A Survey on Neuromarketing using EEG Signals

Vaishali Khurana*, Monika Gahalawat*, Pradeep Kumar, Partha Pratim Roy, Debi Prosad Dogra, Erik Scheme and Mohammad Soleymani

***Abstract*—Neuromarketing is the application of neuroscience to the understanding of consumer preferences towards products and services. As such, it studies the neural activity associated with preference and purchase intent. Neuromarketing is considered an emerging area of research, driven in part by the approximately 400 billion dollars spent annually on advertisement and promotion. Given the size of this market, even a slight improvement in performance can have an immense impact. Traditional approaches to marketing consider a posteriori user feedback in the form of questionnaires, product ratings, or review comments, but these approaches do not fully capture or explain the real-time decision making process of consumers. Various physiological measurement techniques have been proposed to facilitate the recording of this crucial aspect of the decision making process, including brain imaging techniques (Functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG), Steady State Topography (SST)) and various biometric sensors. The use of EEG in neuromarketing is especially promising. EEG detects the sequential changes of brain activity, without appreciable time delay, needed to assess both the unconscious reaction and sensory reaction of the customer. Several types of EEG devices are now available in the market, each with its own advantages and disadvantages. Researchers have conducted experiments using many of these devices, across different age groups and different categories of products. Because of the deep insights that can be gained, the field of neuromarketing research is carefully monitored by consumer and research protection groups to ensure that subjects are properly protected. This paper surveys a range of considerations for EEG-based neuromarketing strategies including, the types of information that can be gathered, how marketing stimuli are presented to consumers, how such strategies may affect the consumer in terms of appeal and memory, machine learning techniques applied in the field, and the variety of challenges faced, including ethics, in this emerging field.**

Keywords: EEG, Neuromarketing, Neuroscience, E-commerce

I. INTRODUCTION

Neuromarketing is an application of neuroscience to marketing research that studies cognitive and affective responses of consumers to the marketed products or services. It is an emerging field which lies at the intersection of neuroscience, psychology and marketing [1]. Neuromarketing not only focuses on impact of variation of market stimuli on sales but also explains how changes in the stimuli presentation affect consumer's choices. Promoters spend around 400 billion dollars every year for advertisement [2], so there is substantial motivation to find efficiencies in the targeting of correct market segments and customers.

Traditional research methods focus mostly on the a posteriori attitude of consumers towards products by asking them to fill out questionnaires after the fact. These responses are therefore delayed and simplified, and fail to represent the actual state of mind at the time of purchase [3]. Conversely, neuromarketing focuses on capturing the in situ response by considering the brain signals at the time of purchase. Fig. 1 shows an example of the typical neuromarketing workflow. Researchers use various techniques such as functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG), Steady State Topography (SST) and Transcranial Magnetic Stimulation (TMS) to measure changes in brain activity. Biometric measures, such as respiratory rate, heart rate, facial expression, skin response and eye tracking are also used to measure changes in the physical, emotional and focal state of consumers. These systems are then used to determine why and how customers make certain decisions about products and which brain areas and physical responses correspond to those decisions [3].

The human brain is made up of neurons that communicate with each other via electrical impulses [4]. EEG signal measurement is a practical way to detect the sequential change of brain activity without appreciable time delay, which is important for the understanding of both the unconscious reaction and sensory reaction of the customer. The field of neuromarketing overcomes the challenge of heterogeneity within and across consumer groups which affects consumer preferences and decisions. This heterogeneity may be based on age, gender, various biological factors like hormones and genes, and various physiological factors [5].

Using neuromarketing, marketers can determine the best strategies (such as celebrity endorsement or linking with social cause) to promote their products, avoiding wasted marketing resources. In the literature, researchers have focused on different marketing parameters such as brand perception [6], [7], brand evaluation decision [8], [9], [10], brand relationships [11], [12], brand preferences [13], [14], [15], pricing [16], product packaging [17], [18], brand naming [19], green consumption [20], store illumination [21], advertisement [22], [23], and new product development [24], etc.

In this paper, we focus on EEG-based neuromarketing because these devices are now relatively inexpensive and accessible, can be connected with mobile devices and thus used outside the laboratory, making this EEG technology of great interest for evaluating the marketing stimuli. We explore

*Both authors contributed equally to this manuscript

[1]Vaishali Khurana, Monika Gahalawat and Partha Pratim Roy are with Department of Computer Science and Engineering, IIT Roorkee, India. vaishali.khurana27,monikagahlawat62 at gmail.com, proy.fcs at iitr.ac.in

Debi Prosad Dogra is with School of Electrical Sciences, IIT Bhubaneswar, India. dpdogra at iitbbs.ac.in

Pradeep Kumar and Erik Scheme are with Institute of Biomedical Engineering, University of New Brunswick, Canada pkumar1,escheme at unb.ca

Mohammad Soleymani is with Institute for Creative Technologies, University of Southern California, USA soleymani at ict.usc.edu

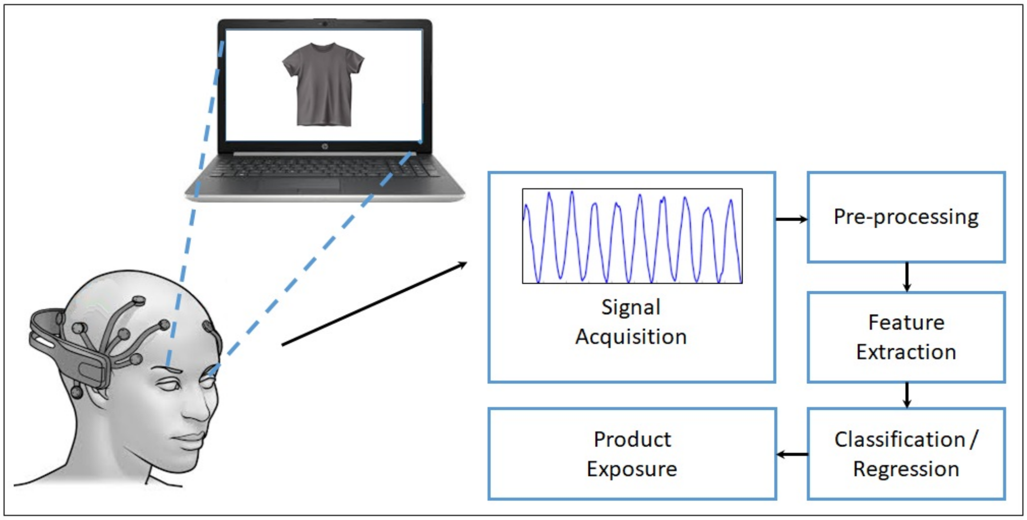

Fig. 1. The process of neuromarketing where EEG response towards a product is recorded and processed to get product exposure.

the effect of its use on consumer appeal and memory, the various machine learning techniques used in this field, and the various challenges faced, including ethics, in the application of neuromarketing. The remainder of the paper is organized as follows. Section II overviews the problem definition and the collection of signals. In Section III, the application areas of neuromarketing are presented. In Section IV, we present computational approaches for neuromarketing including pre-processing methods, feature extraction techniques, and classification methodologies. In Section V, we provide descriptions of the available datasets and data types. In Section VI, the methodological and ethical challenges faced by neuromarketing are discussed, prior to concluding in Section VII.

II. Definition and Terminology

A. Problem Definition

The definition of neuromarketing in the scientific literature is given as the study and analysis of human behavior relating to market exchange [25]. Neuromarketing is an application of neuroimaging technologies that emerged in mid 1980s, along with different fields such as neuropsychology, neurophysiology, neuroethology and neuroanatomy. Neuromarketing, as a term, was coined in 2002 and has gained tremendous popularity in the last few years with researchers focusing on consumer behavior, how they feel when exposed to certain advertisements, or how and why they react the way they do to particular products. One reason behind increases in neuromarketing research is that it does not require any additional explicit (or subjective) participation or response by the consumer [2].

Neuromarketing and consumer neuroscience are often used interchangeably as both terms refer to the intersection of marketing, psychology and neuroscience. Consumer neuroscience is more focused on academic research while neuromarketing more commonly refers to the use of neurophysiological tools [3] such as skin conductance, eye tracking, EEG, fNIRS abnd fMRI, to conduct commercial market research [26].

