Computational Intelligence and Neuroscience

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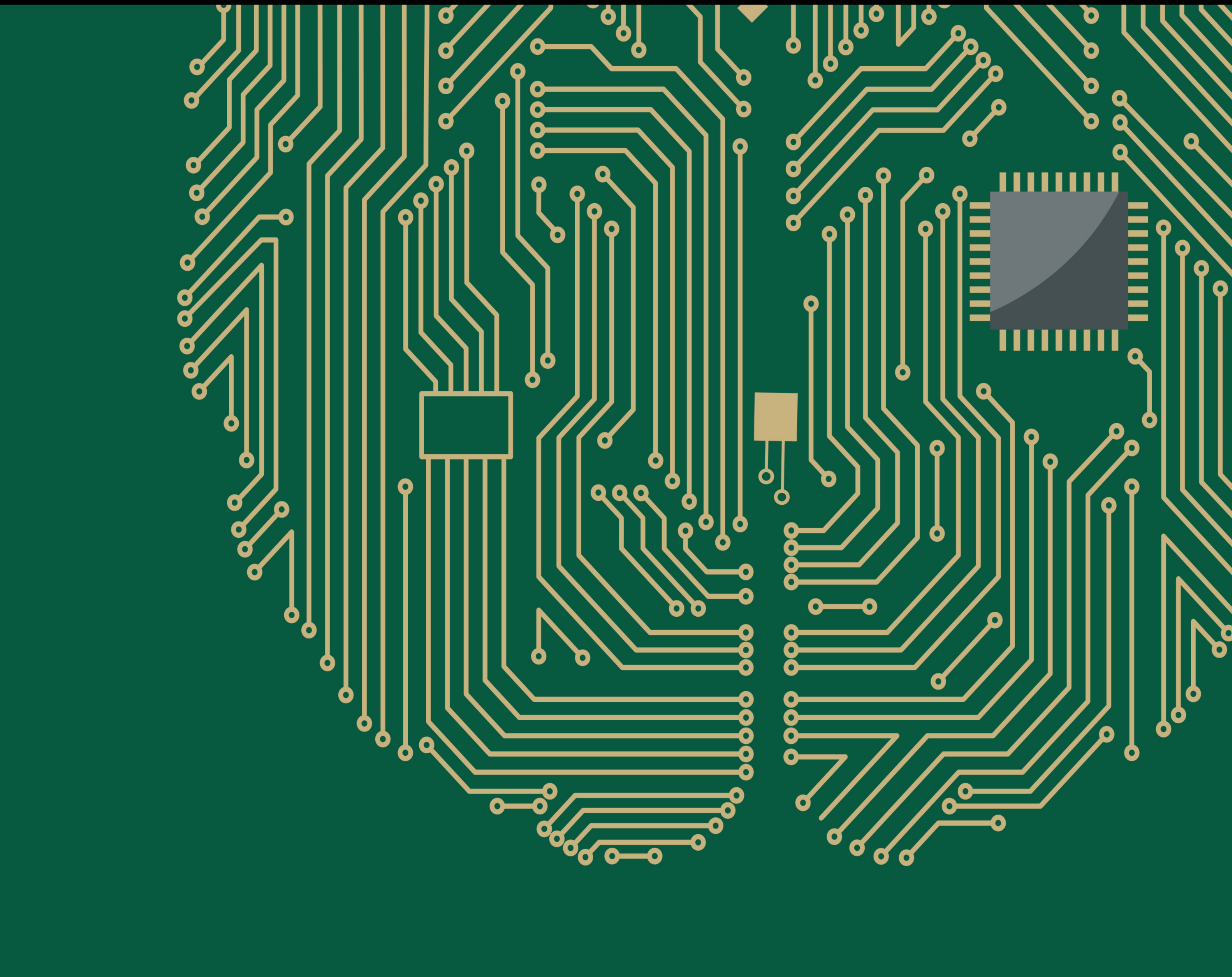
Special Issue Editor in Chief: Pietro Aricò
Guest Editors: Gianluca Borghini, Lewis Chuang, and Jochen Baumeister



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Editorial Board

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Review Article

Consumer Behaviour through the Eyes of Neurophysiological Measures: State-of-the-Art and Future Trends

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Guest Editor: Jochen Baumeister

The new technological advances achieved during the last decade allowed the scientific community to investigate and employ neurophysiological measures not only for research purposes but also for the study of human behaviour in real and daily life situations. The aim of this review is to understand how and whether neuroscientific technologies can be effectively employed to better understand the human behaviour in real decision-making contexts. To do so, firstly, we will describe the historical development of neuromarketing and its main applications in assessing the sensory perceptions of some marketing and advertising stimuli. Then, we will describe the main neuroscientific tools available for such kind of investigations (e.g., measuring the cerebral electrical or hemodynamic activity, the eye movements, and the psychometric responses). Also, this review will present different brain measurement techniques, along with their pros and cons, and the main cerebral indexes linked to the specific mental states of interest (used in most of the neuromarketing research). Such indexes have been supported by adequate validations from the scientific community and are largely employed in neuromarketing research. This review will also discuss a series of papers that present different neuromarketing applications, such us in-store choices and retail, services, pricing, brand perception, web usability, neuropolitics, evaluation of the food and wine taste, and aesthetic perception of artworks. Furthermore, this work will face the ethical issues arisen on the use of these tools for the evaluation of the human behaviour during decision-making tasks. In conclusion, the main challenges that neuromarketing is going to face, as well as future directions and possible scenarios that could be derived by the use of neuroscience in the marketing field, will be identified and discussed.

1. Introduction

In the last years, we have had a growing interest in the use of brain imaging techniques, for the analysis of brain responses to different contexts. Scientific development in recent years was characterized by an expansion in the application of different and multidisciplinary research modalities to answer various questions of a given scientific field. The recent "*boom*" in employing neuroscientific methods to better understand human behaviour in various contexts is undoubtedly interesting and intriguing. Tallis [1] coined the term "*Neuromania*" to refer to the embracing of neuroimaging by various fields of studies to explain all human phenomena in terms of brain activity.

Because of the potential application of neuroscientific methodologies to better understand unconscious reasons of human behaviours, especially in terms of risky behaviours, the interest on such approaches initially focused on the investigation of human factors (HFs) [2]. In fact, this kind of application relies on specific social challenges, such as operational environments where safety of people relies on the work and the efficiency of one or more operators. For example, in the transports' domain, the passengers' safety depends on the performance of the pilot(s) [3–8], of the air-traffic controller(s) [9–14], or of the driver(s) [15–17]. In such contexts, a human error could have serious and dramatic consequences.

In particular, HFs have consistently been identified to be the main responsible factor, in a high proportion, of all workplace accidents. It has been estimated that up to 90% of accidents exhibit HFs as a principal cause [18]. Consequently, the HF construct is receiving more and more attention and has been investigated across a wide range of domains. In many operational environments (e.g., aircraft piloting, air-traffic control, industrial process control, and robot-assisted surgery), operators have to constantly manage complex systems and machines to accomplish operational activities. Improvements in such technologies or even new solutions are often proposed, with the aim to enhance security and efficiency in the human-machine interaction (HMI) and consequently to increase the operator's performance and thus overall safety [19, 20]. In this context, the most studied user's mental state is the mental workload, e.g., the level of cognitive demand induced by a task [21], due to its strong relationship with the user's performance variations [9], but also other mental states such as vigilance, situation awareness, stress, drowsiness, and mental engagement received attention from the scientific community [22–25].

However, until the last decade, these kinds of applications were still seen as pure research, far from being reproducible on large scale outside the laboratory and related to everyday activities.

Nevertheless, thanks to the technological progress and the development of innovative solutions applied to neuroimaging, such as less invasive and wearable devices [26, 27], the neuroscientific approach became a powerful tool to investigate unconscious reactions and the brain functioning during daily life. In other words, it investigates how the human being perceives, processes, evaluates, reacts, and utilizes the external stimuli in the decision-making process in everyday activities and interactions [28].

In this context, *industrial neuroscience* is a new emerging area in which state-of-the-art methodologies are applied in real contexts to evaluate the cognitive and emotional states of humans [29].

Within the last 10 years, the economic world approached those new techniques, leading neuroscience labs to address problems and questions regarding economic transactions. In this framework, neuroscience researchers and economists have to cooperate on the evaluation of brain activity related to economic value judgments and to the understanding of the underlying mechanisms of decision-making processes in real-world settings [30].

This cooperation has given rise to a new area of study called "*neuroeconomics*" that uses all the modern tools of neuroimaging [31–37].

One of the biggest questions in today's market is what drives consumers to decide on one product instead of another, or why consumers interact with a specific brand. So, there is a growing interest in understanding how brain responses reflect the decision-making process of consumers. In this regard, the practical use of neuroimaging neuroscientific tools in real contexts and for real stimuli, i.e., the subject of this article, is named in the literature "*neuromarketing*." The term specifically describes a field of study defined as "*the application of neuroscientific methods to analyse and understand human behaviour in relation to markets and marketing exchanges*" [38]. This definition has two main upshots: (1) it moves consideration of neuromarketing away from being solely the use of neuroimaging by commercial interests for their benefit and (2) the scope of neuromarketing research is widened by solely consumer behaviour to include many more avenues of interest, such as inter- and intraorganizational research, which is common in the marketing research literature.

Neuromarketing studies seek to investigate different brain areas while experiencing marketing stimuli to find and report the relationship between customer behaviour and the neurophysiological system. Using knowledge and know-how from human brain anatomy, and knowing the physiological functions of brain areas, it is possible to model neuronal activity underlying specific human behaviours. Through neuroimaging methods, researchers can compare different brain area activations during a specific task, in order to develop models which can not only describe the dynamics of human decisions but also understand the usual mismatches between consumers' thoughts and their actions [39–43].

This paper describes the state-of-the-art of the discipline of neuromarketing and provides a review of the main studies conducted in the area in the last two decades. Thus, this paper presents a better understanding of neuroscientific technologies and how these can be employed to study the human behaviour in real contexts. This review discusses the ethical issues linked to the use of the neuroscientific tools for the evaluation of the human behaviour during purchases. Finally, future research avenues and possible scenarios are considered.

2. History of Neuromarketing

For hundreds of years, people tried to understand how we make—or should make—a decision. The question kept alive some disciplines, such as philosophy and psychology. Decades of research have shown that much of our mental processing occurs at the subconscious level, including the decision that we take as consumers. These subconscious processes explain why we fail so often to accurately predict our own future choice [44]. Often, what we think we want has little or no bearing on the choices we actually make [45].

"*Consumer neuroscience*" is a new approach within consumer research that has rapidly developed, which aims to enhance the understanding of consumer behaviour using insights and methods from neuroscience.

The birth of the field of consumer neuroscience has generated wide-ranging, ongoing debates of whether this hybrid field benefits its parent disciplines (consumer psychology and neuroscience) and, within them, what forms these benefits might take [38, 46–48]. In order to appreciate the value of a combination of neuroscience with consumer psychology, it is important to understand the broad range of insights available from cognitive neuroscience.

