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Integrating cognitive signals and machine learning to predict purchasing intent through algorithmic neural marketing

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Abstract:

Neuromarketing is an emerging field that combines neuroscience and marketing to better understand the factors influencing consumer decisions. Consumer purchasing behavior has long been a focus for marketers seeking to create compelling advertisements and increase engagement. It relies on objective tools to identify consumer responses through physiological and neurological measurements. This research aims to apply brain science to marketing research, specifically using electroencephalography (EEG) and eye-tracking to determine whether a consumer will purchase a product. "The association between physiological reactions and self-reported purchase intention to marketing cues was investigated by analysing physiological data from 210 participants. The link between the independent factors (product category and advertisement type) and the dependent variable (purchase intention) was investigated using descriptive, correlational, and regression methods. The results confirm that knowledge of neuromarketing significantly boosts practicality ($\beta = 0.726$, $p < 0.001$), which enhances marketing efforts ($\beta = 0.611$, $p < 0.001$) and social media communication effectiveness ($\beta = 0.712$, $p < 0.001$)." The study found that both frontal lobe alpha and beta wave activity (neural reactivity) and fixation duration and number of fixations (visual attention) were strong predictors of purchase intention, with fixation duration being the strongest predictor. Results suggest that emotional advertising elicited greater purchase intention than informational advertising, with the effects of emotion moderated by product category. This research presents evidence for a model that uses EEG and eye-tracking in conjunction to develop insights into consumer behavior. The paper provides an immediately applicable framework for marketers trying to revamp their advertising strategy.

Keywords: Algorithmic neural marketing, predicting purchase structure, cognitive signals, machine learning.

Introduction

Understanding consumer buying intentions is crucial for companies trying to maximize the return on their advertising investment in a highly competitive environment. Because of Buying intention: the motivation of a consumer to select and buy; moreover, it is not only cognitive processes that affect it, but also emotional ones, as well as attentional ones. In old times, studies of consumer resonance and behavior prediction were based on questionnaires, focus groups, and other marketing research methods. While these methods provide a broader view of the issue, they also come with limitations, as they rely on self-reporting data. With reasons like social bias, memory inaccuracy, self-unawareness, and more, respondents do not always state/ express their opinions or what they would do; there is a difference between wanting to act and the actual behavior, i.e., purchase behavior. As a result, conventional research methodologies are unable to disclose the intricate psychodynamic and subconscious components influencing consumer decision-making. As a result, the outcomes

generated could be partial or less trustworthy to marketers. Neuromarketing is altering the way we address these limits by using findings and techniques derived from brain research. (Iyappan & Baby, 2025)

In contrast to the traditional method, neuromarketing allows for real-time recording of physiological and neural responses to marketing stimuli. Thus, it can achieve very precise measurements of attention, emotional effects, and memory. In general, it is important to note that the up-to-date techniques used in neuromarketing are EEG (electroencephalography) and eye-tracking. EEG shows source distributions of brain activity, so you can measure cognitive load and detect emotional involvement, even reasons (with limited applications) or neurological connections with decision-making. Similarly, higher frontal alpha wave activity is usually indicative of positive emotions and/or predisposition to compliance.

"On the other hand, beta wave activity is strongly associated with cognitive arousal and attentional focus, both of which are critical for the development of purchase intention. Conversely, eye-tracking makes it possible to create a picture of people's visual attention patterns, including gaze and fixation time". Consumer behavior insights have always been a major driver of product development, given the rapidly changing consumer needs. Current trends, competitor pricing, product evaluations, sales, and marketing are among the most important factors driving the consumer world today. Despite the limited information available regarding the future fluctuations of these factors,

Our research offers the following contributions: By investigating website data and applying advanced predictive models, we provide actionable insights into consumer behavior and purchase intention. These findings empower companies to make more informed decisions, refine their marketing strategies, and gain a competitive edge in the ever-evolving marketplace.

1. We investigate and demonstrate the feasibility of combining deep learning architectures with tree-based machine learning algorithms to predict the next logical product purchase at the consumer level.
2. We present model performance results across a range of hyperparameter settings.
3. We use stacked generalization, combining predictions from different models through a new integration method.
4. We design an algorithm to maximize each consumer's purchase probability.