B. Decision Neuroscience and Neural Underpinning of Preference

Lee *et al.* [25] showed that neuroscientific methods can be applied to understand human behavior in the context of markets and marketing strategies. Similarly, Garcia et al [27] suggested that neuromarketing can be considered as the intersection between consumer behavior and neuroscience. Prediction of consumer behavior indeed has some biological basis but it also depends on the relevance of the characteristics of the product or offering highlighted to different individuals or groups. Furthermore, purchasing decisions depend on individual beliefs, preferences, and behaviors [28]. Neuromarketing correspondingly employs physiological measurements to examine the brain activities related to the formation of beliefs, the perception of the action set, and the actual choices made. Ohme *et al.* [29] demonstrated how neurophysiology benefits marketing strategies. While capturing consumer reactions to very small differences in stimuli that may not be consciously recognized, they observed that even these slight differences result in significant differences in consumer reactions. Schwarzkopf *et al.* [30] showed how marketing has evolved from 'misery of choice' into 'dreams of fulfilment'. To better understand modern consumer culture, they considered creating desire as a strategy by attaching meanings to a product that result in distinct interpretations and associations in the consumer's mind. Holistically, measurement of neural activity can be used to correlate individual preferences [14], subjective values [31] and choice [32]. Bagozzi *et al.* [33] postulated that physical experiences are derived from mental experiences. Similarly, Raichle *et al.* [34] suggested that the brain is a reactive system in response to sensory input. Whenever some sensory input (stimuli) is presented to the brain, neuronal activity occurs that affects the behaviour and response of the recipient of that input. Given these rationales, it is clear that neuropsychology plays a major role in the field of neuromarketing.

Andrew *et al.* [35] considered three important aspects for purchase decision making: identity, ego and superego. Identity refers to the desirable traits and features that the customer is looking for. Ego relates to the price a customer is ready to pay for the product; this is modulated by identity but controlled by ego. Superego refers to any negotiations that the customer may attempt to make as it relates to the purchase of the product. Here, the equilibrium point of the superego of the seller and customer decides the level of negotiation.

Many earlier studies have employed costly advertising testing methods [36] but emerging technologies are now facilitating more economical and objective opportunities for neuromarketing studies. Lee *et al.* [37] and Dmochowski *et al.* [38] observed that neuromarketing leverages common neuroscience methodologies and modalities used to measure neuronal activities, such as fMRI, fNIRS, EEG and MEG. Although fMRI measures brain activity, it is difficult to identify the corresponding stimulus features that are responsible for that response. EEG and MEG measure the secondary potentials arising from brain activity, but leverage more synchronous brain activity to detect and capture the relevant signals. Nevertheless, EEG is much more cost effective and accessible, making it the most commonly used technique in this domain. Furtheremore, unlike other signal modalities like fMRI, which measures blood oxygenation level but cannot capture weaker neural activity localized outside of cortical areas, EEG measures the neural activity directly [38]. For these reasons, EEG has been widely explored for applications in neuromarketing, as outlined in this paper.

C. Neuroimaging

When using EEG, recording electrodes - often embedded in caps or wearable devices - are positioned directly on the test subject's scalp. These data can then be recorded at very high sampling frequencies (such as 10k on some newer devices) [2]. These high sampling rates are important when endeavoring to capture rapid responses to external stimuli without aliasing. Most of today's EEG devices, however, lack the spatial resolution needed to accurately resolve the position of specific neurons in the brain. Likewise, electrodes placed on the scalp are unable to pick up electrical signals originating beyond the cortex level. Apart from neuromarketing, EEG is also used extensively in Brain-Computer-Interfaces (BCI) to convert brain signals to interpretable commands, allowing users to engage or interact with a variety of external interfaces [39], [40]. Vast improvements have been made in recent years to enhance the practicality of BCI, with gains being made via better signal processing, recording, and interpretation [41], [42]. Similarly, the presence of subject-identifying features in the EEG of different people has also established its use as a potential biometric [43], [44], [45]. Another research domain that has prominently featured EEG is the study of sleep patterns, such as for insomnia patients [46], differences in sleeps patterns between young adults and children [47], or the study of different sleep stages [48].

III. Applications of Neuromarketing

It is known that many complex factors affect a consumer's decision making process, and neuromarketing provides deep insights into consumer behaviors at an individual level. Neuromarketing correspondingly helps marketers develop strategies by using real time measures of brain activities in association with and in response to various marketing stimuli. Unlike traditional inferential approaches to market research, it is used to explain consumer responses in a direct correlational process. This objective approach allows marketers to better understand the detailed and evolving thought process of consumers to develop more effective and efficient strategies. It should be noted that Neuromarketing is not necessarily intended to manipulate the personal choices of specific consumers, but is instead meant to help develop a better understanding of the interests and perspective of potential consumers in order to generate precise behavioral models.

Using neuromarketing principles, for example, the gender, socioeconomic, or age group most attracted to a particular product type may be determined and targeted accordingly [49]. Promotion may then follow standard mechanisms such as offering targeted customer groups exclusive previews, organizing social media contests, hosting events, email marketing, or in-store promotion. But whereas the evaluation of promotional strategies is largely binary (was the item or service purchased or not), consumer cognitive feedback may play an even more important role in understanding customer behaviours. Neuromarketing may also be used to evaluate a particular brand from a customer point of view. It can be used to compare and contrast different brands, gain a better understanding about interactions between them, and which features are desirable [50]. Customer valuation of products has also been evaluated by exploring responses to different pricing or pricing structures, allowing marketers to rapidly hone in on optimum costing relative to competitive products [51]. Consumer behavior is highly influenced by the perception of surroundings. Lighting has also been studied as an important factor on both the consumer emotions and the retail atmosphere [52]. Neuromarketing has been helped to inform the design of in-store environments that are more likely to influence customers and motivate them to stay or return to the store.

Indeed, as marketers continue to strive for new ways to reach their customers, neuromarketing has opened up new avenues through the application of neuroscience principles. Fig. 2 and 3 show two such examples about how EEG signals can be used to obtain a user's response to a product or video, respectively, with the help of BCI models. Table I summarizes the wide variety of applications of neuromarketing techniques. For example, Yu *et al.* [53] found that having consumers play a game before being presented with brand information helps in promoting the brand by inducing an association with positive feelings. Therein, the authors conducted a game based ERP study to investigate whether winning or losing would affect consumers' preferences of unfamiliar brands. In [54], the authors performed a neuromarketing study to discover the relationship between the emotions induced by audio-visual advertisements and their impact on the viewer's memory of the good or service being advertised. It was reported that emotions in advertising messages influence the recall of brands and the messages they transmit. Likewise, the impact of brand perception [55], [3], assessment [56], [57], naming [58], [59], [60], store environment [21], [61] and customer's hidden feedback [62], [63] have been studied using neuromarketing principles.

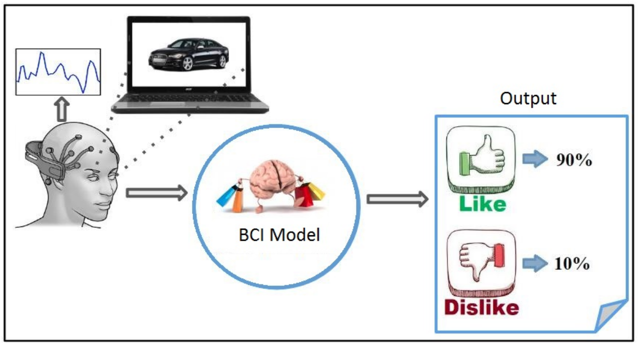

Fig. 2. An example of a neuromarketing scenario: A user is watching an advertisement for a product while EEG signals are simultaneously recorded. The BCI model predicts whether the person likes or dislike the product by analyzing brain signals.