Cognitive neuroscience is the study of the nervous system that seeks to understand the biological basis of behaviour. In cognitive neuroscience, the main distinction is between clinical and nonclinical research. The former, known as neurology, studies the patients and how nervous system disorders, trauma, tumours, and injuries affect their cognition, emotion, and behaviour as compared to healthy subject populations. The second one studies consumer responses in healthy subject populations. A last critical distinction is between consumer neuroscience that, as previously stated, refers to academic research at the intersection of neuroscience and consumer psychology and "*neuromarketing*," which refers to the application of consumer neuroscience in the marketplace using neurophysiological tools, such as eye tracking, electroencephalography, and functional magnetic resonance imaging, to conduct specific market research. Indeed, neuromarketing can be defined as "*the field of study that applies the methodologies of the neuroscience to analyse and understand the human behaviour related market and economic exchanges*" [38]. Hence, neuromarketing is related to marketing as neuropsychology is related to psychology. Additionally, neuropsychology studies the relationship between the human brain and cognitive and psychological functions, while neuromarketing investigates consumer behaviour from a brain perspective [49].

Even if the term "neuromarketing" cannot be attributed precisely to anybody, Professor Ale Smidts of the Rotterdam School of Management of the Erasmus University is known as the first one who used the term "*neuromarketing*" that refers to the use of neuroscientific techniques by the marketing discipline in 2002 [50]. At the time, two US companies—BrightHouse and SalesBrain—became the first ones to offer neuromarketing research and consulting services, promoting the use of technology and knowledge coming from the field of cognitive neuroscience in the business field. Specifically, Atlanta-based BrightHouse announced the creation of a department dedicated to fMRI for marketing research purposes [51, 52]. This demonstrates that even before this scientific approach was provided with the prefix "*neuro*," some companies were already using neurophysiologic techniques, such as EEG, to solve marketing problems [53–57].

Hence, the contribution of neuroscientific methods became significant for the knowledge on the human behaviour in the marketing scope. Recent years have seen a rise in the abilities of neuroscientists to study the brain activity, and in this field, the contribution of neuromarketing has been very useful to answer several questions about which consumers' neural processes are involved in correspondence of behavioural performance and at different levels of consumer research. Moreover, another interesting issue is overcoming the dependence on the verbal answers that nowadays are used for testing subjects in traditional marketing research studies, where insights and indicators depend on the good faith and accuracy of the experimental subject reporting his own sensations and opinion to the experimenter. Indeed, traditional data collection methods have some limitations and are criticized for not revealing accurate results. Some studies set the failure rate of new products at 90% [58–60]. This gives clues that traditional marketing studies conducted prior to the launch of the products do not produce reliable, valid, and generalizable results.

The traditional techniques allow to measure the cognitive and emotional experiences only as verbally expressed at the conscious level during the interview. Instead, by using brain imaging techniques, it is possible to distinguish the unconscious states related to processes that have a key role in influencing behaviours, integrating what can be found by verbal or written declarations.

Interestingly, some experimental evidence suggests that the use of the brain imaging, in the near future, could be placed side by side with classical tests that are mainly used today in the marketing science [61].

Therefore, from the marketing point of view, neuromarketing is an important and revolutionary field of marketing research, and also defined as the "*third dimension*" of it. Because of the reasons mentioned above, neuromarketing has received considerable attention in the corporate world, and the growth of neuromarketing companies in the recent period has been impressive [62].

Moreover, during the last decade, the number of publications in a top marketing journal and Google references concerning this topic has grown exponentially (Figure 1), and the same holds for the number of neuromarketing companies founded.

The total number of neuromarketing papers published so far is 16500 (source: Google Scholar in March 2019). In 2008, Hubert and Kenning [63] reported more than 800,000 Google hits for the term "*neuromarketing*," and in 2012, the same search yielded over 1.4 million hits, underlining the rising interest in this topic. In 2018, there have been more than 3 million hits for the term "*neuromarketing*."

Nowadays, companies around the world that offer neuromarketing research services are growing. Since neuromarketing arrived in the public consciousness levels, it received a tidal wave of enthusiasm, which is ever growing. In Figure 2, the neuromarketing interest growth in the world, in terms of entering the word "*neuromarketing*" in the Google search portal, can be seen.

Given the growing dimension of the neuromarketing phenomenon, the Neuromarketing Science and Business Association (NMSBA; http://www.nmsba.com), an international organization for the coordination of the activities in this new field of market research, was funded in 2012. Its main aim is to diffuse the best practice in the field of neuromarketing and to connect the major companies that offer such services across the world. Today, company members of the NMSBA are found across 42 countries (NMSBA, 2019). The highest concentration of vendors is in Europe (54) and Central and South America (27). Other

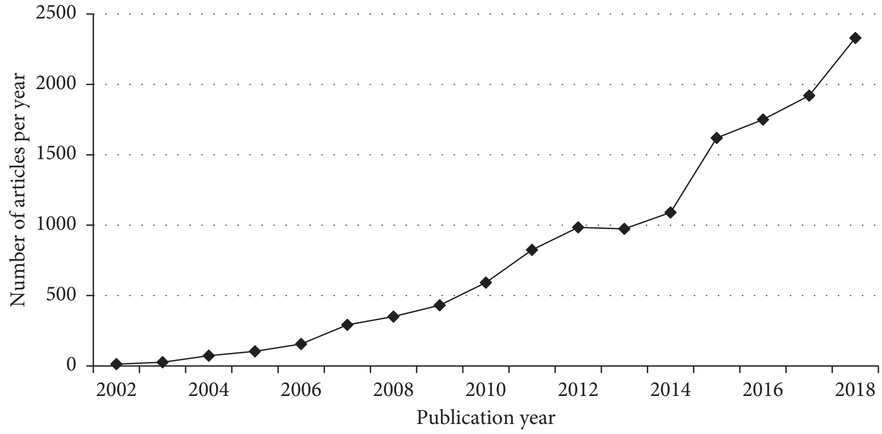

Figure 1: Evolution of academic interest in neuromarketing (as in the number of articles published on the topic) from 2002 to 2018 (source: http://www.scholar.google.com).

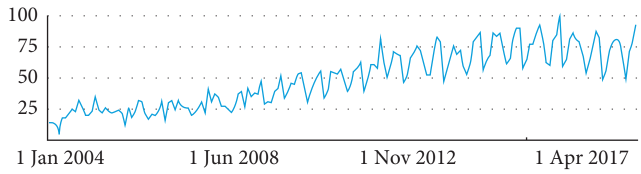

Figure 2: Evolution of general and global interest in neuromarketing since 2004 until recent years (source: https://trends.google.com/trends/).

vendors are located around the globe in Asia (13), North America (11), Middle East (3), and Africa (1). By country, the United States and United Kingdom have the most of members (10 each), followed by the Netherlands (9), Italy and Germany (6 each), and Spain and Turkey (5 each) (https://bit.ly/2JIwmzu). Importantly, neuromarketing today has expanded to the point where buyers can find nearby vendors with global or local expertise in almost every region of the world (https://bit.ly/2UbeWzz).

3. The Added Value of the Neuroscience Techniques

Which is the added value of using neuroelectrical brain imaging tools for marketers? Neuromarketing techniques are commonly used in communication and advertising areas. The use of these technologies makes possible to identify advertising elements that trigger positive feelings [64–66] and which are the features that should not be present in communication as they may cause consumer aversion to the products. They also allow to select visual and audio features, as well as the timing and selection of appropriate media [65]. Neuromarketing in addition has the ability to identify consumers' needs and, therefore, to develop more useful and pleasant products [67]. The contribution of neuromarketing also helps enhancing branding or brand positioning strategies. Moreover, neuromarketing has the capability to adjust strategies of pricing and product development, as demonstrated by several researchers [38, 52, 64, 68]. Neuromarketing has an enormous potential to identify causes of purchasing disorders such as compulsivity [51, 64, 65, 69] and to develop more effective social campaigns, such as encouragement for the use of seat belts in cars [70] and for antismoking campaigns [71–75].

Indeed, by neuromarketing, the strength of emotional attachments to a brand and the instinctive impact of stimuli to be implemented on a point of sale to encourage purchases were also evaluated and studied [76, 77]. This list can be extensive and applied to each specific marketing area, as required by marketing management.

Modern consumers are different from the past and, surely, different from how the future ones will be. In the same way, the present marketplace is fundamentally different because of major societal forces that have resulted in many new consumers and company capabilities. These forces have created new opportunities and challenges and changed marketing management significantly, as companies constantly seek new ways to achieve marketing excellence. Learning about consumers is the key to implementing the marketing concept and exercising marketing imagination.

The American Marketing Association defines consumer behaviour as "*the dynamic interaction of affect and cognition, behaviour, and the environment by which human beings conduct the exchange aspects of their lives*" [78]. Accordingly, this definition includes the thoughts and feelings that people experience and the actions they perform in consumption processes. Thus, it involves all aspects of the environment that can influence human thoughts, feelings, and actions, including opinions from other consumers. For instance, products and packaging, brands, advertisements, price information, and many other aspects can be considered environmental factors. Indeed, consumer behaviour is a complex phenomenon for investigation and thus is a heterogeneous field. Marketing academics have published research papers mostly about consumer behaviour who have a multidisciplinary skill about training, objectives, and methods.

Advances in neuroimaging technology have led to an explosion in the number of research studies studying the living human brain, thereby developing the understanding of its structures and functions. With the explosion of impressive images from brain scans in both scientific and popular media, researchers from other fields in the social and behavioural sciences naturally become interested in the application of neuroimaging to their own research. The possibility to "*get inside the heads*" of customers has aroused an increase of interest in commercial enterprises for discovering the real needs of them and proposing the products or services that meet their specific desires and needs. But it is very important to highlight that, with neuromarketing techniques, companies have "*just*" the opportunity to better understand the consumer behaviour and which are the processes underlying the decision-making process. Accordingly, this does not constitute the "*buy button*" to induce to buy products or services which companies promote.

With the help of advanced techniques of neurology, which are applied in the field of consumer neuroscience, a more direct view into the "*black box*" of a consumer should be possible. Consumer neuroscience should not be perceived as a challenge to traditional consumer research but constitutes a complementing advancement for further investigation of specific decision-making behaviour; as mentioned above, it could be defined as the third dimension of it (after the qualitative and the quantitative marketing research). In such a scenario, brain imaging techniques, applied to human decision-making mechanisms, could be adopted to corroborate results obtained by traditional techniques.

Daniel Kahneman, who in 2002 won the Nobel Prize for integrating advances in psychological research to economic science, analysed the complexity of people's reasoning when making economic decisions and demonstrated that when people choose, they do not always do it objectively. In his book, *Thinking, Fast and Slow*, he described how different systems of thought can affect judgment when people make decisions. The distinction between "*fast*" and "*slow*" thinking has been explored by many psychologists over the last 25 years. Kahneman did not invent the System 1-System 2 model of the brain processes, but his work over the last several decades has popularized it as one of the most useful overarching frameworks for understanding how the human brain works and, in particular, how the unconscious and conscious parts of the mind work together. System 1 and System 2 are neutral terms describing two distinct sensory processing and decision-making systems in the brain. System 1 is fast, automatic, and outside our volitional control; System 2 is slow, voluntary, and under our control [79]. This model is the key to understand why traditional research as interviews, focus groups, and surveys is at risk of bias and why neuromarketing has emerged as an alternative and integrator to them. Traditional marketing research was based on a System 2 view of the brain, assuming that consumers have always access to their mental states and that they can accurately describe what they want and why they choose products and/or services. Instead, neuromarketing has emerged because, through neurometric tools, scientists can offer new research methods that can also measure System 1 processes and provide new insights to understand how and why consumers respond to marketing stimuli and interact in the marketplace [79].

In addition, we know from cognitive psychology that emotions too play an important role in memory processes: emotions can help us learn and remember [80]. Consumers are no longer considered completely rational because emotion and unconscious and automatic processes play a central role in generating behaviour [81, 82]. Therefore, these previous investigations showed that humans are not perfectly rational in making decisions.

