Advances in Consumer Research
ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

Vol. 2, Issue 4 (2025) https://acr-journal.com/

# Decoding the Consumer Mind: A Systematic Review of Technological Innovations and Applications in Contemporary Neuromarketing

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**Cite this paper as:** Aurodeep Kamal, Biswajit Das , (2025) Decoding the Consumer Mind: A Systematic Review of Technological Innovations and Applications in Contemporary Neuromarketing. *Advances in Consumer Research*, 2 (4), 3116-3123

**KEYWORDS**

*Neuromarketing, Behavior Patterns, Neural Communication, Systematic Review*

**ABSTRACT**

Neuromarketing has gained significant academic and commercial traction due to advances in neural recording and data analysis, enabling effective detection of consumers' subconscious responses to marketing. This pioneering systematic review synthesizes technological progress in Neuromarketing over the past five years, analyzing 57 relevant studies from credible sources. Key findings reveal consumer goods as the dominant stimuli (products/promotions) in the literature. Emotion recognition studies frequently focus on frontal/prefrontal alpha signals, aligning with frontal alpha asymmetry theory. For video ad testing, EEG emerged as researchers' preferred tool over fMRI, largely due to its cost-effectiveness and superior temporal resolution. Physiological methods (eye tracking, skin conductance, heart rate, facial mapping) were also commonly employed, often alongside brain recordings. In neural signal processing, Independent Component Analysis (ICA) was the most prevalent artifact removal technique, while Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Linear Discriminant Analysis (LDA) demonstrated the highest average accuracy for consumer response classification. This review aims to provide future researchers with essential insights to drive novel contributions in the field..

## 1. INTRODUCTION

As an implementation of non-invasive brain-computer interface (BCI) systems, neuromarketing has established itself as a transformative interdisciplinary field connecting neuroscience with marketing science. This innovative approach serves as a critical mediator between products and potential buyers, directly influencing purchasing outcomes (Assel,1981). In today's rapidly evolving commercial landscape where consumer preferences shift constantly, even superior products risk market failure without strategic marketing communication to attract and retain their intended customer base. Particularly for new market entrants, effective promotional strategies become essential for competitive penetration.

Traditional market research methodologies, including surveys, focus groups, interviews, and observational studies, provide only retrospective consumer insights (Malhotra, 2020). These conventional techniques suffer from significant constraints including time intensiveness, substantial costs, and questionable data reliability. Neuromarketing overcomes these limitations by enabling real-time measurement of implicit cognitive and affective reactions to marketing stimuli, along with predictive capability regarding purchase intentions.

### 1.1 Neuromarketing Methodologies

Modern neuromarketing employs non-invasive neuroimaging technologies to directly monitor neural responses to marketing stimuli, offering advantages over traditional survey approaches (Vecchiatto et al, 2011). The methodological toolkit includes functional magnetic resonance imaging (fMRI), electroencephalography (EEG), magnetoencephalography (MEG), transcranial magnetic stimulation (TMS), positron emission tomography (PET), and functional near-infrared spectroscopy (fNIRS). These technologies permit examination of neural correlates underlying consumer preferences and decision-making processes (Izhikevich, 2003).

Contemporary signal processing and machine learning techniques facilitate sophisticated analysis of neural data, enabling unprecedented capability to decode and predict consumer behavior patterns. BCI systems can now identify specific mental states - including engagement, excitement, or aversion - during consumer exposure to marketing materials (Custdio, 2010). Complementary physiological measures such as ocular tracking, cardiovascular monitoring, and electrodermal activity assessments provide additional layers of consumer response data (Dimpfel et al, 2015; Kroupi et al, 2014; Khushaba et al, 2013)

### 1.2 Evolution and Current Status

The field initially faced skepticism regarding its ambitious claims about deciphering consumer cognition and identifying hypothetical "purchase decision centers" in the brain (Ariely et al, 2010; Singh et al, 2010). However, accumulating empirical evidence has gradually demonstrated its potential for consumer behavior prediction. The establishment of the Neuromarketing Science and Business Association (NMSBA) in 2012 marked a significant milestone in fostering academic-industry collaboration.