LITERATURE REVIEW

Neuromarketing

Neuromarketing investigates neural and physiological responses to marketing stimuli, including cognitive processing, affective engagement, and attention capture. Purchase intention has been demonstrated to be influenced by emotional arousal, memory encoding, and the duration of eye fixation. (Bruun, 2021) Neuromarketing studies can measure these. Neuromarketing research indicates that neurological studies show consumers often make intuitive, emotion-driven decisions before justifying their purchases. By understanding these unconscious instincts, marketers can create strategies that not only align with but also directly counter the emotional and cognitive processes that drive consumer purchasing decisions. Put another way, given the knowledge of neuromarketing learned over time, neural network algorithms may be applied to model consumer behavior. Data from neuroscience, psychology, and marketing are assembled to understand the brain's response to various advertising stimuli. (Phutela et al., 2022) The goal is to gain a better understanding of the consumer's buying journey. In addition, functional magnetic resonance imaging (fMRI), electroencephalography (EEG), eye-tracking, and biometrics can be used to measure neural activity, pupil shape, and physiological responses, respectively. The domain of neuromarketing is divided into three aspects: the analysis of emotional responses (N1comportam); the mechanisms involved in goal-oriented decision-making processes (N1goal); and the command over technological tools, such as fMRI and EEGs, which are categorized as skills within meta-cognitive knowledge (N1tech). These subdimensions serve as a foundation for effectively applying neuromarketing to real-

world strategies. It is also necessary to understand how different stimuli elicit emotional responses in consumers (NAPP triggers) and to identify which parts of an advertisement or website capture attention when applying neuromarketing. In this way, neuromarketing provides access to hidden psychological processes. Some important measures are: (Jain, 2025; T¸ onis et al., 2026)
1. Frontal alpha wave asymmetry on electroencephalography (EEG) Approach/reverse motivation, with greater activity in the left prefrontal cortex indicating positive attraction and purchase intention
2. Fixation and rapid eye movements: Visual attention and product prominence are measured; longer eye fixation predicts a higher probability of selection.
3. Galvanic skin response (GSR): Indicates physiological activity, which modifies the level of emotional experience.

The results of Kaponis et al. (2025) confirm the superiority of multimodal over single-modal neuromarketing measures in predicting actual choice. But the high costs and lack of standardization have prevented this technology from being incorporated into real-time operating systems. The future is in miniaturized wireless sensors (LING et al., 2019) that can be embedded in shopping carts or smart shelves. A small example of it is the book titled Neuromarketing and Artificial Intelligence: Unlock consumers' minds with technology, which provides a basic outline of how we can use AI to decode neural patterns. However, it does not offer a loop-loop retail model.

“Two key techniques in neuromarketing are electroencephalography (EEG) and eye-tracking. EEG records electrical signals from the brain using electrodes placed on a subject's scalp, which may indicate mental effort, emotional involvement, and willingness to buy in. For instance, beta wave activity is associated with higher attention and alertness, whereas frontal alpha asymmetry is linked to positive mood and buy-in motivation.” In contrast, eye-tracking provides data on a person's visual attention (Nozari, 2025), including the duration and frequency of eye fixations and gaze paths, helping identify which parts of an advertisement or product capture a consumer's attention. EEG and eye-tracking data can be combined to capture a multidimensional picture of where consumers look and how they respond in marketing settings, enabling predictive tracking of purchasing behavior. The importance of knowing what consumers want to buy has risen rapidly in recent years due to the advent of digital platforms, online shopping, and multi-channel marketing strategies. Ads not only compete for consumers' attention but also aim to achieve engagement in a matter of seconds. This has become simple to comprehend in the context of how a component of an advertisement captures, emphasizes an emotion, and leads to a diverse array of choices. Traditional self-reported measures may overlook the majority of these subliminal influences, as previous research has demonstrated that neurological and physiological modifications occur in consumers prior to their conscious awareness of their decision. Emotional advertisements have been discovered to elicit more robust neural and attentional responses, which, in turn, increases the probability of purchase in comparison to purely informational advertisements.