Therefore, the challenge lies on how to use the neuroscientific tools to discover the brain or physiological instinctive reactions to take into account their effects and to define the best strategies to reach better the consumer needs. In such a way, neuromarketing is an exciting promise for marketing evolution in the future and at present.

Nowadays, the most part of neuroimaging studies are conducted in specialized institutes, and most of the largest marketing research companies and advertising agencies have neuromarketing divisions (e.g., Nielsen, Ipsos, and Millward Brown) with clients that represent an impressive list of brands across a variety of product categories (e.g., Google, Campbell's, Estée Lauder, and Fox News) [83].

Nevertheless, the use of neuromarketing activities has aroused some disagreements because critics of the subject believe that the use of such techniques would affect consumers' ability to avoid marketed products, leaving the individuals unable to resist such efforts and making them easy targets for the company's campaigns [84]. Some researchers furthermore believe neuromarketing to be science fiction rather than reality-based science, given that thoughts are individual and strictly dependent on personal experiences and character, which makes virtually and practically impossible to find people with identical thoughts [85]. Supporters of neuromarketing, such as Lindstrom [86, 87] and Dooley [88], on the contrary, discuss the benefits of neuromarketing techniques for both consumers and organizations; they suggest that tailored products and campaigns benefit consumers by facilitating their decisions instead of manipulating them. At the same time, organizations can ensure greater competitiveness by saving a large portion of their budgets currently spent on inefficient and ineffective marketing campaigns.

4. Brain Imaging Tools in Marketing Research

The possibility to acquire signals and images (neuroimaging) from the human body has become vital for early diagnosis [89], not only for marketing research [90] but also for human-machine interaction studies [91, 92], automation, and system design [93, 94]. It is possible to obtain these data in the form of electrobiological signals, for example, from the heart by an electrocardiogram (ECG), from muscles by an electromyogram (EMG), from the brain by an electroencephalogram (EEG) and magnetoencephalogram (MEG), from the stomach by an electrogastrogram (EGG), and finally from eye nerves by an electrooculogram (EOG). Measurement can also have the form of one type of ultrasound or radiograph such as sonograph (or ultrasound image), computerized tomography (CT), magnetic resonance imaging (MRI) or functional MRI (fMRI), positron emission tomography (PET), and single-photon emission tomography (SPET) [95].

As previously seen, psychophysiological techniques have been applied since the 1960s in consumer research to measure pupillary dilation (through the eye tracker) and electrodermal response (through the heart rate) [96]. Similarly, EEG started to be used in such studies in the early 1970s, specifically while a viewer watched television [97]. Subsequently, several researchers followed up on this work [54, 56, 98].

The first official study on neuromarketing was conducted in 2003 and was published on neuron in 2004 by Read Montague's team [99] which used a brand experiment to demonstrate the dominance of the frontal lobe (specialized in executive function) over the limbic system (responsible for emotional and instinctual behaviour) in the product choice. Specifically, in this study, they used fMRI to find correlates of people's preferences for two similar sugared drinks: Coke and Pepsi. The study involved 67 participants divided into four groups; each group was given a separate taste test outside the scanner and a drink delivery paradigm while they were instead inside the scanner. Before conducting the taste test, participants were asked which drink they preferred to consume between Coke and Pepsi, or whether they had no preference between them. The study findings highlighted that different parts of the brain are active if people are aware or not of the proposed brand, and in such a case, a strong brand such as Coca-Cola has the power to "*own*" a piece of our frontal cortex [49]. The Coke and Pepsi study results had many people worried about their potential power because of the fear that they harboured a hidden code to tweak our perceptions below the level of our consciousness. About ethical questions, in 2004, the journal *Nature Neuroscience* published an article entitled "*Brain Scam*" about this issue behind neuromarketing studies questioning the morality of neuromarketers. In response, Dr. Michael Brammer, the CEO of Neurosense, a company that was mentioned in this article, eloquently replied to the editor of the journal agreeing to be careful in the exploitation of any new technology but that the scientific rigour and ethical issue must apply to all scientist activities.

Notably, this short-lived attack from the media did not dissuade Harper Collins from adding the word "*neuromarketing*" to his dictionary in 2005. And by 2006, neither the critical article from *Nature Neuroscience* nor the efforts deployed by the consumer advocacy group Commercial Alert succeeded in curbing the popularity and growth of neuromarketing.

Thanks to the progress and the new development of the technology, the modern neuroscientific tools are always multifaceted and versatile and in the last years have deeply advanced improving spatial and temporal resolution and also improved in their size with the development of some technologies with more wearable, ergonomic devices. So it is easier to investigate the brain functioning: how the human being perceives, processes, evaluates, reacts, and utilizes the personal variation in decision-making in everyday interactions, not only in the laboratory but also outside of it, in real environments when people make choices and decisions [28]. To decode the information about the brain processing and to understand the data obtained by all these tools, mathematical analyses are needed: the signals' interpretation by the experts taking into account different mechanisms of analysis for each tool and certification of reliability signals. Finally, all of these techniques have strengths and weaknesses: their value is related to the accessibility, the time of analysis, the costs of both the equipment and the personnel time, the possibility to manipulate, and the capacity to be portable as well as affordable [100].

5. Brain and No Brain Measure Technologies

For marketing research, starting the analysis from the gaps in traditional measures, it is possible to highlight some advantages and limitations of using these relatively new alternative techniques such as neuroimaging or biosignal analysis, providing a brief analysis on when they are used and what do they measure for each tool. As Reimann et al. [101] confirm, traditional measures, like survey, allow to obtain the subject's judgments after they have finished the task in "*postcondition*" and are based on the ability and willingness of the respondent to accurately report their attitudes or prior behaviours [38]; instead, neuroimaging allows researchers to collect the signal and interpret psychological processes in the brain while people make a task or experience marketing stimuli to highlight a link between consumer behaviour and the neural system.

To do this, when people make a specific task or experience marketing stimuli, the researcher compares the brain activation of the experimental task with the brain activation during a control task. Therefore, neuromarketing research tries to better understand the effects of marketing stimuli on consumers, obtaining objective data using the available technology and advances in neuroscience. But do neuromarketing methods resemble qualitative or quantitative research? Although neuroimaging data collection implies a quantitative approach because it measures brain activity in numbers, neuromarketing research seems to have some aspects in common with the qualitative research. Butler [102] proposes a neuromarketing research model that interconnects marketing researchers, practitioners, and other stakeholders and states that more research needs to be performed in order to establish its academic relevance.

Zurawicki [103], Kenning and Plassmann [35], and Calvert et al. [104] divide the types of tools used in neuromarketing research into the ones that record metabolic activity, the ones that record electrical activity in the brain [105], and the ones that do not record electrical activity in the brain (Figure 3).

Each of the techniques used in neuromarketing research has specific strengths and weaknesses, which make them more or less appropriate for different research conditions. Another classification can be organized on the basis of the time and space resolutions, and depending on specific neuromarketing studies, certain combinations between techniques seem more appropriate to obtain more information about the marketing issue/research questions. However, we will briefly present each technology based on classification by Bercea and colleagues [100, 105].

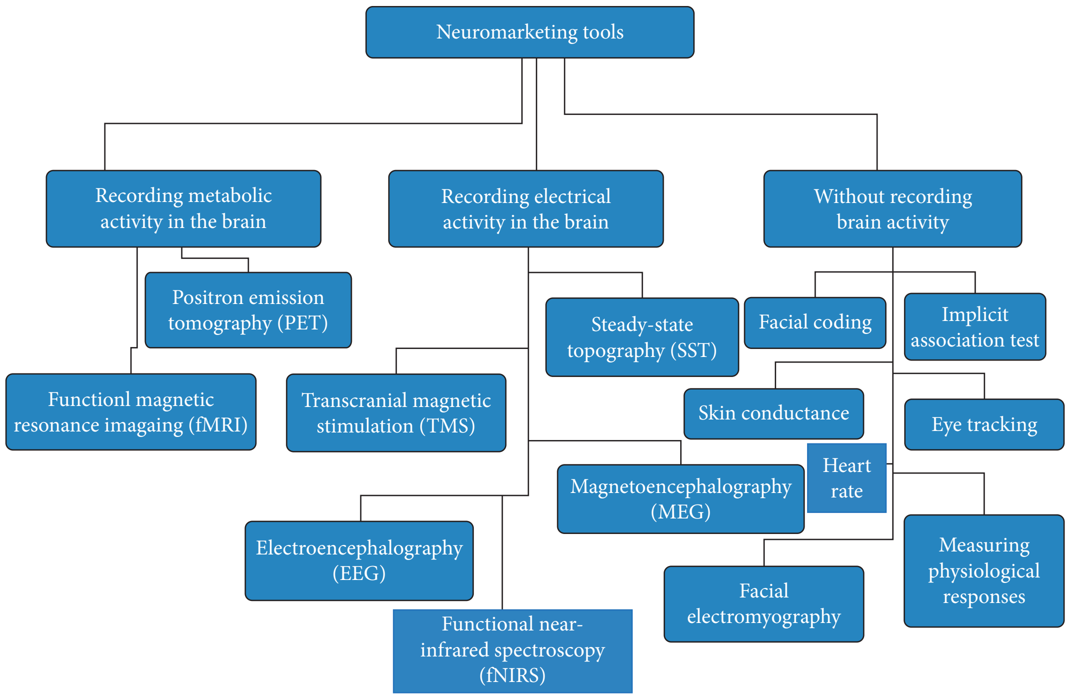

FIGURE 3: Classification of neuromarketing tools modified from the study of Bercea, 2013.

5.1. Brain-Related Activities: Measurement Technologies. The fMRI is characterized by high spatial resolution (<1 mm), and its signal is related to metabolic dynamics. Thus, fMRI is a powerful tool for basic research since it is possible to highlight the activations of different brain structures also from deep areas (i.e., behind the brain cortex). In the same application, it is also possible to combine the use of PET or SPECT and fMRI to enhance results with information on what happens at every moment (with PET) and where the change occurs (using fMRI). However, this kind of instrumentation is very bulky, and it requires wide rooms; therefore, it is not possible to use it in realistic conditions, and last but not least, it is very expensive (a machine can cost more than €e100.000). Furthermore, the time resolution is not comparable with that of EEG or MEG (both have a good temporal resolution, <1 ms, but MEG is more expensive to use). The use of transcranial magnetic stimulation (TMS) with EEG or fMRI is a good combination too, as TMS is used in studying causality of specific brain regions for specific mental processes and EEG and fMRI study only correlations between acquired data and stimuli. In general, EEG or MEG can be used as an alternative if the research requires a high temporal resolution for studying, for example, the processing of TV advertisements moment by moment [106]. Functional near-infrared spectroscopy (fNIRS) is a noninvasive optical imaging technique that creates a map of the blood oxygenation in local brain areas during neural activity through examining the cerebral blood flow (CBF) [107]. Brain activation measurement with fNIRS seems to have great potential as it reduces some critical limitations of the fMRI. It is mobile and lower in cost, enabling use in real-world situations for freely moving subjects [108–111]. As it is comfortable and tolerant of body movements, it is highly portable, and it is described as a major innovation in neuroeconomic research [112]. Despite the novelty of fNIRS in neuroscience, the reliability and validity of the method to measure cortical activation have been shown in a wide spectrum of studies inside and outside the laboratory. Studies trying to focus on more realistic and natural environments have used fNIRS, for example, while walking in a city [112], driving a car [113], flying an airplane simulator [7], playing table tennis and piano [114], or focusing on a realistic grocery shopping atmosphere [115, 116]. In Figure 4, the main differences among different neuroscientific tools, in terms of temporal and spatial resolution, can be seen.