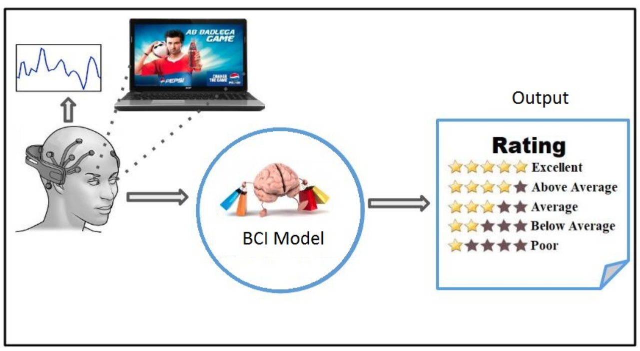

Fig. 3. Another scenario of predicting video ratings using EEG signals. The BCI model predicts level of user interest along a continuous scale.

IV. Experimental Conditions

Despite the power and growing popularity of EEG-based neuromarketing, the process of collecting EEG signals is time consuming and cumbersome. It requires careful preparation of the environment where the signals are to be recorded as any noise or interference during the data collection may lead to erroneous results. Ideally, the location where the EEG signals are to be collected should be insulated from outside noise influences and there should be no additional disturbances while recording signals. Moreover, pilot experimentation is often essential so as to minimize the chances of failure in the actual experiment. These difficulties in the collection of EEG have given rise to the adoption of a variety of devices and the leveraging of existing, pre-recorded datasets.

A. Measurement

1) Available Datasets: Multiple EEG datasets are now available for researchers aiming to leverage previous collections to jump directly to analysis (*e.g.*, LSW-neuromarketing[1] [76]). The NAS dataset[2], contains neuromarketing data about sentiments against smoking collected from participants from all over the world. Delorme *et al.* shared a free EEG/ERP public Dataset[3] [77] [78] that contains EEG data from 14 participants (7 females, 7 males) collected using the Neuroscan software. Similar datasets are available via the EEG Database[4] which contains data measured using 64 electrodes from differnet users with different number of trials. The dataset is available in three versions (small, large and full) that can be leveraged according to the requirements of the researcher. Multiple additional EEG datasets related to advertisement ratings are available online[5].

2) Devices Used: A wide variety of devices are available in the market for acquiring EEG signals, ranging from consumer grade and price to highly specialized and complex. The devices differ not only in the number of channels recorded, but also in the flexibility and fashion in which they are recorded. Various available devices and their placement of electrodes are according to International 10-20 system. Regardless of system, all EEG signals are collected by placing electrodes on the scalp which capture the underlying brain activity by way of the weak electrical potentials generated by the brain. Researcher has to consider multiple aspects before choosing the suitable device. Following is the comparison among popular EEG devices in Table II.

One particularly common system, the 14 channel Emotiv EPOC device, is shown in Fig. 4. This device has been used extensively due to its relative ease of use compared to more complex systems [79], [80], [81], [82], [83], [84], [85].

Collecting EEG signals from more sites, thereby providing better spatial resolution, has generally been found to yield more accurate results. However, the number and placement of channels must also be carefully selected so as to increase the information density and reduce potential sources of noise. Another critical factor is the ease of use: while head-cap style systems such as the 128-channels Quik-Cap from NeuroScan[6] is depicted in Fig. 4(b) provide high resolution and robust signals, many researchers have opted for simpler devices like the Emotiv EPOC+ device. While more limited, than the more complex devices available on the market, it is easy to don/doff, is compatible with a range of operating systems (Windows, Linux, Android, iOS) and is generally more comfortable for the user as it fits easily over the scalp because of its flexible design. Importantly, it is wireless with battery backup for up to 12 hours of continuous use, allowing it to be used outside of the laboratory setting. Despite its lower number of electrodes, it has been shown to be sufficient to capture relevant brain signals [4].

3) Participant Demographics: Numerous research has been conducted in consideration of subject demographics, especially gender and age. In literature, it has been widely reported that males have higher brain weight and sizes whereas females have greater neuronal density of the fronto-basal cor-

[1]https://old.datahub.io/dataset/lsw-neuromarketing

[2]http://www.nmsba.com/neuro-against-smoking/data

[3]https://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html

[4]https://archive.ics.uci.edu/ml/datasets/eeg+database

[5]https://sites.google.com/site/iitrcsepradeep7

[6]https://compumedicsneuroscan.com/

TABLE I
APPLICATIONS OF NEUROMARKETING

Sr. No.	Application	Summary
1.	Brand perception [55], [3]	Regardless of the intended brand messaging, the actual brand is dictated by what consumers think of it and how they respond.
2.	Brand assessment [56], [57]	The evaluation of a brand from the customer point of view, and its re-positioning to reflect changes in the marketplace.
3.	Brand relationships and competition [53], [64]	Neuromarketing help find relationships between different brands and value relative to competitors.
4.	Brand preferences [3], [53]	The identification of brands that are preferable by customers, and what features are most desirable.
5.	Brand naming [58], [59], [60]	Neuromarketing determines how people respond to a brand's name, and whether people are able to identify with the product by its name alone.
6.	Advertising [54], [65], [63]	Neuromarketing is used to compare various advertising campaigns, such as those that contain surprise, which have been found to be more effective.
7.	Product promotion [66], [67], [62], [68]	The strategic promotion of products to target customers identified using neuromarketing principles.
8.	Pricing [69], [70], [64]	Understanding customers' perceived product value relative to competitors can help determine optimal product pricing.
9.	Product packaging [71], [72]	The strategic packaging of products to appeal to a target market.
10.	Product aesthetics [73], [72]	Neuromarketing has been used to explore the choice and impact of product color for specific target markets.
11.	Store environment [21], [61]	Neuromarketing is used to design in-store environments that are conducive to customers staying and returning to the store.
12.	Satisfaction evaluation [66], [74], [75]	The customer response to a particular product can be evaluated using neuromarketing approaches.
13.	Revealing Hidden Feedback [62], [63]	Neuromarketing is able to reveal subtle or hidden thought (using brain signals) helping those who can not openly give their detailed opinion.

tex [86]. In terms of functional connectivity, females shows more within-network connectivity while males display more between-network connectivity in regions within the attention, auditory, memory retrieval and default mode networks. Males perform better in tasks involving visual-spatial processing, motor speed, language accuracy and mental rotation while females are good in tasks considering selective attention, verbal fluency, non-verbal reasoning, and emotion identification [87]. Davidson *et al.* [88] have reported a greater relative right-hemisphere activation in female candidates during emotion and non-emotion recognition process. Likewise, the authors in [89] have used 33 participants' (17 female) EEG data to classify three gesture movements. The authors have recorded more prediction performance while considering the EEG of female candidates only. Considering the EEG for neuromarketing, the authors in [79] predict the product preference among different age group participants. The authors have recorded low classification performance in female candidates due to high-densed hairs which cause noisy EEG.

Researchers in [80], [1] have targeted different age groups depending on the usability of the product type from market point of view. It is good to maintain the heterogeneity within and across consumer groups because different age groups and genders have varying preferences of product types. It has been observed that the middle age group (20-30 years) people have been targeted majorly because they are the active users of majority of the products.

B. Marketing Stimuli

A variety of different types of stimuli have been used to elicit participant responses. Most research has employed video-based advertising while recording EEG signals in an effort to interpret how the subjects felt while watching advertisements [90], [91], [63]. Others have used product images or verbal descriptions, recording participant responses to determine like/dislike sentiments regarding the product [75], [84], [92]. Others have observed more general responses to things such as color schemes (*e.g.*, showing a screen filled with particular color) to understand the objective and subconscious preferences of the participant that directly affects decision making along with subjective evaluation. A taxonomy of the kinds of datasets and their subtypes is shown in the Fig. 5. The dataset types are further described in detail hereafter.