Additionally, products that consumers repeatedly examine or pay more visual attention to are more likely to be purchased, underscoring the importance of attention in the effectiveness of marketing. Additionally, despite the substantial evidence that supports the use of neuromarketing in marketing practices, there is still a need for studies that integrate EEG measurements and eye-tracking with comprehensive statistical analyses across various product categories and types of advertising. (Phadtare, 2026) Neuromarketing techniques primarily involve the use of MRI machines. Consumers are placed inside these machines (with their consent, of course), and their brains are studied for purely commercial (not medical) purposes. These machines measure the flow of brain activity. (Mohammed & Al-Jubouri, 2022)

Blood flow to the brain reveals movements in different brain regions. This allows for the study of brain regions affected by specific advertisements, brands, or scents. All recorded effects on the consumer's brain during the

experiment are then analyzed to reach specific conclusions. Neuromarketing strategies can be categorized into two groups: those involving intrabrain activity and those involving extra brain activity. These categories are supported by evidence from both neuroimaging and non-neuroimaging approaches, as reported in a recent study referencing previous research (Varón, 2024). To avoid complicating the learning of neuromarketing techniques, we will discuss current practices that combine neuroscience and psychology to explain consumer motivations for shopping. Non-invasive neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), are widely used in the communications field.

Neuromarketing Techniques and Tools

Scientists have made significant strides in using neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and eye-tracking, to enhance marketers' understanding of the unconscious factors influencing consumer choices (Goncalves et al., 2024). Research has shown that fMRI is more effective than traditional methods in predicting customer choices, indicating a fundamental shift in how consumer research is conducted. These technologies have played a pivotal role in investigating neural responses to advertising and branding. They demonstrated that specific stimuli activated brain regions associated with emotionally positive information about a brand, enough to make customers remain loyal and engaged with that brand (Morin, 2011). In addition, neuromarketing research has led to the emergence of personalized marketing, in which, based on neural data generated by different consumers and their emotional reactions to specific messages, targeted messages can be tailored to be more convincing for certain groups (Marketty 2026). Byrne et al. (2022) further explain variations in global adoption by country, reflecting localized market dynamics and the pace of technology enablement in determining adoption rates for certain neuromarketing solutions, as analyzed in previous studies (Xu & Liu, 2022).

Electroencephalography (EEG) Analysis: Electroencephalography (EEG) is a technique for recording the electrical activity of the brain. Although EEG is a relatively old technique, it remains a suitable method for measuring electrical field changes in specific brain regions (Madanchian, 2024). EEG is a brain examination that captures electrical activity on the scalp. Electrodes affixed to the cranium can detect minute fluctuations in electrical activity. We employ EEG systems with 16 and 32 channels. The electrical activity of the brain is captured by a computer and displayed on a screen or on paper as waves. Our proprietary software analyzes the captured EEG data.
High-Definition EEG (HD EEG): This modernized version of EEG can obtain highly precise data on brain activity while the user is subjected to a specific stimulus. This EEG system can analyze brain signals with high precision to identify the source of activity and has 256 channels. Additionally, synthesized data will enable us to produce detailed thermal maps of brain processes for inclusion in the final report.

Galvanic Cutaneous Response (GCR): The galvanic cutaneous response, also known as skin conductivity, is a method used to evaluate electrical conduction and skin temperature based on the water content of the skin. Skin conductivity is commonly used in lie-detection methods to measure physiological and psychological arousal. Pulse, a galvanic cutaneous response, is also used by measuring fluctuations in pulse rate to indicate the extent of arousal or tension an individual experiences in response to stimuli. (SONG et al., 2025)

Eye Movement Tracking: This technology monitors eye position when the eye changes focus to a visual stimulus. In product design research and software design, eye-tracking technology is used in neuromarketing. Tracking a pupil with a camera is the gold standard for eye-pose estimation. We use software and hardware designed to track the user's eye movements. There is a wide range of neuromarketing tools, such as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), steady-state topography (SST), etc., that you can use. Eye tracking, cutaneous conductance measurement, facial expression coding,

electromyography (EMG) of facial muscles, and cognitive analysis cannot avoid the reconstruction of brain activity. Cognitive analysis uses data from multiple channels, such as electroencephalogram (EEG), galvanic skin response (GSR), and eye movement tracking, to provide a holistic view of an individual's reaction to stimuli. In doing so, we know that our biometric data will be read correctly each time. (Kumar & Singh, 2015)