Currently, over 150 specialized firms offer consumer neuroscience services to major corporations including technology and consumer goods giants. This commercial adoption has been facilitated by advancements in analytical precision from the engineering domain. While existing literature reviews have addressed theoretical dimensions spanning marketing theory, ethical considerations, and psychological aspects (Cruz et al, 2016; Hsu et al, 2017, Shaw et al, 2018), a systematic examination focusing on technical implementation - particularly regarding neuroimaging technologies and analytical pipelines - remains conspicuously absent.

### 1.3 Research Objectives

This review specifically addresses five key questions:

What varieties of marketing stimuli are employed in contemporary neuromarketing research?

Which neural structures demonstrate activation patterns in response to these stimuli?

Which neuroimaging modalities currently offer optimal utility for neuromarketing applications?

What preprocessing techniques are applied to neural data prior to analysis?

What analytical methods prove most effective for interpreting neuromarketing data?

The subsequent sections detail our systematic review methodology, present current research findings organized by these questions, synthesize major results, and conclude with evidence-based recommendations for future research directions in consumer neuroscience.

## 2. REVIEW OF LITERATURE

Neuromarketing research employs marketing stimuli to evoke, record, and analyze brain activity in specific regions as subjects experience these stimuli. Conducting a systematic review necessitates acknowledging the link between brain functions and the behaviours or actions prompted by external inputs. Understanding brain anatomy, the physiological roles of its areas, and the bodily responses to stimuli enables the modelling of brain activity to predict implicit reactions. Advanced neuroimaging and neural recording technologies play a crucial role in measuring genuine consumer responses. This section outlines marketing stimuli, the corresponding brain areas involved, and the neurophysiological data collection methods commonly used in Neuromarketing studies in recent years (2019–2024). By correlating these signals with anatomical functions, certain studies have achieved significant predictive accuracy. Several selected investigations employed machine learning to forecast test subjects' likes/dislikes and potential preferences.

For Neuromarketing experiments, the cited literature specified participants who were right-handed, had normal or corrected vision, were not taking central nervous system-affecting medication, and had no neuropathology history.

### 2.1 Marketing Stimuli in Neuromarketing

As Neuromarketing targets marketers and consumer behaviour researchers, diverse marketing strategies are applied and quantitatively assessed using neurological data. Neuromarketing is distinct because it circumvents consumers' cognitive processes, directly accessing their brain responses (Nemorin, 2017). Over the last five years, primary stimuli formats were products (with/without price) and promotions. Products—physical items or services fulfilling consumer needs—range from tangible experiences (e.g., beverage tasting) to conceptual representations (e.g., 3D product images). Price frequently intertwines with products or promotions in experiments, critically influencing purchase decisions (Grönroos, 1990).

Consumer responses are gauged through physical product interaction or visualization. Retailers face significant losses from unsuccessful products. For instance, shoe manufacturing involves numerous designs, many of which fail. Baldo et al. (2015) displayed 30 existing shoe images in a mock shop, recording EEG during selection followed by Likert scale ratings (1-5). Brain-response-based sales predictions outperformed self-reports, yielding 36.4% simulated profit growth versus 12.1% for surveys.

Rawnaque et al (2020) reported that, to effectively measure consumer engagement with advertisements, electroencephalography (EEG) is highly valuable due to its precise temporal resolution. This neural data can be supplemented with eye tracking, a method proven effective for pinpointing attention and arousal. For robust results, findings from these tools can be cross-validated with physiological metrics like heart rate and galvanic skin response.

Touchette and Lee (2017) studied apparel choices among young adults using Davidson's frontal asymmetry theory, recording EEG as 34 students viewed attractive/unattractive items. Pozharliev et al. (2015) examined emotional responses to luxury versus basic brands among 40 female students, finding heightened emotional value for luxury items in social settings—a potential marketing lever. Brand image studies compared neural reactions to established brand names (displayed text-only) and popular versus organic food logos, aiding marketers in understanding implicit brand perceptions.