1) Product Images: Khuhshaba *et al.* [84] studied marketing stimuli, in the form of images of crackers, with three different shapes, flavors and toppings to create a sequence of 57 sets of choices. Participants were required to choose the set they liked most and least, and to rank their preferences among all of the sets. This was then used to measure the corresponding degree of change in EEG spectral activities. In [15], different shoe images were used to gather user feedback and EEG in terms of like/dislike. A similar methodology was used in [79], using a 16 second slide of each of the shoes in different styles and colors. Bastiannsen *et al.* used photos of tourist destinations in Bruges [93]. The authors divided the participants into two groups, where one group watched 11

TABLE II
A COMPARISON OF SEVENTEEN DIFFERENT EEG DEVICES

Device	Chann--els	Comm.	SPS	Operating Time (Hr)	Weight	Storage	Acc.	Med. Cert.	Advantage/ Application
NeuroSky-Mindwave	1	Bluetooth	512	8	90 g	N	N	N	Help in improving meditation & sleep
Muse	4	Bluetooth	256	5	200 g	N	Y	N	Help in improving meditation & sleep
Emotiv Epoc	5-32	Proprietary wireless	128	12	125 g	N	Y	N	Wireless, flexibility to move
Open BCI	8-16	Bluetooth	250	24	260 g	Y	Y	N	compatible with any headcap
Wearable Sensing	7-24	Bluetooth	300	8	600 g	Optional	Optional	N	Wireless, mobility, comfort, no gel required
ANT Neuro-eego rt/ eego sports	8-32	Wireless	2048	5	500 g	Y	Y	CE, class IIa	Wireless, comfort, no gel required
ANT Neuro eego rt/ eego sports	64	Bluetooth/ WiFi	2048	6	500 g	Y	Y	CE	Wireless, high density, comfort, no gel required
ANT Neuro-eego mylab	32-256	Bluetooth/ WiFi	upto 16 kHz	5	<500 g	Y	Y	CE	Wireless, high density, comfort, no gel required
Neuroelectrics	8-32	Bluetooth/ WiFi	500	14	65 g	Y	Y	CE / FDA	Wireless, comfort, no gel required
G.tec nautilus wireless / nautilus PRO wireless	8-64	Bluetooth	500	10	360 g	Y	Y	N	Wireless, comfort, no gel required
ABM B-Alert	10-24	Bluetooth	256	6 Bluetooth, 16 SD Card	110 g	Y	Y	N	Wireless, comfort
BioSemi	16	Wired	512	5-6	1.1 Kg	N	Y	N	freely configurable hard--ware and completely open-source software
Cognionics	20-30	Bluetooth	500-1000	6 Bluetooth / 10 SD card	250 g	Y	Y	N	Wireless, comfort, no gel required
mBrainTrain	24	Bluetooth	250-500	5	60 g	N	Y	N	Wireless, comfort
Brain Products LiveAmp	32	Bluetooth	500	3	60 g	Y	Y	N	Impedance check and app--licable with both wet/ dry electrodes
Brain Products ActiCHamp	32-160	Wired	100 kHz	Unlimited (Wired)	1.1 Kg	Y	Y	N	High Resolution
BioSemi	32-256	Wired	2-16 kHz	5 hours/ (unlimited when wired)	1.1 Kg	N	Y	N	High Resolution

min and 42 sec of the movie 'In Bruges' immediately before viewing the pictures and others (control group) watched an unrelated movie excerpt of duration 9 min and 23 sec. The difference in emotional response of these groups was then recorded.

In [81], screen background preference was studied for personal computers. Object images were created with three colors (blue, green and yellow) and three different patterns (bamboo, messy and none) creating 72 choice patterns based on different combinations of patterns and colors.

2) 3D Virtual Products: In [92], 3D virtual jewellery objects were shown to subjects who rated them on a scale of 1-5. Guo *et al.* [82], used 3D virtual products in a virtual environment. The virtual store contained a display of randomly arranged T-shirts which users could try by clicking on or viewing the T-shirt zoomed it or out, from different angles and distances. Users gave pre-purchase ratings of these products as feedback.

3) Advertisement Videos: Multiple authors have used advertisement videos to show different brand advertisements to participants while recording EEG to study how different brand advertisements are perceived by the user and how the advertisement affects the appeal of the brand. Ohme *et al.* [94] studied the frontal cortex activation when participants reacted to three different TV advertisements. Three 'Sony Bravia' advertisements ('Balls', 'Paints' and 'Play-Doh') were examined along with a selecton of 30 other distraction ads shown between them. Similarly, subject response to several video clips of four Malaysian automotive brands, namely Toyota, Suzuki, Proton and Audi were studied by Murugappan *et al.* [83]. Balconi *et al.* [1] used a video dataset based on different commercial sectors (alimentary, pharmaceutical, electronic, financial, clothing) to explore the relationship between explicit preference and implicit EEG responses. In [85], the authors showed video clips of 4 soap brands to the participants namely Lux, Pears, Dove and Cinthol. Djamal *et al.* [95] used video advertisements to study the effect of ads on viewers' neuropsychological behavior. Finally, a set of 15 advertisement clips of different length were also studied based on promotion of different product categories like tourism, home shopping, automobile, sports etc. [80].

4) Color Visuals: Visuals have been used to study cognitive activity and mental arousal levels of the human brain in response to different colors. Color plays a crucial role in the packaging and marketing industries as product choice is highly governed by visual appeal and color. Consequently, Kawasaki *et al.* [96] studied the effect of color on attention related occipital theta oscillations. They showed 2 colored

(a)

(b)

Fig. 4. EEG devices: (a) a 14-channel wireless Emotiv EPOC+ with accessories (b) 128 channel high-density EEG device.

squares with a gray background as visual stimuli to volunteers, and participants were asked to choose their preferred color. An enhancement in theta oscillations were reported when the participants focused on their preferred stimulus. It has also been concluded that brain activity related to visual attention is influenced by subjective preferences. Because colors plays such an important role in marketing and packaging, leading to different cognitive activities and arousal levels, Rakshit *et al.* [73] studied the impact of different colors using EEG. They showed four different colors (red, yellow, green and blue) to users for 10 seconds with a 2 second blank screen in two successive presentations. The recognition process was carried out on PSD features using Interval-Type-II fuzzy space classifier, with the best classification accuracy having been recorded for the color red.

V. Computational Approaches for Neuromarketing

Neuromarketing research is conducted by recording consumer brain signals to understand the process the human mind goes through while selecting one product or advertisement over another. Brain signals serve as the most important measure of consumers cognitive behavior as they are a direct and objective measure of activity. Brainwaves can be recorded at very small time intervals, giving a clear picture of the response to determine a detailed view of user preferences. This section outlines a detailed analysis of current techniques used for preprocessing, feature extraction and classification of EEG signals in the recent EEG-based neuromarketing literature. Tables V, VI and VII summarize the related works done in this field.

A. Pre-processing

Various sources of artifacts like muscular activity, blinking of the eyes, or electrical power line noise may appear while capturing EEG signals [97]. These artifacts may corrupt useful information in the signal of interest, thus, requiring that they be separated or removed. Table III outlines some of the different filters that researchers have evaluated in the preprocessing step towards this end.

Yadava *et al.* [79] used a Savitzky-Golay (S-Golay) filter to remove unwanted noise from the acquired EEG, whereas Gauba et a. [80] have used a moving-average filter (with an average number of points of 5) for signal smoothing. To remove environmental and electrical interference, a notch filter with 50 or 60 Hz can also be used [92], [20]. A surface Laplacian filter has been used along with a notch filter to remove artifacts [83]. Various groups have used bandpass filtering with varying cut-off frequencies to improve signal qualify prior to prediction. Gupta *et al.* [85] used Butterworth 4th order band pass filters with cut off frequencies between 0.5-60 Hz. Others have used cut-off frequencies between 0.01-30 Hz [93], 0.5-40 Hz [81], 4-50 Hz [20], 0.1-45 Hz [84], and 1-45 Hz along with 100^{th} degree FIR1 filter (window-based linear-phase finite impulse response digital filter design) [15]. To detect the effect of various colors on cognitive state, 10th order elliptical band pass and common average referencing spatial filters have been used [73].

Some researchers have also leveraged established artifact removal toolkits. Teo *et al.* [92] used the SDK provided by ABM for the B-Alert X10 headset in MATLAB, whereas Bastiaansen *et al.* [93] used the software package Brain Vision Analyzer (Brain Products GmbH, Germany) and Lee *et al.* [20] used the Telescan data analysis software.

Other artifact removal techniques have also been explored, such as Independent Component Analysis (ICA) [80], [96], [94], [84], Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT) [84].