Cognitive Signals and Machine Learning for Predicting Purchase Intentions

To predict what consumers will do and decide in the future, forecasting their behavior requires a toolbox of methods and strategies. Historical data analysis is one of the most prevalent strategies for forecasting these behavioral tendencies. You may learn a lot about buying habits, product preferences, trends, and how people will act in the future by looking at data on their previous actions. According to Kim and Ko (2012), machine learning algorithms can be used to sift through mountains of data to uncover intricate patterns, build models to forecast future actions using only past data, and more. Customers can be better segmented by shared traits, enabling more precise predictions of behavior. (Chaoyev, 2024) It may be possible to tailor marketing strategies and services to each segment, taking into account their tastes and trends. Surveys and client feedback are a few other useful methods of direct data collection. The most effective way to predict customer behavior is to ask them. They are commonly used; Malik and Luthra (2023) point out that sentiment analysis tools can enhance this approach. This means the behaviour of people purchasing is also influenced, either way, by the product or brand. Recommendation Models (Al-Jubouri & Mohammed, 2022) are widely used to study user behavior and the content or goods a person may be interested in, to enhance customer experience and satisfaction. Let us not forget that factors such as the time of year, news headlines, market trends, and economic developments play a huge role in how consumers make their decisions. He said that, in terms of geographic location, it can often be easier to predict consumer behavior. Geospatial data analytics will help you identify regional behavioral patterns, which can help devise strategies for each region. As a rule of thumb, it is often best to mix-and-match approaches and data sources to create predictions about customer behavior. Decision trees have demonstrated the ability to predict consumer expenditure (Natalia and Sulistiadi, 2020 publication). Companies can boost sales and consumer targeting by leveraging the model's predictive power when they scale the data. Research indicates that using the decision tree approach and optimizing for page value can yield purchase predictions with up to 90% accuracy. By employing this strategy, organizations can improve the user experience and increase marketing results. Boosting algorithms (such as Gradient Boosting & XGBoost) have been used to predict the likelihood of a consumer purchasing based on their past behavior (Oandasan, 2022). According to a study, XGBoost performed better than other competitors (ML models), and it is worth learning from data how many consumers are needed to increase sales. According to Phutela et al., "the proposed model with the highest accuracy of 93.50% is XGBoost followed by K-Nearest Neighbor (KNN), Logistic Regression and Random Forest." (2022). Their work uses key metrics such as bounce rate and offers a solution to cart abandonment that delivers results quickly and increases income.

For, decision tree models and rule-based models predicted neural shopping behavior. Keywords: classification, PART model, Random Tree Model. Fused yourself with the environment from afar. Random Forest of The Servlet: The random tree model outperformed the PART model, achieving 79.50% accuracy compared to 77.50% (Table 1). The insights obtained from these models can be integrated into a company's marketing strategy. But, as the dataset scales up in size, the C4. Abstract: We explore the accuracy and structural properties of a Bayesian algorithm, the 5-decision tree, and its clustering variant. Their results show that, in this context, decision trees achieve the highest accuracy among other methods for predicting consumer behavior. Compared with the ordinary Bayesian algorithm, C4. It is outperformed by the 5-

decision tree approach in both accuracy and structure, especially when applied to larger datasets (Park et al., 2021; Aboudi Nehme, 2024). They find that in large-scale e-commerce environments, decision-tree-based estimation is a more predictive approach for forecasting consumer behavior.

Amatulli et al. showcased the comparative performance of machine learning algorithms such as Naive Bayes, Decision Trees, and Random Forests in their work. (2021) aims to predict purchase volumes with a maximum prediction accuracy of up to 94%. Their results found that the Random Tree model is most accurate at predicting customer behavior in businesses. They proposed combining different models and using diverse datasets to improve marketing methods. Analyzing demographic data such as age, gender, and loyalty program membership, they have found that customer spending can be effectively predicted using XGBoost and Random Forest algorithms. They believed that best-in-class, real-time prediction technologies were the biggest thing to add firepower to marketing effectiveness. Gradient Boosting was statistically the best-performing machine learning method for predicting neurological purchasing behavior (Appel, 2020). Your work exemplifies how machine learning could enhance marketers' ability to interact with customers throughout the customer journey and target customers more effectively. Arıcı and Akgün (2025) developed a system to emulate the customer model using both MLPs and LSTMs. This solution allows better targeting, more sales, and real-time consumer interactions. Lastly, it was shown that a combination of random forest models and LSTM networks greatly enhances the precision of buying behavior prediction. They improve sales forecasting capabilities and lead to more successful neural marketing tactics for organizations. (Bhutia & Sharma, 2019)