Considering their pro and cons, it can be derived that the joint use of some of these techniques with the traditional marketing research methods (as neuromarketing alone is not always capable of answering the research questions) could lead to better results, capable of finding new valuable consumer insights and revolutionizing marketing research itself. According to the research questions and objectives, in fact, there is a proper neuromarketing technique. The tools presented are the key points of understanding mechanisms underlying consumer behaviour, and they add value to traditional marketing research techniques. Using them, researchers can discover what people do not what to reveal and what exactly influences their decisions, even things they are not aware of [105].

5.2. No Brain-Related Activities: Measurement Technologies

5.2.1. Heart Rate and Galvanic Skin Response. Measuring emotion is one of the most widespread aims of many scientists' research studies. There are a few dimensions that organize emotional response. The two most common ones are valence and arousal. The first one contrasts states of

	Temporal resolution	Spatial resolution	Origin of the signals
EEG MEG	<1 ms	Poor	(i) Cortical columns* (ii) Their primary sources are the synaptic currents flowing through the apical dendrites of pyramidal neurons (cortical layers)
fMRI	Every 2″ but it is improving	3 mm	(i) Haemodynamic events (ii) BOLD contrast ⟶ deoxyhaemoglobin is paramagnetic (iii) Its concentration depends (inversely) on blood oxygenation levels (on demand of metabolic demands) (iv) Reflects more synaptic activity than spiking activity (not action potential firing)
PET SPECT	1 min	1 cm	(i) The radioactive decay involves the creation of positrons which are quickly annihilated when interacting with nearby electrons, and then creates two photons (ii) PET captures the photon pairs
NIRS	Good	Poorer	(i) Noninvasive measurement of the amount and oxygen content of haemoglobin (ii) NIR can typically penetrate much farther into a sample than midinfrared radiation

*The columns facilitate the formation of regionally synchronized synaptic currents

Very poor
Poor
Good

Figure 4: Temporal resolution, spatial resolution, and origin of the signals of the main neuroimaging technique. Source: [100]

pleasure (e.g., happiness) with states of displeasure (e.g., sadness), and the second one contrasts states of low arousal (e.g., quietness) with states of high arousal (e.g., surprised) [117, 118]. Specifically, the galvanic skin response (GSR) is typically quantified in terms of the skin conductance level (SCL) or short-duration skin conductance responses (SCRs), while the most commonly used cardiovascular measure is the heart rate (HR). Using devices able to record the variation of the GSR and HR, it is possible to monitor autonomic activity and to assess the internal emotional state of the subjects. In fact, the GSR is considered a sensitive and convenient measure for indexing changes in sympathetic arousal associated with emotion, cognition, and attention [119]. Instead, several papers reported that the HR correlates with the emotional valence of a stimulus, e.g., the positive or negative component of the emotion [120]. Moreover, in experimental psychology, the circumplex plane of affects has been proposed and used, in which emotions are mapped in a two-dimensional space where horizontal and vertical axes are related to valence and arousal, respectively [118, 121]. Thus, the joint measurement of the HR and GSR and their positioning on the affect circumplex return the emotion perceived by the subject during a specific experimental task [61]. Even the HR and GSR could be used simultaneously with other tools (i.e., EEG) to obtain information about both the emotional and cognitive responses.

5.2.2. Eye Tracker. To get information about where people look and to track their eye movements, the eye tracker (ET) tool has a special place among modern neurophysiological techniques. It allows to measure different processes of the human brain to salience stimuli, giving a useful insight into advertising and marketing stimuli. Based on the relationship between visual attention and eye movements [122], the ET is an effective tool for experimental psychology and neurological research. It detects eye position, gaze direction, a sequence of eye movements, and visual adaptation during cognitive activities and allows users to analyse behaviour and cognition by exploring the subject's gaze. It records where and what the person is looking at (fixations), the time of fixations spent on a specific area of interest (AoI) on the stimulus, the movement of the eyes in relation to the subject' head to get information about specific patterns of visualization, pupil dilation, and the number of blinks [103, 123, 124]. The main types of eye movements which can be detected by ET are saccades, smooth pursuit eye movement (SPEM), and vestibuloocular reflex [125]. Eye fixations usually range from approximately 200 ms during the reading of a text to 350 ms during viewing of a scene. The saccadic movement to the new target takes approximately 200 ms [126]. The resulting series of fixations and saccades is called the scan path and allows to analyse visual perception, cognitive intent, interest, and relevance [103]. There are different techniques for measuring the movement of the eyes: contact lens-based, electrooculogram-based, and video-based [127] eye trackers. The latter is the most commonly used that captures the gaze while the viewer looks at stimuli and provides a more comfortable alternative to the electrooculography-based ET. More performing devices facilitate obtaining a three-dimensional representation and capturing fast movements of the eyes, such as microsaccades. They provide a quantitative and qualitative analysis of the gaze, which is very useful in understanding the choice and perceptual decision-making. In the high-tech era, the ET has several applications related to the interaction between humans and computers. In marketing studies, the ET is usually used to evaluate the customer' reactions to information on websites, different packaging product designs, the spatial orientation of attention, the performance in visual tasks, the customer response to the advertisement or to the shelf in a store, and the emotional and cognitive impacts of various spurs on the brain [75, 128]. Additionally, the ET can be used in both laboratory settings and field environments [129].

Understanding the mechanisms that guide consumers to select specific elements in an image has many applications in the business world [130]. Therefore, the ET can make available information on what is more appropriate to the involvement of attention, as it is related to patterns of visual fixations, in many different marketing issues [131]. The ET can also be used with other tools (i.e., EEG) to measure cognitive and emotional responses and lead synergy for new insights, particularly in relation to consumer behaviour and marketing communications.

Other eye-tracking uses have been reported by Chaen and Lee [132] in several studies such as usability, marketing, cognitive psychology, and behavioural psychology. Thanks to eye-tracking results, more effective ways of producing online sales and difficulties during the customer checkout process are identified.

Orquìn and Loose [133] argue that the eyes movements during the decision-making process depend on the requirements of a given task and on the characteristic of the stimuli (that are causing a bias to capture information) where salient visual stimuli are preferred. Finally, it is possible to distinguish two factors that contribute to attention and influence the meaning of a stimulus to an individual, and they are top-down and bottom-up factors [134]. To Pieters and Wedel [135], bottom-up factors are intended as the characteristics of the stimulus itself, and they are a rapid form of attentional capture. Instead, the second one is previous ideas about the product that a consumer already had. Top-down factors require consumers to voluntarily search and pay attention to specific information [136].

5.2.3. Facial Expression. Human face is considered to be the richest source of information among nonverbal channels for emotion expression [137]. In everyday life conditions, humans frequently exchange social information since they are a highly social species, and one of the richest and most powerful tools in what is called "*social communication*" is the face, from which people can quickly and easily get information about identity, gender, sex, age, race, ethnicity, sexual orientation, physical health, attractiveness, emotional state, personality traits, pain or physical pleasure, deception, and even social status [138]. The analysis of facial expression in market research studies is very useful, and one of them has been conducted by Hazlett and Hazlett [139] who revealed that facial electromyography (fEMG) can return information about the perception of different commercials. Somervuori and Ravaja [140] reported that when people look at a static image, the activity of the zygomaticus major, a muscle responsible for smiling, may serve as a good predictor of purchase decisions. Another study [141] used a specific software program to record and analyse facial expressions to construct online purchase decision classifiers. Through these classifiers, it was possible to predict the online purchase substantially above the chance level. Also, another model based on the activity of facial muscles was able to forecast purchase intentions with 78% accuracy [142], and from these results, it seems that the predictive power of facial expressions remains regardless of the software used to gather and analyse the data. For instance, Lewinski et al. [143] used in their study FaceReader 5.0, provided by Noldus: also in this case, the usefulness of facial expression analysis in assessing the effectiveness of marketing video messages is confirmed [144]. In a similar way, FaceReader was applied to measure the intensity of human emotions in the static advertising context [145]. Notably, FaceReader enables researchers to identify real-time facial expressions of customers and classify emotions into diverse types [146]. FaceReader can combine both basic emotions and dimensional emotion approach (i.e., arousal and valence) [146].

5.2.4. Reaction Time Test. To measure brand perception, brand awareness, degree of positivity, or negativity associated with a product, image, or brand, it is possible to use indirect measures based on the testers' reaction time to a stimulus during a comparison process among two or more stimuli. In order to overcome the lack of inner knowledge on consumer behaviour based so far only on questionnaires, consumer psychologists have developed these techniques that rely on nondeclarative features of people's responses [147]. Those indirect measures are used to predict consumer behaviour. This approach measures consumers' reaction times and/or accuracy on tasks that are systematically biased by their reactions to brands or ads and measures the buyer's attitude. Implicit associations are linked to unconscious automatic attitudes. There is evidence that brands have implicitly engaged in specific positive associations (e.g., quality, value, youth, strength, and speed). Such implicit associations may be critical for the consumer's decision to buy products/services [148]. There are different examples of such methods based on reaction time (RT), for instance, the implicit association test (IAT [149]), the extrinsic affective Simon task (EAST [150]), and the implicit relational assessment procedure (IRAP [151]) as well as various lexical decision tasks where primes and targets are sequentially presented [152, 153]. In all these mentioned cases, the aim is to identify the presence and quantify the strength of semantic or evaluative associations between objects and attributes.

Implicit association methods have a long history, but the IAT was introduced in the scientific literature in 1998 by Anthony Greenwald et al. [149] to measure individual differences in implicit cognitions because at the beginning, the IAT was used to study racial attitudes, self-concept, and self-esteem. Currently, the IAT is used in different areas, including consumer attitudes (toward brands or categories), and it can be considered one of the neuromarketing tools. Specifically, the IAT measures the underlying attitudes (evaluations) of the subjects by assessing reaction times on two cognitive tasks, identifying the speed with which they can associate two different concepts (stimuli such as advertisements, brands, and concepts) with two different evaluative anchors (attributes). As Zurawicki [103] states, measuring the reaction time between stimulus appearance and its response (response time or reaction time) can inform researchers about the complexity of the stimulus to an individual and how the subject relates to it. A shorter latency time in recognition or association (of positive or negative adjectives) to a stimulus indicates a more embedded attitude towards that particular stimulus. Although the difference in response is a few milliseconds, this is a very effective indicator for the assessment of the preference. This method can be used on recalling studies or on measuring the subject's attitude towards certain stimuli [105].

In Table 1, a list of the main neuromarketing tools can be seen, in addition to what they measure, when they could be used, and their advantages and limitations.

In a survey conducted by the NMSBA (https://bit.ly/2UbeWzz), the results show that the mix of methods and tools offered by neuromarketing vendors in 2018 is quite heterogeneous and quite different from the mix that existed as recently as four years ago. Through a survey, the respondents were asked which methodologies, kind of services, techniques, and equipment they used in their marketing research studies. The NMSBA ranked methods by their relative popularity compared to the most-often mentioned specialty offered in 2014 and in 2018 by neuromarketing vendors listed in NMSBA company directories. In Figure 5, all the relative popularity of selected methods is shown.