B. Feature Extraction

In their raw form, EEG signals are time domain signals so they are typically first transformed to the frequency domain. Researchers have explored a variety of different features for evaluation based on their requirement, including the Gamma (32-100 Hz), Beta (13-22 Hz), Alpha (8-13 Hz), Theta (4-8 Hz) and Delta (1-4 Hz) frequency band spectra. Yadava *et al.* [79] applied DB4 (Daubechies 4) wavelet decomposition with each of the resultant five coefficients corresponding to a

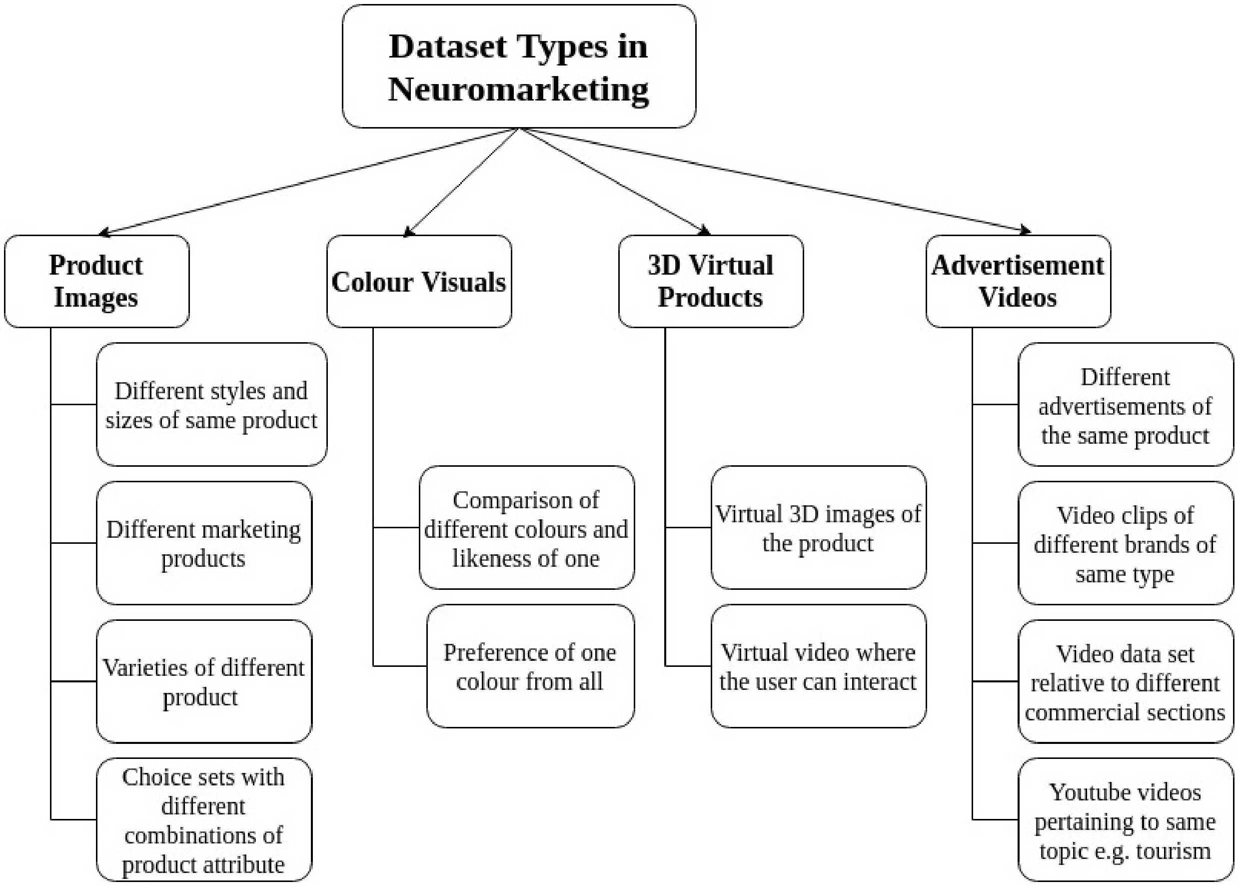

Fig. 5. Various dataset types in Neuromarketing.

frequency band. Kawasaki *et al.* [96] used wavelet transformation using Morlet wavelets with a Gaussian shape. Many have used the FFT directly [20], [94], [83]. or with zero padding [84]. Similarly, the STFT [92] and DFT techniques [73] have been used. Others used FFT with a logarithmic transformation because the extracted power feature of the EEG varies less linearly in the normal scale than in the logarithmic scale [81]. Djamal *et al.* used the FFT with 50% overlap windows to reduce lobes fluctuations [95]. Table IV outlines various feature extraction techniques that have been employed in EEG-based neuromarketing studies.

Different statistical features have also been extracted. Yadava *et al.* [79] extracted the Mean (M), Standard Deviation (SD), Root-Mean-Square (RMS) and Energy (EN) whereas Gauba *et al.* [80] used just the statistical mean for all 14 electrode channels. Others have extracted normalized features so that their mean is zero and variance is unity, using the Welch method for power spectral density estimation [73] and the Burg method [15]. Some have taken the average mean across participants [93], [96], whereas Guo *et al.* [82] extracted the averaged relative power and then generated ratings accordingly. Many have extracted the power spectral density [1], [20], [94], [99], and spectral moments extracted from power spectral analysis [81]. Khushaba *et al.* [84] extracted a moving-average power spectral density feature with normalized averaged power spectrum on a logarithmic scale to their benfit. Murugappan *et al.* [83] extracted other statistical features such as, Spectral Centroid and Spectral Energy with Power Spectrum Density.

C. *Classification and Results*

With applications beyond neuromarketing alone, the classification of EEG has been a widespread research endeavour and has recently expanded to include deep learning approaches [102], [103], [104], [105].

1) Deep Learning and EEG: Bashivan *et al.* [106] trained a deep Recurrent Convolutional Neural Network (RCNN) to classify EEG signals based on visual pictorial stimuli. Zhang *et al.* [107] proposed spatio-temporal EEG data classification models using both cascade and parallel RNNs for movement intension recognition using EEG, achieving accuracies of 98.3%. Schirrmeister *et al.* [108] used Convolutional Neural Network (CNN) with advanced visualisation techniques to classify EEG into 4 categories of imagined movements (right/left hand, feet, rest) with an accuracy of 92.40%. Hershey *et al.* [109] compared the performance of logistic regression dense neural networks, with two hidden layers with RNN and CNN for epileptic seizure detection and concluded that a 5 layer CNN followed by 2 dense layers achieved the best accuracy of 95%.

TABLE III
PREPROCESSING FILTERS USED IN THE FIELD OF NEUROMARKETING

Filter	Details	References
Savitzky-Golay (S-Golay) filter	frame span = 5 with a quadratic polynomial	Yadava *et al.* [79]
Moving-Average filter	average number of points = 5	Gauba *et al.* [80]
Notch filter	Frequency = 50 Hz in [92], [83] and 60 Hz in [98]	Teo *et al.* [92], Murugappan *et al.* [83], Lee *et al.* [20]
Surface Laplacian filter	–	Murugappan *et al.* [83]
Butterworth bandpass filter	Order = 4 with a cut off frequency between 0.5 Hz and 60 Hz	Murugappan *et al.* [83], Gupta *et al.* [85]
Elliptical bandpass filter	Order = 10	Rakshit *et al.* [73]
Common average referencing spatial filter	–	Rakshit *et al.* [73]
Bandpass filter	cut-off frequency between 0.01 and 30 Hz in [93], 0.5 Hz to 40 Hz in [81], 4 to 50 Hz in [20], 0.1-45 Hz in [84]	Bastiaansen et al [93], Khushaba *et al.* [81], Lee *et al.* [20], Khushaba *et al.* [84],
FIR1 bandpass filter	100th degree cut off frequency 1 and 45 Hz	Yilmaz *et al.* [15]
ICA (Independent Component Analysis)	–	Gauba *et al.* [80], Kawasaki *et al.* [96], Ohme *et al.* [94] and Khushaba *et al.* [84]
PCA (Principal Component Analysis)	–	Khushaba *et al.* [81]