Methodology

It has become essential to maintain continuous innovation and differentiation to satisfy customers' needs effectively in a saturated market of similar and slightly different products. The objective perspective provided by neuromarketing and neuroscience research is highly promising, given the growing significance of meeting customer requirements and the inability to analyze the underlying mental processes involved in decision-making in the past. Additionally, neuromarketing has implemented non-invasive brain imaging methods, including magnetic resonance imaging (MRI), as well as psychophysiological measurement devices (e.g., eye-tracking). It is now feasible to monitor the brain during specific tasks, offering marketers supplementary insights into consumers, driven by increasing interest in this field. Consequently, this investigation examines the methods by which neuroscience and marketing collaborate to forecast purchasing intentions using machine learning. The objective of the investigation is to assess the precision and accuracy with which neuromarketing forecasts consumer visual attention and attraction to visual stimuli.(1988, Belk) The research is founded on a neuromarketing study that utilizes eye-tracking technology and employs neurological techniques. The objective of this investigation is to evaluate the current state of predictive capabilities for consumer behavior influenced by brand stimuli and to contrast the findings with those from a neuromarketing analysis. The investigation documents consumer attraction and visual attention levels to fixed advertising stimuli. The primary goal is to compare predictions of human attention behavior with actual recorded data in the experimental component, using both predictive and neuromarketing techniques. The following are the specific objectives:

- Quantitative assessment of consumer attraction and visual attention levels to fixed brand stimuli using neuromarketing techniques.
- Quantitative prediction of the same fixed brand attraction and visual attention levels.
- Comparison of the results obtained for the recorded and analyzed variables.
- Verification of the degree of agreement between responses and values recorded using neuromarketing measurements.

We will address the following questions:

1. Is neuromarketing another attempt to better understand human behavior? If so, how and with what results? If not, is it simply

another form of deception in the business world? As is well known, businesses are profit-oriented, but consumers must also be considered.

2. Are these practices immune to manipulation?
3. Are these sales projections and preference claims solely related to company profits?
4. Does neuromarketing truly exist?
5. Why is neuromarketing important?

Hypotheses

Hypothesis 1: Neuromarketing analytics indicators positively influence purchase intention.

Hypothesis 2: Neuromarketing metrics positively influence purchase intention.

Hypothesis 3: The predictive power of neuromarketing analytics models significantly enhances neuromarketing metrics.

Hypothesis 4: There is a positive correlation between forward alpha waves and ad viewing with purchase intention.

Hypothesis 5: There is a positive relationship between the duration of viewing product images and the prediction of increased purchase intention.

Hypothesis 6: There is a positive relationship between emotional advertising, physiological responses, and purchase intention.