Given price's pivotal role, numerous studies incorporate it alongside products. Baldo et al. 2015 explored corporate social responsibility's impact, finding consumers preferred conventional companies over socially responsible ones due to lower prices. Marques et al. (2016) assessed price influence on national versus store brands. Çakir et al. (2017) presented products and prices pre-decision, recording brain activity via fNIRS. Price also manifests passively in promotions: Gong et al. (2018) compared discount (25% off) versus equivalent-value gift strategies, concluding discounts (lower ambiguity) better motivate decisions. Hsu and Chen (2019) controlled for price (~$15) in a wine-tasting EEG study.

Yang et al. (2015) analyzed six smartphone ads for cognitive/emotional indices (happiness, surprise, attention) and behaviour (memory, preference). Standard protocols involve comfortable settings, ads spaced ≥10s apart, and neutral stimuli (e.g., blank screens) between ads for participant stabilization.

Soria Morillo et al. (2015) measured brain electrical activity during taste-relevant ads (14 commercials, 10 subjects), predicting liking via algorithms. Cherubino et al. (2016) studied age-related cognitive/emotional changes during seven TV ads, analyzing reactions to intense imagery.

Other promotion studies include: Vasiljević et al. (2019) (Nestle ad attention via pulse); Daugherty et al. (2018) (TV/print ad replication of Krugman (1971)); Royo et al. (2018) (sustainable vs. conventional product ads); Venkatraman et al. (2015) (ad success via neuroimaging/biometrics); Randolph and Pierquet (2015) (Super Bowl ad neural response vs. class rank); Nomura and Mitsukura (2015) (emotional states during 50 award-winning/favorable vs. 50 unfavorable ads); Singh et al. (2019) (static/video ads for omnichannel prediction); Ungureanu et al. (2017) (web ad attention via eye-tracking); Goyal and Singh (2018) (automated video ad review via facial biometrics); Oon et al. (2018) (merchandise ad preference). Most TV commercials (TVCs) were 30s, embedded in videos (documentaries, games, dramas) to capture authentic responses.

Neuromarketing also examines social/gender-related ads. Social ad studies predict message reach to target groups. Chen et al. (2018) (adolescent neural response to e-cigarette ads); Yang (2018) (smoking cessation frame attention among smokers/non-smokers). Gender-focused research includes Missaglia et al. (2017) (FMCG ads with celebrity/non-celebrity spokeswomen) and Casado-Aranda et al. (2018) (gender-targeted ads with congruent/incongruent product-voice pairings), demonstrating stimulus diversity for future applications.

### 2.2 Brain Region Activation by Marketing Stimuli

The human brain's complexity underpins daily cognitive and emotional processes. MacLean's Triune Brain model (1988) proposed vertebrate brain evolution in three phases: the reptilian complex (instincts; basal ganglia); the paleomammalian complex (motivation/emotion; limbic system: septum, amygdalae, hypothalamus, hippocampus, cingulate cortex); and the neomammalian complex (higher cognition; cerebral neocortex—unique to humans, featuring four lobes governing sensory, motor, emotional, and cognitive functions. While modern neuroscience critiques the model due to brain interconnectivity, its anatomical framework aids in understanding cognitive/emotional/behavioural processes.

Brain anatomy is crucial in Neuromarketing for interpreting neural responses. The cerebral cortex comprises four lobes with distinct functions: Frontal (thought, conscious decisions, cognition in prefrontal areas, movement); Parietal (taste, touch, movement processing); Occipital (vision); Temporal (visual memory, auditory recognition, sensory-memory integration). Cortical folding creates gyri (increasing processing surface area) and sulci. Lobes and their gyri serve as Regions of Interest (ROIs) in neural imaging (Beeson et al, 2003).