TABLE IV
FEATURE EXTRACTION TECHNIQUES & EXTRACTED FEATURES USED IN THE FIELD OF NEUROMARKETING

Feature Extraction Techniques/Extracted Features	References
DB4 (Daubechies 4) wavelet decomposition technique, Statistical Mean, Standard Deviation, Root-Mean-Square, Energy	Yadava *et al.* [79]
Statistical Mean	Gauba *et al.* [80], Bastiaansen *et al.* [93]
Wavelet transformation by using Morlet wavelets with a Gaussian shape, Statistical Mean	Kawasaki *et al.* [96]
FFT, Power Spectral Density	Khushaba *et al.* [81], Lee *et al.* [20], Ohme *et al.* [94], Khushaba *et al.* [84]
FFT	Djamal *et al.* [95]
FFT, Spectral Centroid and Spectral Energy	Murugappan *et al.* [83]
STFT, Power Spectral Density	Rakshit *et al.* [73]
DFT	Teo *et al.* [92]
Relative Power	Guo *et al.* [82]
Power Spectral Density	Yilmaz *et al.* [15], Balconi *et al.* [1], Vecchiato *et al.* [99]

Hosseini *et al.* [110] proposed a cloud based BCI system for epileptic seizure prediction. They developed a series of dimensionality reduction algorithms using ICA, PCA and stacked autoencoders to reduce the computation and necessary communication bandwidth. Similarly, Li *et al.* [111] used neural networks for Autism Spectrum Disorder detection using EEG signals. Ren *et al.* [112] used a convolutional deep belief network for EEG feature extraction with benefit as compared to hand-crafted features such as common spatial pattern and band-power.

2) Classification based on different brain lobes: Activity in different parts of the brain have been found to correspond to different brain function. Briefly, the pre-frontal lobe corresponds to complex thinking, reasoning, attention [113]; the frontal lobe integrates thoughts and emotions [114], [115]; the parietal lobe relates to touch, taste and body awareness [116], [117], [118], [119]; the temporal lobe relates to hearing and recognition [120], [121] and the occipital lobe corresponds to vision [116], [122] as shown in Fig. 6. The lobes that relate most to the field of neuromarketing are therefore the pre-frontal and frontal lobes. Some researchers have focussed specifically on these areas [14], [123], [124], [125], [126], [94], where as others have more globally considered all areas of the brain [127], [128], [129], [130], [131], [84].

Ioannides *et al.* [127] and Ambler *et al.* [128] showed the effect of advertisements on neural activities using MEG in different cortical centers. Rossiter *et al.* [123] used EEG to show the effect of visual scenes specifically on the activation of the left frontal cortex. Dmochowski *et al.* [134] analyzed EEG data recorded from participants while watching advertisement

TABLE V
RELATED WORK DONE IN THE FIELD OF NEUROMARKETING CONSIDERING "PRODUCT IMAGES" AS DATASET

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Khushaba *et al.* [100], 2012	Bandpass filter, PCA, FFT, Mutual Information Classifier	Choice sets of images that vary in color and pattern	18 participants, Aged 25 to 65 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Khushaba *et al.* [81], 2012	Bandpass filter, ICA and DWT for denoising, FFT with zero padding, Mutual Information Classifier	Used objects pictures to choose as screen background	18 Participants, Aged between 25 and 65 years	14 channels(AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, 01, 02)
Yilmaz *et al.* [15], 2013	FIR1 and bandpass filter, Logistic regression, GLM	Powerpoint slide of images containing women's shoes in different styles and colors	15 participants, No male and 15 females, Aged 20 to 40	21 channels; 19 of them used for like/dislike analysis(Fp1, Fp2, A1, A2, O1, O2, C3, Cz, C4, F3, Fz, F4, F7, F8, T3, T4, T5, T6, P3, Pz, P4)
Bastiaansen *et al.* [93], 2016	Bandpass filter, automatic artifacts removal	photos of the tourist destination Bruges	32 participants, 8 male and 24 females, Aged 18 to 26	61 electrodes
Yadava *et al.* [79], 2017	S-Golay filter, DB4 wavelet decomposition, HMM Classifier	14 different product images with 3 varities of each	40 participants, 25 male and 15 females, Aged 18 to 38	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)

TABLE VI
RELATED WORK DONE IN THE FIELD OF NEUROMARKETING CONSIDERING "ADVERTISEMENT VIDEO" AS DATASET

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Vecchiato *et al.* [101], 2010	Average classifier	Different commercial video advertisements about a naturalistic documentary	A mannequin as subject	Brain Amp (61 channel system)
Ohme *et al.* [94], 2010	ICA, FFT, Mean classifier	3 Video advertisements from same product	45 Participants, 21 male and 24 females, Aged 26 to 45	16-channel
Lee *et al.* [20], 2013	60 Hz Notch filter, Bandpass filter, FFT, General Linear Model (GLM)	Written description of products with their prices without visual depiction of the product	19 university students, 12 male and 7 females, Mean age 23.4	Niteen channel(Fp1, Fp2, A1, A2, O1, O2, C3, Cz, C4, F3, Fz, F4, F7, F8, T3, T4, T5, T6, P3, Pz, P4)
Murugappan *et al.* [83], 2014	50 Hz Notch filter, Butterworth 4th order bandpass Filter, Surface Laplacian filter, FFT, KNN, Probabilistic Neural Network(PNN)	Video clips of four Malaysian automotive brands	12 Participants, 9 male and 3 females, Aged 22 to 24	14 channels(AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, 01, 02)
Gupta *et al.* [85], 2017	Butterworth 4th order bandpass filter	Video clips of 4 soap brands, namely, Lux, Pears, Dove and Cinthol	18 subjects, 9 male and 9 females, Aged 22 to 24 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Esmeralda *et al.* [95], 2017	FFT with windowing, nonlinear SVM	TV Advertisements	30 subjects, Aged 20 to 25 years	4 channels (AF3, AF4, T7, and T8)
Gauba *et al.* [80], 2017	Moving Average filter, ICA, Random Forest Regression	Video advertisements from different promotional categories(home, shopping, sports, automobiles)	25 participants, Aged 20 to 42 years	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)

videos and performed an EEG-informed fMRI activation study to identify brain areas that are systematically more (or less) active during stimuli. Consideration of both predictable and unpredictable choices are further discussed in [129], where predictability depends on earlier use of the product and the time duration between the stimulus and decision making. They showed that the activation of different brain regions is related to silent vocalization and an internal reward system. Different brain regions associated with pleasure and reward are discussed in [130], where the authors presented a distributed human neural system for face perception. It was concluded that assessment of facial beauty occurs in the sublenticular extended amygdala (SLEA) and the ventral tegmentum (VT), where activity is reflected with a positive signal response in the orbitofrontal gyrus (GOb), nucleus accumbens (NAc), and ventromedial prefrontal cortex (VPFC) for rewarding beauty. It has also been reported that products with high social value result in high reward brain activity of the orbito-frontal cortices, occipital cortices and anterior cingulate regions than products with low value [124]. Moreover, the emotional connection with a particular brand affects the hippocampus and dorsolateral prefrontal cortex areas of the brain [125]. Importantly, the neural activity of superficial cortical areas is highly reflected in EEG [131], whereas neural activity in the ventral striatum and medial prefrontal cortex is related to both individual subjective value [126] and the purchasing behaviour of largeer populations [14].