As can be seen from the figure, the fMRI shows a small decline during the period 2014–2018; instead, the response time studies have had the greatest increment in popularity in the same period. Brand measurement also shows a growing trend: this probably happens because response time techniques opened new possibilities for exploring the implicit mental connections that consumers make with the brands. Similarly, in 2018, vendors looked much more for services like biometrics, consulting, eye tracking, and shopper studies than they were in 2014. The neurophysiological techniques, from the most to the least offered by vendors, were EEG, eye tracking, various biometrics, implicit response tests, surveys, facial coding, and interviews. In contrast to the increased focus on brands, references to advertising research have remained relatively flat.

6. Main Brain Areas and Processes of Interest for Consumer Neuroscience

The main aim of neuroimaging technique application in consumer neuroscience is to measure processes such as decision-making, reward processing, memory, attention, approach and withdrawal motivation, and emotional processing, by means of specific brain area activations. Advanced neuroimaging techniques facilitate precise identification of neural responses across specific brain regions. This anatomical localization is important for consumer research because of the role specific brain regions might play in different cognitive and emotional functions [30]. The following section will describe the main brain regions and processes and some (most popular) indexes cited in scientific publications.

6.1. Decision-Making. One of the leading questions in marketing research focuses on consumers' decision-making processes: how does a consumer cope with different product alternatives based on personal perceived benefits and costs? Several regions of the prefrontal cortex (PFC), situated in the frontal lobe of the brain, play an important role in the underlying processes of human decision-making. Several studies in particular highlight that both the orbitofrontal cortex (OFC) and the ventromedial prefrontal cortex (VMPFC) are involved in decision-making processes by assessing the (perceived) value of different options and potential outcomes [154, 155]. Importantly, the OFC is associated with the evaluation of trade-off and the expected capacity of the outcomes in terms of the capability to satisfy one's needs [156]. It plays a central role in choosing appropriate behaviours, especially in unpredictable situations [157]. The dorsolateral prefrontal cortex (DLPFC) plays a critical role in decision-making as well, given its involvement in cognitive control over emotion [158]. In particular, it contributes to impulse control for complying with social norms, while the ventrolateral prefrontal cortex (VLPFC) potentially plays a role in motivating social norm compliance by projecting the threat of punishment from others in case of noncompliance [159]. The cognitive effort in the PFC interestingly appears to be higher in risky situations as compared to when a sure gain is expected [160]. Measuring the activity of these regions can thus provide useful insights into marketing constructs such as perceived value and the neural foundations of consumer choices.

6.2. Reward Processing. Other brain regions which respond to subjectively attractive rewards such as food [161], money [162], and drugs [163] are involved in the reward system process. Attractive elements like product design or a preferred brand can be considered rewarding stimuli within consumers' brains, which may trigger the psychological motivations that influence purchase behaviour. To monitor the reward process activated by stimuli, the activation of the striatum—a striped mass of white and grey matter located in the basal ganglia inside the forebrain—can be measured. While planning and controlling movements are the main

Table 1: Overview of neuromarketing tools in marketing research.

Neuromarketing tools	What is measured?	Business application	Advantages	Limitations
		Metabolic activity in the brain		
Functional magnetic resonance imaging (fMRI)	Human memory encoding, sensory perception, craving, trust and brand engagement, loyalty, preference, and recall	It is used to test products, advertising campaigns, packaging, designs, and prices; to predict customers' choices or identify their needs; to reposition a brand; and to test sensory characteristics and a celebrity endorsement.	High spatial resolution, ability to localize neural processing during consumer choices and consumption experience, valid measure for cognitive and affective responses, and ability to detect changes in chemical composition or changes in the flow fluids in the brain	Low temporal resolution, expensive, immobility of participants during the experiments, nonscalable, and ethical barriers
Positron emission tomography (PET)	Sensory perception and valence of emotions	It is used to test new products, advertisements, and packaging designs.	High spatial resolution, valid measure for cognitive and affective responses, and ability to detect changes in chemical composition or changes in the flow fluids in the brain	Poor temporal resolution, expensive, and invasiveness by the application of radioactive contrast
		Electrical activity in the brain		
Magnetoencephalography (MEG)	Perception, attention, and memory	It is used to test new products, advertisements, packaging design, and sensory studies and identify needs.	Has good temporal resolution and spatial resolution better than that of EEG	Need for a room free from the earth's magnetic field, expensive, and ethical barriers
Electroencephalography (EEG)	Attention, engagement, excitement, emotional valence, cognition, memory encoding, recognition, approach withdrawal, and mental workload	It is used to test advertisements, movie trailers, website design and usability, app and social media, in-store experiences, print and image design, new product, packaging design, pricing, sensory studies, outdoor advertisements, political debate, and other marketing stimuli.	High temporal resolution, relative low equipment costs, noninvasiveness, valid measure for cognitive information processing, and portability	Low spatial resolution, nonscalable, and susceptibility of the results to the influence of the moving artifacts
Transcranial magnetic stimulation (TMS)	Attention, cognition, and changes in behaviour	It is used to test new products, advertisements, packaging design, and other marketing stimuli.	Portability and possibility of studying specific brain areas	Expensive and ethical barriers manipulating brain activity
Steady-state topography (SST)	Memory encoding, engagement, emotional engagement, attention, and processing visual and olfactory input	It is used to test advertisements, movie trailers, prints and images, and brand communication.	High temporal resolution and tolerance for high levels of noise or interferences	Low spatial resolution
		No brain activity		
Eye tracker	Visual search, fixation position, eye movement patterns, spatial resolution, excitement, attention, and pupil dilation	It is used to test websites and usability, app and social media, in-store reactions, packaging designs, advertisements and video materials, print and image design, shelf layout, product placement, and aesthetic stimuli. It can test how a consumer filters information and determines the hierarchy of perceptions of the stimulus material.	Portability and noninvasiveness	Low flexibility since it does not work efficiently with glasses and contact lenses

Table 1: Continued.

Neuromarketing tools	What is measured?	Business application	Advantages	Limitations
Physiological response: HR and GSR	Emotional engagement, valence, arousal	It is used to test advertisements, movie trailers, website design, app and social media, product perception, aesthetic stimuli, and other marketing stimuli. It can measure reactions and consumer measures in both laboratory settings and the natural environment (i.e., store).	Portability and noninvasiveness	More informative if combined with other neurometric tools
Indirect measures: reaction time	Reaction time and underlying attitudes/ evaluation	It is used to test consumer attitudes (for brands and categories), celebrity endorsement (choosing the right option), and salient packaging features/brand image.	Less biased	Responds depending on the subject collaboration
Facial coding	Unconscious reactions and emotions	It is used to test advertisements (e.g., dynamic and static) and movie trailers.	Real-time data and noninvasiveness	Subjectivity

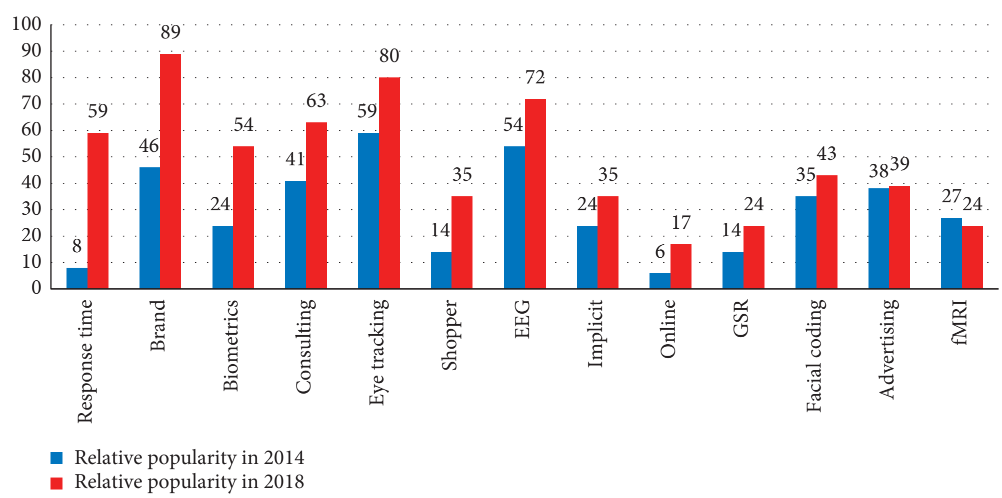

Figure 5: Relative popularity of selected methods in 2014 vs. 2018. Source: https://bit.ly/2UbeWzz.

function of the striatum, it also plays a role in the brain's reward system; there is evidence of the role the striatum and its components (putamen, caudate nucleus, and nucleus accumbens) play in the evaluation of one's expectations compared to actual rewards received [164] and the influence of social factors on this region's reward-related activity [165]. Even the ventral tegmental area (VTA) is part of the reward system, which passes the neurotransmitter dopamine to other brain regions, enabling the modulation of decision-making and affecting in goal-seeking behaviours [166].

6.3. Attention and Memory. Every day, consumers are exposed to an enormous amount of information, even though their processing capacity is limited. Each second, people receive 11 million bits of unfiltered information (in the form of advertisements, products, brands, images, colours, sounds, etc.) through all their senses. Most of the input goes by unnoticed, given that humans are capable of processing a small part of it, around 50 bits [167]. It is reasonable to assume that it has a profound influence on consumer behaviour of how they represent, attend to, and perceive incoming information. A key question is what consumers direct their attention towards (i.e., focus on) once they are exposed to several rapidly identified choice alternatives (i.e., brands and communications). Paying attention to something, a mechanism of selecting information that gets prioritised over other available information, means a person needs to be aware they are paying attention to it. A recent neuroscientific review identifies four conceptual components, fundamental to attention: bottom-up or saliency filters, top-down control, competitive visual selection, and working memory [168]. Since aesthetic components are a prominent part of advertisements, logos, and product designs, they are components processed by the brain in the form of visual stimuli and are deconstructed by the brain into their constituent elements such as shapes and colours [30]. For this reason, the underlying brain mechanisms of attention and visual processing are for sure of interest for consumer research. The prefrontal cortex directs towards and focuses on attention and has been shown to connect with the neurons responsible for processing visual stimuli in the occipital lobe, the vision centre of the brain [169].

Similarly, studying memory-related mental processes might provide useful insights into variables influencing consumer behaviour such as brand awareness, product experience, and advertising recall. Within the very complex memory variable, marketers are above all interested in encoding or storing memories in retrieving or remembering memory processes as well as in short- and long-term memory processes [170]. Furthermore, to perform complex cognitive tasks, people must maintain access to large amounts of information. The hippocampus, located in the temporal lobe, plays a major role in generating different forms of memory as well as in memory processing and consolidation [171], i.e., in long-term memory, and in the acquisition and recall of declarative memory [172]. Additionally, the amygdala, situated next and closely related to the hippocampus, is an important modulator of the memory system, particularly in memory consolidation [171].

6.4. Mental Workload. While making decisions, people invest effort to process information. In cognitive psychology, this process is called mental workload, and its theory was developed out of the study of problem-solving by John Sweller in the late 1980s [173]. A unique definition of it doesn't exist, but specifically for the operative environment, it has been given various definitions in the last decades. For example, Gopher and Donchin (1986) defined mental workload as a hypothetical construct that describes the extent to which the cognitive resources are required to perform a task actively engaged by the operator [174]; Hart and Staveland (1988) considered workload as the process that emerges from the interaction between the requirements of a task and the circumstances under which it is performed and the skills, behaviours, and perceptions of the operator [175]; Eggemeier and Wilson (1991) defined mental workload as "*the amount of the resources required to meet system demands*" [176]. However, mental workload cannot be considered a unitary concept because it is the result of different aspects interacting with each other. Psychophysiological measurements are often used to evaluate the level of cognitive demand induced by a task [21].