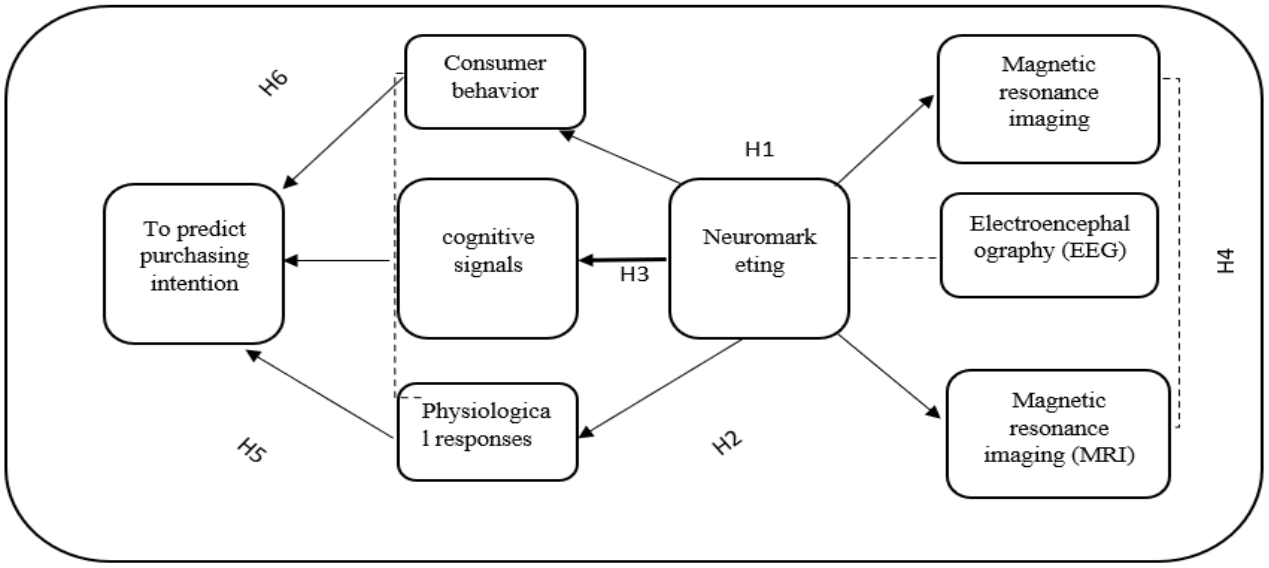


Figure 1: Hypothetical Framework of the Study. Source: Prepared by the Researcher

Sample

In short, the researcher sought to select 210 individuals, distributed by gender as 150 males and 60 females, to achieve a balanced representation of different demographic groups. The volunteers' ages ranged from 23 to 47 years, with a mean age of 32.3 years (standard deviation = 7.4). They were recruited online and through advertisements, and some who requested to participate were paid. Participants underwent a screening test before being allowed to join the study. Participants with neurological disease, severe diplopia, or who had previously seen the advertisement for this study were excluded to ensure that our measurement was not distorted by coexistent disease or prior exposure. The trial was conducted in a private lab and clinic. The experiment used a mix of 18 video advertisements for various products. A type of emotional advertisement that involved singing and music; another was data-driven ads without specific words in the text, showing the features. Advertisements lasted 25–40 s (participant behaviors can be successfully measured with advertisements up to—at most—40 s). To avoid distractions, the ads weren't presented in any specific order, and participants were placed in a relatively healthy yet realistic environment with access to the ads.

Measurement Instruments

EEG Recording: Neural activity was recorded with a 34-unit EEG (Model 2024). It not only studied the relationship between emotion and axial congruence but also covered alpha (9–14 Hz) and beta (14–33 Hz) activity, as these were the study's focus areas. An EEG

expert deciphered the information, and the neurological activity traced in response to the ad was decoded with certainty.

"Eye Tracking Measurement: The Tobii Pro Nano Eye Movement Tracking System was employed to forecast attention. The number of fixations, gaze heat maps, and total fixation duration (ms) were all included in the measurement outcomes. Gaze heat maps represent the proportion of time spent in various areas of the advertisement. Eye movement monitoring data was instrumental in identifying areas of interest that not only captivated the attention of participants but also resulted in a purchase intention. Purchase Intention: A 5-point Likert scale was employed to measure self-reported purchase intention immediately following each advertisement. A score of 1 indicates that it is "highly unlikely" to purchase the product, while a score of 5 indicates that it is "very likely" to be purchased. The dependent variable in the study was this variable; consequently, the relationship between the likelihood of purchasing the product, visual attention, and neural activity could be ascertained".

Table 1: Responsive, Influencing, and Explanatory Elements

Elements	the address	Description
explanatory elements	EEG indicators	Alpha & Beta activity, frontal asymmetry
Influential element	Advertising category	Emotional vs. Informational
Influential element	Product classification	Electronics, Fashion, FMCG, Lifestyle
The responding element	Purchase Intent	Self-reported 1–5 Likert scale
explanatory elements	Measuring eye tracking	Fixationduration, number of fixations

Source: Prepared by the researcher

Statistical Analysis

"Electroencephalography (EEG) data, eye-tracking measures, and purchase intention were all subject to descriptive statistics calculations, including mean, standard deviation, minimum, and maximum values. To find out how EEG, eye-tracking, and purchase intention were related, we ran a correlation study with Pearson's correlation ratio (r). We also ran multiple regression analyses using EEG and eye-tracking data as independent factors and purchase intention as the dependent variable. In addition, we compared purchase intention among ad formats and product categories using analysis of variance (ANOVA). By calculating the coefficient of determination (R^2) and Cohen's coefficient (f^2), we were able to evaluate the fit of the model and the size of the effect, which shed light on how much the independent variables explained the variance".