Frontal brain activations have been investigated using a mean classifier on the alpha power in the ipsilateral electrodes [94]. They aimed to study the reaction of frontal cortex activation against three different TV advertisements. The videos were selected based on the emotional engagement (picturing vitality, joyfulness and colorfulness) and product information (benefits, product and brand scenes) criteria. However, the results of dominant reactions were only seen in one of the advertisement video in both the emotional and informational parts. An interesting and distinct concept is discussed in [135] wherein they focus on the pre-frontal cortex of brain to

TABLE VII
RELATED WORK DONE IN THE FIELD OF NEUROMARKETING CONSIDERING "COLOR VISUALS AND 3D VIRTUAL PRODUCTS" AS DATASET

Author, Year	Approach Used	Dataset	No. of subjects	Channels
Kawasaki *et al.* [96], 2012	ICA, Wavelet Transformation, Mean classifier	Color visuals, choose color from 2 colors presented simultaneously	19 participants, 11 male and 8 females, Aged 18 to 27 years	60 electrodes
Guo *et al.* [82], 2013	Adapted Collaborative Filtering for making recommendation on basis of EEG ratings	3D virtual website where the user can easily interact with the interface	–	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4)
Rakshit *et al.* [73], 2016	elliptical bandpass filter of order 10 and Common average referencing spatial filter, DFT, SVM, T1FS, BPTT Neural Network	visual stimuli consisting of four colors (Red, Yellow, Green, Blue) and each color appearing randomly on the screen	7 subjects, 4 male and 3 females, Aged 22 to 30 years	10 channels (F3; F4; Fz; P3,Pz; P4; 01; 02; T7; T8)
Teo *et al.* [92], 2017	50 Hz Notch filter, Automatic Artifacts removal, STFT, Deep Neural Network	3D visual jewellery type objects stimul	16 subjects, 8 male and 8 females, Mean age 22.44	9 channels (POz, Fz, Cz, C3, C4, F3, F4, P3 and P4)

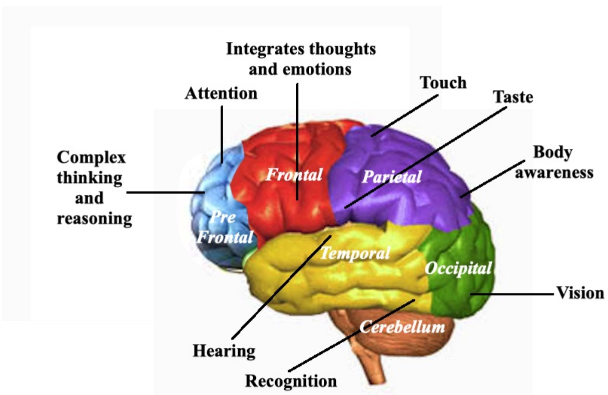

Fig. 6. Different brain regions and their significance in neuromarketing [132], [116], [133]

understand left-right alpha asymmetry in response to mobile application brand perception and popularity. Subjects' emotional feedback was recorded before and after the experiment, and supported the importance of clarity and a simple interface for a better user experience. Also, their results reveal that excessive browsing in the application leads to negative emotional engagement possibly due to a more complicated interface that spoils the user experience. Lee *et al.* [20] explored the behaviours of green consumers, who try to choose environment-friendly products. They tried to identify these consumers by finding differences in the frontal theta brain waves. A General Linear Model (GLM) for multivariate analysis was used to analyze the frontal brain waves and resulted in a significant difference between the frontal theta activations of the green and non-green consumers.

In addition to focusing on specific brain regions, researchers have also explored complete brain activations, and the interdependencies between regions, in response to human preferences. One such study [84] investigated the psychological process of decision making by the participants with a focus on the different brain regions' cortical activity and their interdependencies using mutual information analysis.

3) Classification based on User preferences: While much of the research in neuromarketing and EEG is focused on the likes/dislikes of consumers, here, the focus is on the qualitative features of the product that result in the subject making a particular decision. Results reveal that more positive cognitive processing can be initiated by specific attributes or combinations of attributes. A combination of two non linear classifiers, Probabilistic Neural Network (PNN) and k-Nearest Neighbor (KNN), were used in [83] to better understand the objective of participants decision making processes.

Kawaski *et al.* [96] studied the impact of consumer color preference on the visual attention-related section of the brain to understand brain activations and oscillatory activity between the left and right occipital electrodes while the consumer focused and preferred one color over the other. Using a mean classifier across single trials, a non-parametric Wilcoxon signed rank test on the difference in alpha and theta waves found that the theta amplitude increased as the preferred color is focused upon and selected.

4) Comparative Analysis: Comparisons between different classifiers or combinations of classifiers have been conducted to better understand brain activations or to identify more discriminative channels or features. Yilmaz *et al.* [15] used logistic regression to identify the most discriminative frequencies for user preference of consumer products utilizing GLM. Along with finding the most discriminative channels, the authors also studied the timing differences in forming a like decision between female and male participants.

User preferences have been studied by focusing on frontal spectral activations of the brain while the subjects record their preferences [100]. Mutual information was used to investigate left-to-right and front-to-back hemisphere differences, and used eye tracking to record eye placement on images presented to the subject while they clicked the most preferred image. Similar studies have found that theta bands are more relevant when extracted from symmetric occipital, frontal and parietal regions when considering information exchange between the right and left hemisphere. Conversely, beta bands dominate the temporal and occipital regions and alpha band waves domineer in the parietal and frontal regions of the brain [81]. Rakshit *et al.* compared Interval-Type-II fuzzy classifiers and other standard classifiers such as Support Vector Machine (SVM), Type 1 Fuzzy System (T1FS), and backpropogation-through-time Neural Network (BPTT-NN) [73] to explore the cognitive bias of different colors and its impact on the subject's mental arousal level.

Accuracy based on EEG from the frontal, parietal, occipital and temporal brain lobes has been compared using Hidden Markov Model (HMM), SVM, Artificial Neural Network (ANN) and Random Forest (RF) [79]. Similarly, RF, Decision Trees and Linear Regression classifiers were contrasted in [80].

5) Error Analysis: Some research has also been conducted to better understand the errors that can occur during the process of EEG data collection and their subsequent analysis. Vecchiato *et al.* [99] expounded the use of adequate statistical techniques in neuro-electromagnetic brain mapping frameworks. They used a mannequin as an experimental subject to study the type I errors that can happen during the recording and execution of statistical tests. The main focus of this work was to study the statistical differences in the data recorded using the mannequin and the data aggregated while watching a documentary. The authors used various state-of-the-art methods to determine the strength distribution of the cortical level dipoles. They also emphasized the use of Bonferroni adjustment as it produces better results for type I errors, though increases in type II errors limit its usefulness. Mental fatigue can also be considered as a form of EEG error as it limits the performance and working capability of the user due to reduction in situational awareness. Consquently, fatigue estimation has been considered in the design of BCI systems. Talukdar *et al.* [136] reported that, when a person experiences fatigue, their concentration, attention, focus and vigilance level decreases, requiring greater attention which leads to increase in alpha power. Other proposed metrics used in fatigue estimation include increased RMS in EEG bands [137] and changes in the ratios of powers between different frequency bands [138].

VI. Challenges and Ethics

A. Methodological Challenges

Current neuromarketing research still lacks a deep and thorough understanding of how the brain operates and it affects specialized human behavior and decision making processes. Currently, the dominant techniques used for neuromarketing (EEG, MEG, and fMRI) are unable to record brain activity at the individual neuron level. Consequently, improvements in acquisition and analysis methods are required in order to completely understand these complex relationships. Continued advancements in both domains will help inform the development of products and services that definitively meet the demands of consumers, both consciously and unconsciously. Moreover, brain-inspired computing and Field programmable gate arrays (FPGA)-based architectures can also be used to simulate the dynamics generated by biologically-plausible synthetic neuronal assemblies in real-time [139], [140], [141], [142].

In this paper, EEG-based neuromarketing systems have been reported. The major challenge using EEG for such research is the noise interference. EEG includes unwanted electronic activity from brain [143]. The high amplitude of background electrical brain activity due to unrelated marketing stimulus is hard to remove. To correctly estimate the actual ERPs, a large number of trials per condition need to be performed, which is not an easy and feasible task [144]. Preprocessing techniques such as filtering and regression are proposed in literature to remove the unwanted signals. The source of artifacts can be environmental noise, experimental error and physiological changes in body, such as eye movement, cardiac activity and muscle activity, etc. [145]. The experimental error can be reduced by carefully handling the setup and following the procedure [146]. The environmental noise frequency bands does not overlap with the desired signal frequency bands and can be removed using filtering [147], whereas the physiological artifacts interfere with neural frequency bands which are tough to remove [148]. According to Sweeney *et al.* [149], the low-pass, high-pass or band-pass filters can only be used in case of non-overlapping frequency bands, rather adaptive and Bayes filtering can be used. Other preprocessing techniques like common average referencing [150], blind source separation [151], wavelet transform [152], Principal Component Analysis (PCA) [153], Independent Component Analysis (ICA) [154] and Canonical Correlation Analysis (CCA) [155] techniques can also be used [147].