Deeper structures include: Thalamus (sensory info, attention, memory); Amygdalae (emotion); Hippocampus (memory); Hypothalamus (autonomic control: sleep, hunger, thirst, BP, temperature, arousal) (Nolte et al, 2009).

Neuromarketing experiments target specific brain areas: e.g., frontal lobe for attention; deeper structures for motivation (Venkatraman et al, 2015). Soria Morillo et al. (2016) classified ad liking using prefrontal cortex (PFC) signals alone via single-electrode EEG. Cherubino et al. (2016) emphasized the PFC's role in conscious/unconscious cognitive/emotional processing, making it ideal for single-sensor devices. Ventromedial PFC activity (imaged via fMRI/MEG) can reveal purchase motivations (Marques et al, 2016).

Neural communication occurs via action potentials (neuron firing) (Vecchiato et al, 2011), producing non-linear electrochemical patterns (brainwaves). These waves, categorized into frequency bands (rhythms), correlate with brain states/functions: Delta (δ: 0.1–4 Hz; deep sleep; limited BCI use) (Abdullah, 2013); Theta (θ: 4–8 Hz; sleep/adult disorders); Alpha (α: 8–12 Hz; relaxed wakefulness); Beta (β: 12–30 Hz; motor control, engagement, decision-making); Gamma (γ: 30–90 Hz; movement; prominent in invasive recording). In Neuromarketing, beta wave amplitudes link to reward processing and product/TVC success prediction (Boksem, 2015).

## 3. RESEARCH METHODOLOGY

A systematic literature review represents a rigorous scholarly process involving comprehensive literature collection, screening, selection, evaluation, and synthesis to achieve objective evidence-based conclusions. This methodology requires clearly defined research questions and explicit inclusion-exclusion criteria to establish proper study boundaries. Following an exhaustive literature search, relevant articles must undergo careful selection, with subsequent critical analysis and synthesis of their findings to derive meaningful insights (Khan et al, 2003).

For the current review, we focus on three key aspects of recent neuromarketing research (2015-2025):

Marketing stimuli employed and their corresponding neural activation patterns

Neuroimaging technologies utilized to capture these brain responses

Signal processing and analytical methods implemented in these studies

### 3.1 Inclusion Criteria:

Peer-reviewed neuromarketing studies published between 2015-2025

Research incorporating brain-computer interface (BCI) or physiological monitoring devices

Studies presenting empirical findings derived from neural or biometric data

### 3.2 Exclusion Criteria:

Existing literature reviews on neuromarketing topics.

Book chapters (with exception for empirical BCI studies, given the field's emerging nature).

Non-English language publications.

The systematic search strategy employed the keywords "Neuromarketing" and "Neuro-marketing" across major academic databases, yielding 931 initial publications. After applying our selection criteria, we identified 57 relevant articles and book chapters containing primary neuromarketing research, as detailed in Table 1.

**Table 1: Selection of Relevant Articles**

| Name of Database | Results for “Neuromarketing” | Results for “Neuro-marketing” | Articles Selected |
|---|---|---|---|
| Science Direct | 282 | 54 | 11 |
| Wiley Online | 109 | 12 | 8 |
| Emerald Insight | 114 | 7 | 16 |
| IEEE | 35 | 1 | 12 |
| Sage | 11 | 16 | 7 |
| Taylor Francis Online | 107 | 35 | 3 |

Source: Own Source (2025)

To ensure a thorough review of existing literature, we conducted searches across six key academic databases: Science Direct, Emerald Insight, Sage, IEEE Xplore, Wiley Online Library, and Taylor & Francis Online. After initial retrieval, each article was meticulously screened by the research team based on titles, abstracts, keywords, and research objectives to confirm relevance to our study. Only publications that met our predetermined selection criteria were included for detailed analysis and assessment.