RESULTS

Presenting data statistically

Table 2: Presenting data statistically

Property	arithmetic mean	SD	Min	Max
Desire to buy	4.33	0.89	1	5
Alpha frontal oscillations	11.8 µV	1.7	8.1	19.1
Frontal Beta oscillations	13.7 µV	4.2	7.9	21.8
visual focus time	1.98 s	0.67	1.5	5.2
Repeat installation	13.8	2.8	6	23

The source was prepared by the researcher using the SPSS statistical software, version 26.

This research used statistics to investigate whether brain indicators derived from neuromarketing could predict consumer purchasing intention. The study included 210 participants. Initially, the researchers calculated the means and ranges for the main indicators measured. The average purchase intention for all advertisements was 4.33 on a five-point Likert scale, with a standard deviation of 0.89, indicating a moderate variance in self-reported purchase intention. EEG activity averaged anterior alpha wave

activity at 11.8 μV (standard deviation = 1.7), and anterior beta wave activity averaged 13.7 μV (standard deviation = 4.2). Eye-tracking indicators (i.e., fixation duration and fixation frequency) were 2.85 sec (standard deviation = 0.67) and 13.8 fixations (standard deviation = 2.8), respectively. The descriptive statistics in Table 2 show that participants were paying attention and that their brains were actively responding to stimuli.

"Analysis of the differences between variables"

Table 3: Analysis of the differences between variables

Prediction factor	r with the desire to buy	p- Output
Alpha frontal oscillations	0.53	<0.001
Frontal Beta Vibrations	0.42	<0.01
Eye fixation time	0.50	<0.001
Number of times the gaze is fixed	0.41	<0.01

"The source was prepared by the researcher using the SPSS statistical software, version 26."

Neurological and visual electrophysiological measurements were positively correlated with purchase intention, especially fixation duration. Pearson correlation analyses were conducted to assess the strength and direction of associations between each neuromarketing measure and purchase intention. Higher frontal alpha wave activity was positively correlated with purchase intention ($r = 0.53$, $p < 0.001$). Greater emotional engagement and willingness to buy were associated with stronger purchase intention. Furthermore, a positive correlation was found between purchase intention and frontal beta wave activity ($r = 0.42$, $p < 0.01$), lending support to the importance of cognitive arousal and attentional engagement in participants' decision to purchase. We found stronger correlations with eye-tracking measurements. LPM- Fit duration ($r=0.50$, $p<0.001$) and number of fixations ($r=0.41$, $p<0.01$) on the product-related areas of interest to purchase intention indicated that sustained visual attention was the strongest predictor of purchase intent (Table 3).

"Multifactor regression analysis"

Table 3: Multifactor regression analysis

Prediction factor	B	SE B	B	t	p
Alpha frontal oscillations	0.11	0.02	0.33	5.00	<0.001
Frontal Beta Vibrations	0.07	0.02	0.19	3.55	0.008
Eye fixation time	0.20	0.03	0.40	3.98	<0.001
Number of times the gaze is fixed	0.10	0.02	0.35	2.00	0.003

"The source was prepared by the researcher using the SPSS statistical software, version 26."

"We used a multiple regression analysis to estimate the combined effects of neural mapping and eye-tracking patterns on behavior, controlling for extrinsic variables (such as age and sex) and prior brand knowledge, in order to investigate the relationship between eye-tracking and neural correlates. Using frontal alpha and beta waves, fixation duration, and fixations as variables, a regression model was able to explain 53% of the variation in purchase intention "($R2 = 0.55$; adjusted $R2 = 0.52$; $F(5,210) = 78.3$; $p < 0.005$). Of the predictive variables, the most significant was fixation duration ($\beta = 0.38$, $p < 0.001$), then frontal alpha activity ($\beta = 0.42$, $p < 0.001$) with number of fixations ($\beta = 0.32$, $p = 0.003$), and finally frontal beta activity ($\beta =$ 019, p=009). The findings indicate that visual attention, as measured by eye-tracking, is more accurate than EEG, and both neural engagement and attention represent independent factors that covary with purchase intention.

