SVM
	Share		67.60%	68%	SVM-kNN
	Like	Beta power	51.30%	51%	NN-kNN
	Share		67.70%	68%	SVM-kNN
	Like	Mean spectral power of all bands	54.50%	51%	SVM-kNN
	Share		67.60%	68%	SVM-kNN
	Like	Mean spectral power of all bands	54%	51%	SVM
	Share		68.20%	68%	NN
	Like	Beta/(alpha+theta) power ratio	75.60%	51%	Tree
	Share		83.50%	68%	SVM
Eye Tracker	Like	Mean number of eye fixations per unit time	81.90%	54%	Tree
	Share		72.30%	60%	Tree
fNIRS	Like	Mean amplitude of blood flow signal	64.70%	56%	SVN
	Share		61.50%	63%	SVM

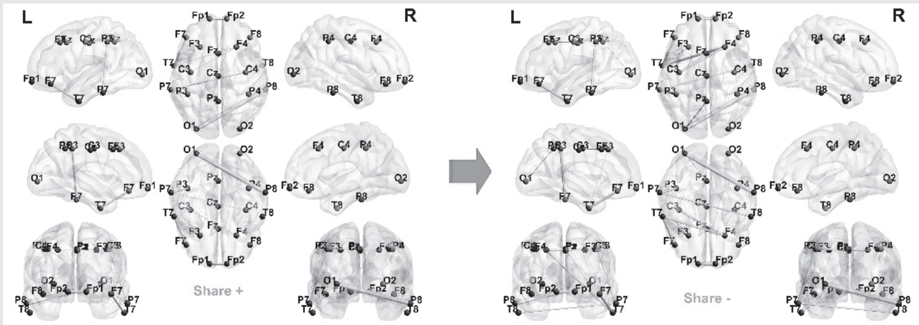
Source: Authors

Figure 5: Comparison of brain activity differences for positive and negative liked videos



Source: Authors

Figure 6: Comparison of brain activity differences for positive and negative shared videos



Source: Authors

6. CONCLUSION

Neural network (NN) models are often regarded as "black boxes," making their interpretation challenging. They require substantial preprocessing, including data normalization and feature engineering, and are highly effective for high-dimensional datasets, such as EEG and fNIRS signals, that contain numerous features and exhibit complex nonlinear relationships. Although they demand large training datasets to prevent overfitting, NNs are well-suited for large-scale and complex data, including multimedia inputs. Decision Trees are highly interpretable and transparent, with decision rules that are easily understood. They require minimal preprocessing and can operate directly on raw data; however, they may be prone to overfitting in high-dimensional settings, necessitating parameter tuning (e.g., tree depth). Support Vector Machines (SVMs) offer moderate interpretability, though complexity increases when kernel functions are employed. They require data normalization for optimal performance and can perform well with small datasets, but computational costs may be high for large datasets. K-Nearest Neighbors (KNN) models are relatively interpretable, as decisions are based on the nearest neighbors. However, they require data normalization due to their sensitivity to distance metrics, and their performance may degrade in high-dimensional spaces because of the "curse of dimensionality". They are best suited for low-dimensional datasets with limited complexity. In neuromarketing, data collected from EEG, eye-tracking, and fNIRS devices typically exhibit high dimensionality, complexity, and large data volumes. Considering these characteristics and our findings, SVMs and Decision Trees appear to be the most suitable choices due to their feature extraction capabilities and strong performance with such datasets.

6.1. Implications

This study carries significant theoretical and practical implications for the field of neuromarketing. Theoretically, it offers empirical validation for a framework that moves beyond traditional metrics to capture the unconscious drivers of consumer engagement with video advertising. By triangulating data from EEG, eye-tracking, and fNIRS, our findings challenge overly simplistic models of advertisement reception and contribute to a more nuanced, neuromarketing-grounded theory of how creative clips are encoded in attention processes. Practically, this research provides marketers with a foundation for pre-testing and optimizing advertisements with greater predictive accuracy. The identified biomarkers of effectiveness, such as the beta/(alpha + theta) power ratio, eye fixation patterns, and blood flow measures, serve as tangible diagnostic tools for refining content before launch, thereby reducing wasted media spend and enhancing return on investment (ROI). Ultimately, this work bridges the gap between neuroscience theory and marketing practice, demonstrating how a multi-tool approach can yield deeper insights and produce more compelling advertising outcomes.

6.2. Limitations and future research

This study faced several limitations. First, it employed only 10 advertising videos to assess their impact on viewers; increasing the number of advertisements could yield more robust and generalizable results. Second, the videos encompassed a wide range of domains, from industry to services, suggesting that future research should focus on advertisements within a single domain to control for content-related variability. Third, given the present study's focus on short-form videos, it is recommended that separate investigations be conducted on other formats, particularly long-form video advertisements. Finally, future studies are encouraged to employ connectivity and synchronization technologies to record viewers' brain signals while they watch advertising videos simultaneously across all three measurement tools, enabling integrated analysis of the results.

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ETHICS STATEMENT

This study was approved by the Ethics Committee of Islamic Azad University – Bandar Abbas Branch (Approval No: IR.IAU.BA.REC.1402.093).

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Apstrakt

Kako meriti efektivnost video oglasa: studija slučaja sa upotrebom više neuromarketinških alata

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Napredak u najsavremenijim tehnologijama i uspon interdisciplinarnih nauka transformisali su brojne aspekte ljudskog života. Poslednjih godina, među različitim disciplinama, neuronauka i veštačka inteligencija (AI) imale su najdublji uticaj na marketing, dajući podsticaj razvoju novih oblasti kao što su neuromarketing i inteligentni marketing. Iako je sproveden veliki broj istraživanja u različitim oblastima neuromarketinga, i dalje postoje dva glavna nedostatka. Prvo, zbog ograničenog interdisciplinarnog znanja među stručnjacima za marketing, većinu studija vodili su istraživači iz oblasti neuronauke, sa pretežnim fokusom na koncepte iz te oblasti. Drugo, pošto je analiza video materijala suštinski složenija od analize slika, relativno je mali broj studija ispitao efektivnost video marketinga u okviru neuromarketinškog pristupa. Ova eksplorativno–primenjena studija, koja polazi iz marketinške perspektive, predlaže praktičan metod za procenu efektivnostii video marketinga pomoću neuromarketinških alata. Dok nudi vredne praktične uvide istraživačima u marketingu, ona odgovara na ključno pitanje: može li se video marketing pouzdano evaluirati kroz neuromarketinške tehnike? Primarni podaci prikupljeni su korišćenjem etabliranih metoda neuronauke, EEG, fNIRS i uređaja za praćenje pokreta očiju, a analizirani su putem modela veštačke inteligencije u MATLAB-u. Rezultati pokazuju da neuromarketinški alati mogu pouzdano meriti efektivnost video oglasa pre lansiranja kampanja, čime se smanjuju nepotrebni medijski troškovi i optimizuje povrat na investiciju.

Ključne reči: *neuromarketing, video marketing, EEG, fNIRS, praćenje pogleda, funkcionalne moždane komunikacije*

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