On the other hand, the artifact removal process cannot be easily automated due to the availability of multiple types of artifacts in EEG. Also, it is not feasible to have a reference channel for each muscle producing the artifact [156]. While ICA is the most commonly used algorithm for artifact removal by estimating original signals which are non-Gaussian, but usually the nature of signal sources, *i.e.*, whether it is Gaussian or non-Gaussian is unknown. Many researchers prefer to use hybrid methods to improve the performance. Methods like Independent Vector Analysis (IVA) combines the advantages of both ICA and CCA to remove muscle artifacts by extracting sources with maximum independence and correlation [157]. Chen *et al.* [158] has combined Multivariate Empirical Mode Decomposition and Canonical Correlation Analysis (MEMD-CCA) by decomposing EEG signals into Multivariate Intrinsic Mode Functions (IMFs) and then applying CCA to further decompose IMFs into corresponding sources. There have been ample research on artifact detection and removal from EEG recordings, but the researchers have not yet agreed upon any one of the optimal solution.

Due to the limitations of EEG data acquisition setup, usually the size of dataset is small in comparison to the number of features. It is always preferable to do feature selection to avoid the curse of dimensionality and increase training and testing speed [159], [160], [161], [162]. Al-Qammaz et al. [163] have compared the performance accuracy before and after feature selection where the mean accuracy is found to be increased by around 10%. The extraction of non redundant useful information from EEG signal is quite complicated as the signal is non-stationary. However, current literature rely on different feature extraction methods including spatial, spectral or temporal. The various feature extraction methods can be FFT [81], [20], [94], [84], [95], [83], STFT [73], DFT [92] and Wavelet transform [79], [96]. However, the power spectral density (PSD) [81], [20], [94], [84], [73], [15], [1],

[99] is the most commonly used feature extraction method. Hybrid feature extraction technique can also be applied using PCA and cross-covariance technique to extract discriminatory information from EEG data [164]. Khushaba *et al.* [81] has applied FFT with a logarithmic transformation because the extracted power feature of the EEG varies less linearly in the normal scale than in the logarithmic scale.

For classification, researchers have used various Neural Network based classifiers such as Convolutional Neural Network (CNN) [108], [109], [112], Recurrent Neural Network (RNN) [107], [109], Recurrent Convolutional Neural Network (RCNN) [106]. Others have used conventional machine learning methods such as k-Nearest Neighbor (KNN) [83], logistic regression [15], Support Vector Machine (SVM) [73], [79], Random Forest (RF) [79], Linear Discriminant Analysis (LDA) [165] and Hidden Markov Model (HMM) [79]. Although neural network has shown better performance [166], [167], the researchers still recommend conventional machine learning approaches over deep neural networks, as complex classifier like deep neural network needs large number of samples for training. And it is not easy to collect sufficient number of data samples using EEG. Due to the simplicity of SVM, it is the most commonly used classification method in neuromarketing [168], [169], [79]. However, the selection of machine learning models should be considered carefully as some methods may have better prediction rate but less interpretability. In such case, model transparency could help in mitigating some of these problems. A transparent model would be able to provide the details of relevant features and their description which contribute to prediction accuracy of the system. Lipton *et al.* [170] described that transparency can be achieved at different levels including the entire model (simulatability), individual components such as parameters (decomposability), and level of the training algorithm (algorithmic transparency). Recently, Ulysse et al. [171] proposed a topological data analysis scheme to find the relation between hand-crafted features and deep-learned representations. Moreover, SHAP (SHapley Additive exPlanations) [172] a game theoretic approach can also be used to explain the output of any machine learning model. Such an interpretation between models are useful in better understanding of machine learning systems.

The activation in brain regions is not robust to psychological and physical changes such as aging [173], [174], pain [175] and stress [176], etc. [177]. Also, the response to the marketing stimuli varies with change in surrounding environment and situation [25]. For consistent results, it is recommended to carry out the study on subjects of same age group who possess same mental level, under same surrounding environment.

According to Noreika *et al.* [178], it is hard to decide the optimal location of reference electrodes. The authors have summarized the pros and cons of various locations such as scalp which sacrifices one of the recording channel, neck vertebra which is prone to motion and nose which can be the cause of distraction. And concluded that the change in the location of reference electrode may change the area of effects. However, the authors in [179] suggested that the exact location of reference electrode does not make large difference as long as the electrode is well attached and is not affected by subject's movements. The preferred locations are the nose, earlobes and mastoids, as the temporal bone separates them from brain which is not the case for other electrodes on the scalp [180].

The observed electrical brain signals are mainly a result of activity in the cortical portion of the brain. As a result, the electrical activity generated by the deep structures, such as limbic system, in the brain which regulate emotional processing are extremely difficult to get from commercial EEG electrode systems [2]. However, the issue can be resolved by attaching more electrodes to the skull [143]. Moreover, the high-resolution EEG technology provides more information about brain activity with a spatial resolution of a squared centimeter and time resolution of milliseconds [181], [182], [183].

The decision about the kind of electrodes to be used for data acquisition is also important. The features of data acquired by dry and wet electrodes are different and hence the feature extraction methods for one will not work for other [184], [177]. It has been reported that wet electrodes provide more relevant information than dry electrodes which are having more noise than wet electrodes [156].

An outstanding challenge in the field is the absence of established and commonly accepted experimental methods across researchers in the neuromarketing field. Recently, Li et al. [185] discussed careful considerations of experiment protocol where stimuli of the same class should not be presented together to a participant while recording EEG response. In such a scenario each test trial would result in a part of training trials and this will lead to classification of arbitrary temporal correlations in EEG data instead of stimulus-related activity. Rather, stimuli of different classes should be randomly intermixed in order to capture the stimulus-related activity and to remove the temporal correlations among training and testing sets while recording EEG data block. Moreover, open sharing of knowledge and best practices between researchers could drive significant steps forward in the field, and promote the adoption of more defined experimental paradigms. This would provide a shared platform for interpreting study outcomes and give direction for future research.

B. Ethical Challenges

The continued development of methods that can monitor, and ultimately alter, human decision making raises ethical challenges. The major ethical concern is that neuromarketing should not overpower the free decision making of consumers. As outlined by Consumer Alert (2003), continued developments in the field of neuromarketing could influence consumers and eventually lead to an end to their free will. Potential threats include the ability to predict consumer choice, influence consumer choice, transparency, quality certification and privacy [186]. The physical and emotional attachment to the products and attraction in advertisements influence the customers' preferences and decision making [143]. Advertisements generate comforting emotions which create a sense of empathy and affinity in customers [187]. Another challenge in study is the absence of integrity and reliability of the information provided by researchers. The information itself can be biased [188], [189]. Conversely, it is possible that careful and ethical research in the field may actually help to reduce the risk of such problems [190]. Standard rules need to be implemented to use neuromarketing only to enhance customers' shopping experience and not to convert them into programmed buyers by taking full control over their decision making [24], [191]. Despite these challenges, and in large part due to the potential commercial gain, neuromarketing continues to be a growing field. Consequently, maintaining an open discussion and scientific understanding based on the principles of neuroscience and psychology are essential to ensure that consumers and society benefit and are protected from continued advances.

VII. Conclusions

EEG has been widely used to monitor the electrical activity of the brain for many years. In addition to its clinical and diagnostic significance, its use is growing due to the development of new BCI applications. Similarly, neuromarketing is an evolving field of research that seeks to understand the internal thought processes a consumer faces when they choose one particular product over the other. This knowledge is highly sought after because of its potential implications as companies aim to objectively improve their marketing strategies according to what creates positive or negative impression in consumers' minds. Various neuromarketing strategies, types of obervable information, how marketing stimuli is presented to consumers, what effect it has in terms of pleasantness and memory, current machine learning approaches, and various challenges faced have been reviewed and discussed.

As marketing continues to evolve, such as from television to shorter, internet-based advertising, marketing strategies must also adapt, intensifying the importance of neuromarketing. Concerns over potential ethical issues may be limiting entry into the field by other researchers, but with careful governance and continued development, neuromarketing may yet prove to be beneficial for consumers and marketers alike.

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Khurana, Vaishali

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