By systematically evaluating these chosen studies, we were able to identify and classify emerging trends and technological developments in neuromarketing, organizing them into five essential categories.

a) **Marketing Stimuli**: Types and applications in neuromarketing research

**b) Neural Activation Patterns**: Brain regions responsive to marketing stimuli

**c) Neuroimaging Technologies**: Techniques for recording neural responses

**d) Signal Processing Methods**: Approaches for analyzing brain signal data

**e) Machine Learning Applications**: Predictive analytics in neuromarketing

Notably, several included studies incorporated supplementary physiological measures - including ocular tracking, cardiac monitoring, electrodermal activity, and facial expression analysis - either independently or in conjunction with neural recording methods. These autonomic nervous system (ANS) indicators have demonstrated significant value in assessing consumer attention, emotional arousal, and approach/withdrawal behaviors. Consistent with our engineering-focused perspective, we specifically included studies employing these empirical measurement tools to address neuromarketing research questions. However, studies relying exclusively on statistical analysis of neural data without engineering applications were considered beyond the scope of this review.

## 4. RESULTS AND DISCUSSION

This section synthesizes insights from prior research articles, book chapters, and empirical neuromarketing studies conducted between 2015 and 2025. To enhance the validity of the findings, most of the reviewed literature adhered to a statistical significance threshold of *p* < 0.05.

Advances in technology have redefined marketing stimuli, with a growing emphasis on TV advertisements and digital product visuals over tangible items. The use of 3D product modeling has further enhanced virtual purchasing behaviors. Given the rise of online shopping, e-commerce products have become a focal point in research. The scope of stimuli has expanded to encompass novel online shopping interactions and digital booking interfaces. In addition to commercial applications, several studies investigate social campaigns—such as anti-smoking and anti-alcohol initiatives aimed at younger audiences—leveraging neuroimaging and neural decoding techniques to evaluate message effectiveness among target groups.

**Table 2: Brain State Functionalities in Neuromarketing**

| Brain States | Functionalities |
|---|---|
| Theta (4-8 Hz) | Cognitive processing is linked to theta wave activity in the frontal lobe.<br>(Gordon et al, 2018)<br><br>Cognitive processes in the frontal lobe correlate with theta wave activity, and preferred colors trigger stronger theta amplitude responses.<br>(Yadava et al, 2017) |
| Alpha (8-12 Hz) | Frontal alpha activity relates to cognitive function, with amplitude inversely reflecting neural activation in asymmetry measurements.<br>(Touchette and Lee, 2016)<br><br>Alpha asymmetry patterns vary with emotional valence, whereas vigilance states associate with enhanced alpha power in posterior brain regions.<br>(Hoefer et al, 2016) |
| Beta (12-30 Hz) | Reward processing correlates with beta frequency oscillations in the medial-frontal region, while imaginative processes demonstrate correspondence with beta activity in the right parietal area.<br>(Gordon et al, 2018) |

Source: Own Source (2025)

EEG devices, particularly commercially available research-grade systems, have surpassed fMRI scanners in popularity within consumer neuroscience over the past five years. EEG's high temporal resolution makes it ideal for evaluating dynamic TV advertisements. While fMRI appears less frequently, it is primarily utilized when subjects view product images and make purchase decisions (Wang et al, 2015), as fMRI can localize activated brain regions indicative of positive/negative experiences. However, fMRI's slow image refresh rate (2–5 seconds) renders it unsuitable for tracking millisecond-level TVC stimulus changes. fNIRS is emerging as a viable alternative; its portability facilitated studies on purchase behavior and consumer reactions, achieving >70% accuracy and a reliability score of 0.7/1, respectively, indicating promise for future applications.

Among EEG devices, Emotiv Epoc/Epoc+ were most prevalent in academic studies. Other utilized systems include the 10-channel BrainAmp and 32-channel eego Sports. Despite its single sensor, NeuroSky MindWave delivered denoised data with >70% accuracy.

All fMRI-based neuromarketing studies during this period employed 3-Tesla scanners (Magnetom Trio or Siemens Verio), valued for high spatial resolution. A noted limitation is the potential for BOLD signal confusion due to head/muscle movement affecting blood flow.