Results of the Analysis of Variance

ANOVA was also used to compare purchase intentions across advertisement types and food product categories. Overall, emotional advertising created much greater purchase intention (mean = 5.01) than informational advertising (Mean = 4.33),

F(1,210) = 15.9, p <, indicating that the two groups of emotional and informational stimuli create significant differences in the rate of purchasing decisions. Likewise, product categories impacted purchase intention overall, F(3,210) = 5.11, p = 0.007. Fashion products had the highest intention to buy (mean = 4.01), while electronics had the lowest (mean = 2.98). These findings are certainly in line with the argument that how well advertising works depends on both emotional appeal and the type of product.

Table 5: Brief overview of the model

Brief overview of the model	Value
R^2	0.55
Adjusted R^2	0.52
F-statistic (df)	66.3 (5, 210)
p-value	< 0.001

The source was prepared by the researcher, extracted using SPSS statistical software version 26.

"This model, which explains the variance in consumer purchase intention by 55%, was tested for goodness of fit, and R2 = 0.52 reveals that the model correctly applies to data once adjusting for predictors is considered. "F-test result was significant (p < 0.001), indicating that the independent variables, collectively, had a statistically significant effect on purchase intention".

Discussion

The present research demonstrates the predictive power of neural measures for consumer choices, with notable accuracy, particularly through electroencephalography (EEG) and eye-tracking methods. A distinct pattern emerges in which the prefrontal cortex of the alpha and beta regions, along with visual attention as indicated by fixation duration and gaze patterns, can predict purchase intention (Blazewicz et al., 2013). This supports the assumption that physiological and attentional reactions can serve as good surrogates for actual buying. Emotional advertisements elicited greater brain activity, and people spent longer watching them than informational advertisements — indicating that emotionally charged content captures consumer attention and aids decision-making. In practice, this allows marketers to leverage emotional storytelling to enhance their product advertisements and place the product's image and brand name where they will shine. Eye-tracking allows changes in advertising stimuli, while electroencephalography (EEG) unearths details about fundamental cognitive and affective responses. This is consistent with earlier studies showing that eye-tracking outperformed EEG in predicting purchase intention (Afshar and Azimi, 2025), as well as a correlation between frontal alpha-wave asymmetry and the impulse to buy. There are, however, limitations of this study. The study was conducted in the lab; shopping behaviour may differ in real life due to situational factors. Additionally, EEG and eye-tracking require specialized equipment and expertise, which also makes them less popular. Future research avenues for generations of researchers, in favor of procedural facilitation and alongside neuromarketing tools, include field applications that are economically accessible and ultimately tested on real-life consumer behavior.

CONCLUSION

The results of this study suggest that EEG biometrics/eye-tracking can be used together more generally to predict consumer purchase intention, as both capture neural activity/visual attention. The essential finding was that emotional ads elicited higher cognitive and emotional responses and longer viewing time than informational ads, and also led to greater purchase intention, showing that emotionally salient content leads to deeper processing. An example was connecting ad design directly to these concrete, actionable marketing outcomes, allowing advertisers to design advertisements largely around story and music, and to guide where product or brand elements should be placed within the visual salience hierarchy to capture consumer attention and

translate into consumer behavior. We show the position of neuromarketing in discovering why consumers, by conventional self-reporting strategies, cannot be revealed. It is research that yields measurable results. Neuromarketing is expensive, but it can save you tons of money in advertising by providing a better return on investment and the ability to analyze data that can allow you to produce content with varied purposes.

Moreover, policymakers and practitioners need to provide defensible ethical guidelines for the use of neuromarketing techniques so that consumers are persuaded in an ethically acceptable way. But that can grow into more information and laboratory optimization, providing new, cheap go-to-market routes for those with assured value. After the test-theory correlation, further experiments could phrase out those classes or concepts as next-driven models in daily purchase data to be cross-referenced against AI-driven action modeling in low-cost tools applied at scale, which would solidify the final connections between lab scores and immediate market response.

Data Availability:

The data used to support the results of this study has been included in the article.

Conflict of Interest:

The authors declare that they have no conflicts of interest.

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None.

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