Characteristic changes in the EEG spectra reflecting levels of mental workload have been identified in different works [25, 177–179]. Several studies described the correlation of spectral power of the EEG with the complexity of the task that the subject is performing. In fact, an increase in the theta band spectral power (4–7 Hz), especially on the frontal cortex, and a decrease in the alpha band (8–12 Hz), over the parietal cortex, have been observed when the required mental workload increases [23]. Because of its close relationship with human performance (i.e., the human performance generally decreases when mental workload becomes too high or too low), it is considered a very relevant mental concept in cognitive neuroscience applied to those fields where human decision-making is crucial, such as neuroeconomics and neuromarketing. In marketing research, it is very important to measure this index when customers are involved in a specific operational task. It could be useful, for instance, in a website usability test, when people look for a landing page, or when people visit a store, or in general for whatever cognitive task relevant in a marketing research.

6.5. Approach and Withdrawal Motivation. When people interact with a stimulus (i.e., a product, a brand, an image, etc.), they can be either attracted to it or not. Contemporarily, researchers attempt to investigate brain activity signals correlated with an increase of emotional involvement during the interaction with marketing stimuli [180, 181]. Researchers have found strong relationships between people's behavioural approach system (BAS) and behavioural inhibition system (BIS) and their consumer-related activities. Indirect variables of emotional processing in fact could be gathered by tracking the activity of specific anatomical structures' variations linked to the emotional processing activity in human beings, such as the prefrontal and frontal cortexes (PFC and FC, respectively) [182]. In particular, the structurally and functionally heterogeneous PFC region plays a well-recognised role in the generation of emotions [183]. EEG spectral power analysis indicates that the anterior cerebral hemispheres are differentially lateralized for approach and withdrawal motivational tendencies and emotions. Specifically, findings suggest that the left PFC is an important area in a widespread circuit mediating appetitive approach behaviour, while the right PFC appears to form a major component of a neural circuit instantiating defensive withdrawal [183, 184]. fMRI studies have shown that, at the time a reward is being enjoyed, activity in the orbitofrontal cortex (OFC), in particular in its medial parts, correlates with subjective reports about the pleasantness or valence of the experience. An interesting open question is which neural systems encode negative experiences. Several studies imply that unpleasantness of taste correlates with brain activity in the lateral OFC and left dorsal anterior insula/operculum [185, 186]. O'Doherty and colleagues found that the size of abstract punishments (i.e., losing money) activates lateral parts of the OFC [187]. A problem in investigating negative experience is to dissociate it from intensity, given intensity's negativity bias: negative experiences are usually perceived to be more intense and thus are often confounded [186], in particular for visual stimuli such as facial or object attractiveness. As previously presented, by utilising a different methodological approach to investigate positive versus negative emotional experiences, neuromarketing studies are based on the idea that there is a left-right asymmetry of frontal EEG signals [188]. Related studies suggest that relatively greater activity in the left frontal region is associated with either positive emotional experience or the motivational drive to approach an object [30]. The approach-withdrawal index [188] is considered in several neuromarketing studies to evaluate TV commercial advertising, to investigate the consumer's gender differences during the observation of TV ads, and to evaluate the olfactory stimuli in young subjects [90], in user experience research studies [189], in the context of online interactive shopping environments [190, 191], and during neuroaesthetic studies [192–196] and taste experience [197–199].

6.6. Emotional Processing. Emotions drive consumer choices and are very important in the decision-making process. The amygdala, a central brain structure, has a pivotal role in regulation of emotional responses. It is involved in the processing of negative emotions and unknown stimuli, as well as in aversive responses to inequity [159]. It is also known as a locus of aversive and fear memory. Concerning positive emotions, it has been shown to be involved even if with a minor extent than for negative emotions, usually in relation to rewarding stimuli [200]. Another key emotion-related region is the insula (or insular cortex) which plays an important role in the processing of negative experiences such as the perception and expectation of risks, especially when making decisions for which a social or financial risk is expected [201, 202]. Likewise for the amygdala, the activation of the insula has been associated with anger and disgust in response to unfair economic situations [179]. Additionally, as well as being involved in the evaluation process of stimuli, the aforementioned OFC plays a role in experiencing and anticipating the emotion of regret when outcomes differ from expectations [203]. Finally, another area that evaluates emotional and motivational information is the cingulate cortex, which includes the cingulate gyrus. It integrates the emotional information in the decision-making process [30, 204]. Moreover, the anterior cingulate has been associated with the experience of an internal conflict between alternative options, and its activation could reflect the conflict between cognitive and emotional motivations [179]. The role of emotions in decision-making has been further explained through neurological and cognitive frameworks such as the somatic marker theory [205]. Overall, the study of these brain mechanisms is likely to be central in consumer neuroscience because of the importance of the emotional component of purchase decisions in traditional consumer research [206]. However, there is not a single brain region responsible for emotional processes, and no single brain region is activated in relation to one particular type of emotion as the interconnected cerebral network involved in emotion is really complex [30, 207]. Nowadays, it is also possible to assess the emotional state of the subject by monitoring autonomic activity such as the heart rate (HR) and skin conductance (SC). Indeed, emotions are accompanied by (bodily) reactions that are partially beyond an individual's control. These autonomic reactions include facial expressions (e.g., smiling and frowning) and physiological reactions (e.g., sweating) primarily caused by changes in the autonomic nervous system (ANS) [208, 209]. In fact, the autonomic reactions are manifestations of lower-order emotional processes. Over the years, as the validity of self-reports for measuring lower-order emotions is often biased by cognitive or social desirability constraints, several instruments have been developed to capture autonomic reactions. So, the measurement of autonomic reactions can overcome the validity problem of self-report because they measure emotional responses beyond the respondents' control. SC or electrodermal activity is a frequently used measure of activation of the autonomic nervous system [210]. SC gives an indication of the electrical conductance of the skin related to the level of sweat in the eccrine sweat glands. These sweat glands are involved in emotion-evoked sweating. They cover the whole body but are most dense on the palms and the soles of the feet [210]. When there is more activation of the autonomic nervous system, there will be more sweat secretion and consequently a higher level of SC. Because the increase in activation of the ANS is an indicator of arousal, SC can be used as a measure of arousal [211]. When measuring SC in real settings, electrodes that register the level of conductance (or inversely, resistance) to a light electrical current are placed on the sweat-sensible places in the palm of the hand.

Regarding the HR, in psychophysiological research, it is mostly operationalized as the number of milliseconds since the previous heart beat [212]. To distinguish HR measures indicating attention to commercials from measures indicating arousal responses to commercials, Lang [213] looked at phasic (i.e., short term) changes in the heart rate for attention and at tonic (i.e., long term) changes as an indication of arousal. She concluded that, for both attention and arousal, the heart rate can be a valid, real-time, and continuous measure. When attention increases, there is a phasic deceleration in the HR. Arousal, furthermore, is accompanied by a tonic acceleration in the heart rate. At the same time, the heart rate can give an indication of the valence of an emotional response. Compared to neutral stimuli, both positive and negative stimuli first exhibit a phasic decrease in the HR. At a tonic level, positive stimuli evoke an increase in the heart rate, while negative stimuli generally lead to a decrease in the heart rate [214, 215]. These findings were replicated in advertising studies using the heart rate to measure emotional responses to advertising stimuli [213, 216]. The HR is mostly not detected directly in the heart but in other—more convenient—places such as the fingertips. Placing a device that registers the heart rate on one finger has the advantage of requiring little interference with the subject (noninvasiveness). In this way, the registration of the heart rate can be considered an easy and cheap way to measure psychophysiological reactions evoked by advertising and other marketing stimuli [212].

7. Value Proposition and Marketing Operation: How Neuromarketing Can Improve Customer Value?

The neuromarketing applications have grown significantly in the last years in each marketing area such as communication, product, packaging, brand, retail, and pricing. The following section will describe, for each area, the main studies conducted so far and in which way neuromarketing tools can improve the customer value.

7.1. TV Commercial Advertising and Public Service Announcement (PSA). "*I know that half of money spent in advertising is wasted, but I don't know which such half is*": these are the words that John Wanamaker, the builder of the first mall in the US in 1876, said joking [217]. Every year, companies spend huge amounts of their budget on advertising campaigns, with growing questions among managers as to how effective and profitable these expenses might be.

Advertising is the marketing area that has benefited the most from neuromarketing techniques. If it is true that the average of consumers' purchases is made with the heart and justified with the mind, it is necessary to create campaigns that stimulate both hemispheres, right more emotional and left more rational. Every day, people are exposed to several stimuli, and they watch or listen to even hundreds of ads that are placed in mass media (TV, radio, Internet, press, etc.) but are also visible in other places (streets, buses, mailboxes, stadiums, etc.) [218]. The question of how the brain processes and stores advertising stimuli may be of essential importance [219]. In the age of multimedia and multitasking, finding ways to get consumers' attention, emotion, and memorization has become a primary focus of the advertisers. Providing entertainment in ads is regarded as an effective approach to capture the consumers' initial attention and interest in viewing the entire ad [220] and to enhance the message memorization; however, it has not always been like this. Many years ago, in the fifties or sixties, the most television ads demonstrated product features and concentrated on selling [221].

Today, some ads are probably more humorous than their programs, and millions of viewers choose to watch commercials online for their entertainment value on social networking sites such as Facebook or YouTube. Since television is mainly used as an entertainment medium, it is not surprising that advertising is well perceived in this medium as entertaining and creative. For example, entertaining content has been shown to increase brand purchase intentions by reducing the consumer's resistance to persuasion [222]. Thus, the measurements of the emotional correlates of the observation of TV ads could give additional information besides that already obtainable with the traditional methodologies (e.g., questionnaires and verbal interviews).

For the analysis of the impact of a TV commercial, nowadays it is possible to obtain, through consumer neuroscience models, information about the following:

(i) Evaluation of efficacy of an advertisement by neuromarketing indexes as a whole or for particular frame segments (i.e., introduction, product, service, testimonial, claim, brand, payoff, etc.)

(ii) Measurement of different impacts on the perception of the TV commercial by two or more subgroups (male, female, young, adult, user, no user, etc.)

(iii) Definition of a reduction criteria of TV commercials in time, based on neuroindicators and producing a shorter but also effective version (i.e., 30″ to 20″ or 15″)

(iv) Pretesting of an advertisement

(v) Analysis of the impact of repeated exposure (to test the optimal grossing rating point (GRP))

(vi) Measurement of what and where people look at on a screen, when attention is placed on certain advertising visual elements and how long each fixation lasts for

The impact of advertising on the recipient depends on several different factors, such as the type of the product, the nature of the target group, or the value of the decision for the consumer [223]. However, the effectiveness of achieving the intended goals at some steps can be well analysed by applying modern research techniques, such as cognitive neuroscience techniques. It is possible to examine which emotions are caused by particular scenes of advertising, which elements of advertising the recipients were paying particular attention to, or which was remembered [218, 224, 225]. The main point is to link—in terms of superior cognitive functions—a particular neuroelectrical brain imaging state to an index related to the "*success*" of the TV ad analysed rather than to the content of the brain. However, it is not easy to know a good metric for the success of a TV advertisement. In fact, the historic trend of the selling of the product related to the advertisement broadcast and the cost of an advertisement or advertising program are known by the company placing the advertisement, and the value, the GRP, and the effectiveness of ads performed are less apparent and usually unknown to the scientific researchers.