For signal preprocessing, MATLAB and EEGLAB served as the primary analytical tools. In addition to standard band-pass filtering, researchers increasingly implemented independent component analysis (ICA) for enhanced spatiotemporal data processing. The preprocessing pipeline typically included temporal segmentation of neural signals. For functional MRI data analysis, most studies utilized Statistical Parametric Mapping (SPM) software.

A notable trend in the examined research was the application of machine learning techniques for predictive modeling and classification tasks. Table 3 presents a comparative analysis of classification performance metrics across different AI algorithms as reported in the neuromarketing literature.

**Table 3: Mean Accuracy Comparison for Study Classifiers in Neuromarketing**

| **Classifiers** | **Neuromarketing Studies** | **Mean Accuracy** |
|---|---|---|
| Support Vector Machine (SVM) | Like/Dislike paradigm for three-dimensional visual stimuli. (Chew et al, 2015) | 68% |
| | Neocube Based Differentiation for Attention Bias (Doborjeh et al, 2018) | 48.5% |
| | Emotions towards E-Commerce Products (Yadava et al, 2017) | 62.85% |
| | EEG Device for Emotional Valence (Ogino and Mitsukara, 2018) | 72.4% |
| | fMRI Data for Purchase Decision Behavior (Wang et al, 2015) | 55.70% |
| | GSR Biometric Data for Facial Emotion (Goyal et al, 2018) | 81.65% |
| | EEG Signal for Seven Emotion Recognition (Bhardwaj et al, 2015) | 87.5% |
| | EEG Signal for Color Differentiation (Rakshit and Lahiri, 2016) | 78.81% |
| K-Nearest Neighbor (KNN) | Like/Dislike paradigm for three-dimensional visual stimuli. (Chew et al, 2015) | 64% |
| Hidden Markov Model (HMM) | Emotions towards E-Commerce Products (Yadava et al, 2017) | 70.33% |
| Linear Discriminant Analysis (LDA) | EEG Signal for Seven Emotion Recognition (Bhardwaj et al, 2015) | 82.5% |
| | Car Stimuli and ERP Signal for Like Dislike Classification (Hsu and Chen, 2019) | 61% |
| Naïve Bayes | Neural Impulse Actuator (NIA) for Purchase Decision Behavior (Taqwa et al, 2015) | 48.5% |

| | | |
|---|---|---|
| Artificial Neural Network (ANN) | Facial Action Coding for Consumer Gender Prediction (Gurbuj and Toga, 2018) | 83.8% |
| | EEG Signal for TV Advertisement Liking Recognition (Soria et al, 2015) | 80% |
| | Emotions towards E-Commerce Products (Yadava et al, 2017) | 60% |

Source: Own Source (2025)

Comparing machine learning algorithm performance revealed Artificial Neural Networks (ANNs) yielded the highest accuracy (~80%) (Soria et al, 2015). However, ANNs demand substantial training data (typically 70% for training vs. 30% for testing), raising viability concerns. Support Vector Machines (SVMs) were the second most common algorithm, achieving accuracies exceeding 70%. Hidden Markov Models (HMMs) outperformed K-Nearest Neighbors (KNN) across neuromarketing applications.

## 5. CONCLUSION

Neuromarketing, a growing field applicable to commercial, social, and political advertising, needs thorough documentation to capture its current state. This study aimed to explore its technological scope and potential opportunities. Findings indicate that over the past five years, neuromarketing research primarily used consumer goods (products or promotions) as stimuli, though its application in social advertising is emerging. Researchers commonly target the frontal and prefrontal cortex to study consumer cognition and emotion. EEG has become the dominant brain signal recording tool, particularly for TV commercial (TVC) analysis, valued for its cost-effectiveness and high temporal resolution. However, researchers must consider EEG's varying sampling rates, which limit the highest analyzable frequency. Independent Component Analysis (ICA) is widely used for noise and artifact removal in signal processing. For classification tasks, Support Vector Machines (SVM) are the most frequently used algorithm, likely due to their simplicity..

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