From an economic and marketing perspective, the aim of a neuroscientific approach is to get a better understanding on how mass consumer advertising of (established) brands affects the brand systems themselves. From a neuroscience perspective, the broad goal is better understanding of both the neural mechanisms underlying the impact of affect and cognition on memory and the neural correlates of choice and decision-making [44]. Several studies have been conducted to evaluate the efficacy of commercial advertising.

Ioannides et al. [226] have employed MEG to study the neuronal responses in subjects viewing the same TV advertisements as used by Ambler and Burne [227]. The results show that cortical centres associated with the executive control of working memory and maintenance of higher-order representations of a complex visual material are activated by cognitive advertisements rather than affective ones. Interestingly, neuronal responses to an affective visual material seem to exhibit a greater intersubject variability than responses to a cognitive material. Young [228] has used the EEG to detect putative "*branding moments*" within TV commercials. Other neuromarketing studies have been conducted for the assessment of the efficacy of TV advertising stimuli [44, 61, 181, 229–235], to investigate the consumer's gender differences during the observation of TV commercials [236, 237].

Typically, these are commercials, but there are other advertising categories, such as social issue and political advertisements. Social campaigns, as well as commercials, are based on similar principles and techniques, although their goals are different. The aim of commercial advertising refers usually to advertising products or services whose sale will bring measurable benefits and profits. On the contrary, the aim of the social campaign refers to providing and widening of social knowledge, engaging in social affairs, or sensitizing to certain issues [238]. Nonprofit organizations (NPOs) rely on donations to keep functioning and to continue making an impact, and each detail needs to be carefully thought in order to promote their cause and to encourage people to donate and support them, or to sensitizing to certain behaviour. The rules determining the effectiveness of social issue advertising are comparable to the rules of commercials' assessment. Advertising is effective when the recipient notices and then remembers a content which are the intent of the message (company logo, product name, name of a candidate in election, desired social behaviour, call to action, etc.). If the result is different, it means that an ad is pointless. A vast majority of social issue advertising is based on emotions, and these are usually messages associated with fear or compassion. NPOs are often told that, to attract funding, they need an emotional appeal, but which kind of emotional appeal? Fear is usually used in social issue campaigns, which focus on care of oneself or one's family welfare (to quit smoking, to drive safely, etc.), while compassion is where one should help others (giving blood, helping the hungry people, etc.) [239]. However, heavy guilt-tripping messages could produce an ineffective reaction when using overly negative images, or at the same time and analogously, the arousing of only positive emotions can have an unsuccessful effect. Methods of public service announcement (PSA) evaluation are often performed *a posteriori*, while an appropriate pretesting of the PSA material would be extremely useful to check the impact of the particular creative solutions on the target populations. It could be of interest to understand if the PSA assessment (e.g., effective or ineffective) can be performed through the study of the neurophysiological reaction to the exposure to the PSA itself. It could be hypothesized that possible different cerebral patterns could be obtained in response to different kinds of effective (e.g., successful) or ineffective PSAs or in the perception of the consumer's gender differences during the observation of charity campaigns by using neurophysiological measurements, such as EEG [240]. Therefore, obtaining measurable neurophysiological parameters, collected through direct analysis of the measured cerebral/emotional/visual attention (VA) in response to the observation of PSAs, represents an important question [73]. PSAs are at the core of many public health campaigns against smoking, junk foods, abuse of alcohol, and other possible threats to the health of citizens. But the content of these PSAs could also be directed for the promotions of "*positive*" social collective behaviour, for instance, calling against racism, supporting the integration of different cultures in the country, or promoting a healthy drive style, for the road security. Therefore, effective PSAs provide a great public health benefit [241, 242]. Using neuromarketing tools, in the last years, several studies have been conducted to develop more effective social campaigns, such as promoting the encouragement of the use of seat belts in cars or promoting smoking cessation with antismoking campaigns [52, 70–75].

7.2. Product Choice. It is easy for a company to keep track of what people buy, but it is harder to figure out why. Despite the laborious process to design and select the products, a large portion of them turns out to be a failure because they do not meet the customers' expectations or needs. These unpopular designs generate large amounts of unsold stocks, which end up being sold at discount prices. Several fundamental marketing factors—such as inadequate pricing, design and packaging, or the position of the product on the supermarket—may cause these failures. As a result, (a) the satisfaction of customers decreases as they cannot find their desired products in stores, (b) the brand image is devalued [243], and (c) customers lose faith in the brand and tend not to come back to the shop but instead shift to another vendor or get used to buy only at discount prices. These damages are long term and hard to recover as in competitive commercial markets, regaining customer trust and rebuilding brand image are expensive tasks which may take years. So, it is very important to consider these aspects during the product marketing strategy, and the main questions of many industries are if there is a way to reduce the chance of failure and if it is possible to develop a predictive tool that could predict the success of a product even before it is launched, very finely tuned to customer expectations and desires [244].

As far as it concerns the product choice, the consumer's choice is like a complex sequence of cerebral activations. From a behavioural point of view, choices with a high probability are faster than those less predictable. This can be interpreted by supposing that, in the case of more choices, all difficult, the cortical activities are more complex than the activity that would occur in the choices simple to make.

Hence, as the ability of neuroimaging to predict or influence postdesign purchase decisions seems to be limited, neuroimaging may be better suited to gauging responses before products are launched on the market. The primary reason is that neuroimaging may yield insights into the product experience itself, allowing to compare different premarket products proving information about which is the best to put on the market.

In fact, the neuroscience contribution to the world of management highlighted that the rational component of decisions counts little: on a scale from 1 to 100, it counts 5%. This is one of the reasons why up to 80% of new product launches fail within a year [245]. For decisions, the irrational component is more important, and neuroscience is providing a great help to marketers to better understand how and why consumers choose and what are the levels of cognitive and emotional involvement activated during the perception of a product during the decision-making process.

People are generally not able to reconstruct and interpret their thoughts and feelings, which is why self-reports often do not yield the desired information about consumers' real opinion of a product. For example, self-reports are frequently in contrast with the actual inner states of the subjects [208]. In product choice, consumer neuroscience can yield a more complete and objective understanding of a consumer's inner desires and may consequently assist companies to fine tune their strategies according to the latter. One important aspect of product policy is the optimal design of a product according to the preferences of the customer [246].

For example, the investigations by Erk et al. [247] provided the first central insights into how the brain processes differently designed goods (e.g., sports cars, limousines, and small cars). The study conducted with the fMRI showed that reward-related brain areas are activated by objects that have gained a reputation as status symbols through cultural conditioning that signal wealth and social dominance: picture of some cars, in fact, led to activation of the left anterior cingulate cortex, the left orbitofrontal cortex, and the bilateral prefrontal cortex, as well as the right ventral striatum. According to the present standard of knowledge, these regions are associated with motivation, encoding of rewarding stimuli, prediction of rewards, and decision-making [248, 249]. A very interesting finding for the optimal design of a product is that the authors reasoned that the relative activation in the ventral striatum, in which the nucleus accumbens is located, can be seen as an indicator for how attractive a visual stimulus (i.e., product design or shape) is evaluated to be [219].

7.3. Packaging. The role of packaging in marketing is becoming increasingly important, as it is one of the main product attributes used by companies to distinguish their products from competitors. In order to be competitive among many others, the company must study how to make packaging attractive and immediately recognizable among thousands of products in a store. The visual aspect of packaging is a very important carrier of a specifically encoded market communication system. It is a particular form of language that should lead to attracting the consumer's attention to a product and then decode the message, generate interest, trigger a purchase decision, and leave a long-lasting positive connotation [250]. The role and importance of packaging are demonstrated in many studies for its ability to communicate relevant product information, its influence on consumers' attention, perception, and purchase intentions [251, 252]. Expressions such as "*the silent salesman*" [253] are commonly used to describe the role of packaging. Packaging has become a significant marketing channel because of its presence in the shops, combined with its strong influence on customers' decisions [254]. More recently, there has been a growing interest surrounding the influence of the sensory characteristics of packaging on consumers' expectations and on consumers' subsequent food experience [255, 256]. In fact, the product could be perceived as a combination of different items: the package, the brand, the aesthetic side (colour, graphic, image, and shape), and the context of usage [257]. Each of these items may elicit different cognitive and emotional reactions with different meanings for consumers. Several studies have demonstrated that packaging has an important role both in the moment of the purchase and during the phase of usage and usability of the product, known as the first and the second moment of truth, respectively [258, 259]. To be considered useful and effective, the package must be easy to use; the information on it must be relevant so that consumers do not misuse the product; it must fit in storage spaces; if the product should be dosed, the package must facilitate this; and so on. In addition, when it refers to services, companies should design packages with user-friendly prerequisites because there are no employees present during the service consumption process. In such a case, the package could be considered the component that bridges the gap between production and consumption [260].

In 2005, Campbell was one of the first companies to decide to use neuromarketing techniques to know which factors lead consumers to choose on buying a soup, and if a new label design would enhance the sales of the soup. Campbell spent two years studying the emotional and cognitive reaction in response to pictures of bowls of soup in logo design. Throughout the results obtained, Campbell redesigned its labels [261].

In one fMRI experiment, Stoll and colleagues [262] measured the brain activity of subjects who had to make decisions about the attractiveness of certain fast-moving consumer good packages finding that attractive and unattractive packages can trigger different cortical activity changes. The study revealed significant cortical activity changes in visual areas of the occipital lobe and the precuneus, regions associated with the processing of visual stimuli and attention for two different packages. On the individual level, a significant activity change was found within the regions of reward processing. Specifically, when people looked at unattractive packages, the researchers found an increased activity in areas of the frontal lobe and insula cortex, regions often associated with processing aversive stimuli such as unfair offers or disgusting pictures. With these results, they explained why attractive packages gain more attention at the retail, and this, in turn, positively influences turnovers of fast-moving consumer goods [263].

A study of Reimann et al. [264] found that aesthetic packages significantly increase the reaction time of consumers in choice responses: among a set of offered products, people chose the ones with well-known brands in standardized packages, despite higher prices. This choice resulted in an increased activation in the nucleus accumbens and the ventromedial prefrontal cortex, according to functional magnetic resonance imaging (fMRI). Such results suggest that reward value plays an important role in aesthetic product experiences. A study of Baldo et al. [244] found that brain scan predicts consumer behaviour much better than questionnaires. Specifically, their study showed that self-report-based methods cannot accurately foretell success, while using brain data, the prediction accuracy reached 80%. They also compared how these two different methods might influence the company gross profit. Simulation based on sales data showed that self-report-based prediction would lead to a 12.1 percent profit growth, while brain scan-based prediction would increase profit by 36.4 percent. Brain data analysis (using the preference index by Davidson [188]) demonstrates that the brain produces significant emotional responses within one second after a product picture (shoe in such case) is presented on the screen. Thus, this innovative neuroscientific approach greatly improves brand image and brings considerable value for organizations, shareholders, and consumers.

A study of Modica and colleagues [260] has investigated the cognitive and emotional reactions to the cross-sensory interaction (sight and touch) with products belonging to different categories. They have found that people have a higher tendency of cerebral approach in response to comfort food during the visual exploration and the visual and tactile exploration phases and towards foreign food products in comparison with local food products. For this latter interaction, also a higher mental effort index (measured as the increment of the theta band in the frontal lobe) has been found.

7.4. Service. Services are, by definition, intangible and produced and consumed simultaneously. Also, for services, neuromarketing tools can be used to help researchers evaluate both pre- and postpurchase. With regard to service products, it is possible to affirm that they exhibit no immediate rewards (e.g., home protection systems, insurance policies, and preventative medicine), do not generate much emotional involvement, and, therefore, may receive relatively low processing priority, unless emotional rewards can be invoked. Using fMRI, it was highlighted that when customers think they are being treated unfairly, a small area called the anterior insula becomes active. It means that transactions between a service provider and a service customer are presumed to be based on trust. When trust is high, a hormone called oxytocin fills different areas of the brain. As a result, service marketers could theoretically experiment with different levels of trust to see which one generates satisfying levels of oxytocin given by service production parameters. It would also allow the service marketers to determine how quickly these levels are internalized, meaning the level of trust might need to be increased in order to maintain that sense of pleasure. This information would allow the service product marketer to determine which critical incidents are most damaging, so he/she could plan more efficient and targeted recovery effort for service failure and thus reduce customer loss [265]. Neuromarketing can be used to help service researchers in developing more effective pricing strategies. When customers think they are being treated unfairly, the brain's response is similar to that of smelling a skunk. Such a powerful, negative, and primitive reaction easily overwhelms the deliberation of the more logical prefrontal cortex region. Under these conditions, the perceptions of exchange fairness by a service consumer probably take on even a larger role than first imagined. If unfairness is perceived, it is very difficult to reestablish the relationship as the brain has neural wiring from its early formative period that protects it from known dangers—just as it continues to repeat "*safe*" behaviours. It would be possible to set up experiments depicting various acts of service delivery "*unfairness*." Neural scanning of the anterior insula would detect and measure the degree of activity generated by various depictions. This information would allow the service product marketer to determine which critical incidents of this type are most damaging, plan more efficient and targeted recovery effort for service failure, and thus reduce customer loss [266].

7.5. Pricing. Pricing is one of the key components overseen by companies in positioning their products and represents a fundamental variable affecting the organization's business result and benefits [267–270]. Some scholars have explored the impacts of pricing on shoppers' purchase decision-making and product choices [271]. Despite the amount of academic knowledge available, companies appear to use little of it when setting prices, leading to suboptimal situations for both consumers and companies. Understanding the psychology and neuroscience process of pricing evaluation may be of crucial importance if companies want to get optimal decisions, and recent behavioural research, for instance, has explored mistakes made by consumers when they process prices ending in 0.99 rather than those represented by a whole number: this entails that individuals pay less attention to the last numbers of a sequence [272]. Other research has started to examine the social role of pricing and how individual differences can influence the perception of prices by consumers [273].

A markable phenomenon often observed in price policy is the following: a similar price can be perceived by the shopper in two different ways, depending on diverse product categories: It could be perceived higher when customers consider buying a product at that price as a loss [219]. Instead, high prices can be perceived as an indicator for high quality and can enhance the product value and the probability that customers buy the goods [270, 274]. This is particularly true when customers have uncertainty about buying a product because they are not familiar with it yet. However, asking consumers about pricing issues can sometimes be ineffective. For instance, consumers are often not able to recall prices [275, 276], and it is very difficult for them to specify abstract economic concepts like the "*willingness to pay*" or experienced utility. In addition, they might respond strategically when asked about constructs like price fairness. Knutson et al. [68] examined the neural correlates of the negative price effect. Using an fMRI scanner, subjects in the first task saw a product and then saw the same product with its corresponding price information. In the end, they had to decide whether to buy the product or not. The results resembled those of studies examining the neural correlates of anticipation and the receipt of gains [277, 278] and losses [179]. Hence, the activation of the nucleus accumbens (activation through the anticipation of gains) correlates with product preferences, the activation of the insula (activation through the anticipation of losses) with high prices, and the activation of the medial prefrontal cortex (activation through the processing of gains and losses) with reduced prices. This result supports the speculation that activity changes in the insula might reflect the perception of a loss and, thus, the neural representation of a negative price effect [219]. This information can be important, for example, in identifying the price limits. Another important issue in price policy is the opportunities to customize the pricing for a specific customer segment. For this, it is necessary to know how people calculate their individual "*willingness to pay*" (WTP)—the maximum price that a buyer is willing to pay for a specific object [279]. As mentioned above, the determination of this abstract concept is very difficult with the current research methods. An fMRI study conducted by Plassmann et al. [48] observed that hungry subjects, while placing bids for the right to eat different foods in a Becker–DeGroot–Marschak auction [280], offered a specific amount of money that suited the subject's personal WTP. The results suggested that the activity in the MOFC and in the dorsolateral PFC encodes subjects' WTP for the items supporting the hypothesis that the medial orbitofrontal cortex encodes the value of goals in decision-making.

Another relevant matter is the correlation between price and satisfaction. In 2008, a study performed by Plassmann and colleagues [47] demonstrated that the MOFC activity is influenced not only by sensory components but also by cognitive stimuli (e.g., the price of an item). In their fMRI study, they asked participants to drink three different Cabernet Sauvignon wines. The subjects were told that they would be sampling five different wines, identified by their retail price—\$5, \$10, \$35, \$45, and \$90, respectively. The study was manipulated, unknown to the participants, and the \$5 and \$45 bottles of wine and \$10 and \$90 ones were identical. When people tasted the same wine twice in raw (unconsciously), the MOFC area was increased when they thought to enjoy the more expensive vintage. Similarly, the effect of price on MOFC activity was higher for the cheaper wine over the more expensive wine. Hence, this suggests that the effect of a price increment on MOFC activity might be relatively great at low prices compared with high prices. In contrast, no price effect on primary taste areas was reported because the cognitive processes that encode both the flavour expectancies and the sensory properties of the wine are integrated in the MOFC. Additionally, the flavour expectancies determined by the price change do not influence the sensory representation. The conclusion of Plassmann's work was that the MOFC, an area that modulates the hedonic experience of flavour and taste, is itself modulated by intrinsic qualities of a consumed item and by extrinsic factors, such as expectations and price.

In 2013, Kai Müller, who was working in Germany, in the Neuromarketing Labs, performed the "*Starbucks study*," one of the most mediatized studies on pricing. Subjects' brain waves were recorded via EEG and indicated when the price was right. Kai Müller developed a way to measure brain waves and hit upon feel-good prices. He stated overtly that "*classic market research doesn't properly work*," adding that people usually involved in market researches cannot always be trusted to honestly state how much they would be willing to pay for something, while it is harder to fool such neurophysiological techniques. There is a region in our brains that monitors proportionality. When proportions are radically off, for example, when a cup of coffee costs 10¢ or \$100, this region sends an alarm. In Müller's Starbucks study, an undisclosed number of subjects were shown several images of the same cup of coffee, each paired with a different price tag. Judging by neuroimages, he concluded that Germans would happily pay 33% more than the current price for a small cup of Starbucks coffee. If he is right, Starbucks would be missing out on a whole slice of profit. In a follow-up experiment, Müller tried to understand how much people are willing to pay for a coffee. Specifically, Müller and his staff, at the Munich University of Applied Sciences, installed a caffeine vending machine that dispensed coffee for 70¢, cappuccinos for 80¢, and then left students to pick an appropriate price for macchiato. After several weeks, the macchiato price levelled off at 95¢. When Müller performed his neuropricing lab experiment, he found out that subjects' brain waves also indicated 95¢ as the ideal price for the vending machine's macchiato, thus exactly matching people behaviour. These experiments appear very interesting because the methods look affordable and not too much difficult to be applied, being about an EEG tool.

7.6. Brand. A brand refers to the identity of a company. It represents the products or services a company offers, highlights their quality, and can help create a follower base for the latter. To succeed, a brand must be recognizable, steady, and specific and must fit or support the company's products and services. The application of neuroscience to the consumer psychology of brands has gained popularity over the past ten years within the academic and the business world. Plassmann et al. [47] reviewed the previous neuroscience work relevant to the understanding of underlying brand decision processes. They structured the review using a simple framework for consumer decision-making (Figure 6) based on previous works in consumer psychology [281–283].

Moreover, as shown by several recent reports during the past few decades, the search for unconscious processes and implicit measures of branding is an active field of inquiry in consumer psychology [284–299].

One central topic of brand research is whether the consumer's decisions are influenced by brand information. Deppe et al. [300] addressed this question in a study designed to determine which neural processes are involved in the brain during the processing of brand information [219]. In their fMRI study, participants were asked to make fictitious buying decisions between two similar products that were differentiated only by brand information. In one part of the study, subjects had to choose between the brand with the greatest market share—which had been declared as the target (T) brand in the preliminary phase—and diverse (D) brands (TD decisions). In the second part of the study, they had to decide between two diverse brands (DD decisions). The data analysis showed a significant difference in brain activity between the TD and DD decisions, if the subjects had declared the target brand as their preferred brand (first choice brand (FCB) group) in the pretest phase. A closer look into the brain activities of the FCB group showed a reduced activity in the DLPFC, left premotor area, posterior parietal cortex, and occipital cortex—areas that are generally associated with working memory, planning, and logic decisions. Deppe et al. [300] assumed that, for decisions comprising the favourite brand of the consumer, strategic processes are no longer relevant. The responsible brain region is deactivated, and a "*cortical release*" occurs [301]. In contrast, an increased activity was measured in the VMPFC, the inferior precuneus, and the posterior cingulate cortex. These areas operate as association cortices and have important functions in combining incoming information with background knowledge, as well as the recall of episodic memories, and self-reflection. The increased activation in the ventromedial prefrontal cortex during decisions in the FCB group could be interpreted as the integration of emotions into the decision-making process [81, 219].

The results, therefore, revealed a so-called "*winner take all*" effect: only the subject's favourite brand can emotionally move the decision-making process—the finding is crucial for marketing research because it runs against the well-established concept of the consideration set.

While the consideration-set theory assumes that there is a set of goal-satisfying alternatives [302], the results of Deppe et al. provide evidence that only the favourite brand can trigger significant cortical activation patterns. Intriguingly, a lesion study conducted by Koenigs and Tranel [303] confirmed the suggestions of Deppe et al. [300]. People with damage within the ventromedial prefrontal cortex that exhibits irregularities in emotional processing did not show the normal preference biases when exposed to brand information. Plassmann et al. [304] provided additional support for the investigated "*first choice brand effect*." Their study aimed to explain the influence of brand information within uncertain situations, by investigating the role of the prefrontal cortex during decision-making under risk. The subjects participated in a brand choice task where they had to choose between sixteen travel brands, for travel to a risky and a less risky destination. In addition to the "*first choice brand effect*," the data analysis exhibited a more prominent activation of the medial prefrontal cortex when the subject faced risky decisions. Plassmann et al. reasoned that the integration of emotions in the decision-making process, as opposed to analytical decision strategies, is of particular importance in risky decision-making. One potential reason for this might be that emotions could provide additional conscious or unconscious information.

Finally, neuroscientific tools can be used to evaluate the rebranding process. Rebranding is costly and time-consuming, and as the number of corporate rebranding practices increases, the failure rate is high compared to the successes [305, 306].

A rebranding exercise for a new logo is a key task for a big company. Kapferer [307] also agreed that brand transfers would pose risks such as loss of choice, loyal customers, and market share. So, it is very important to do several studies to design a new logo. In 2016, Telecom Italia (the main and historical telecommunication company in Italy) launched an initiative after three years of strategic study which focused on transforming its brand into a combined service brand (that was previously separately positioned as Telecom Italia and TIM).

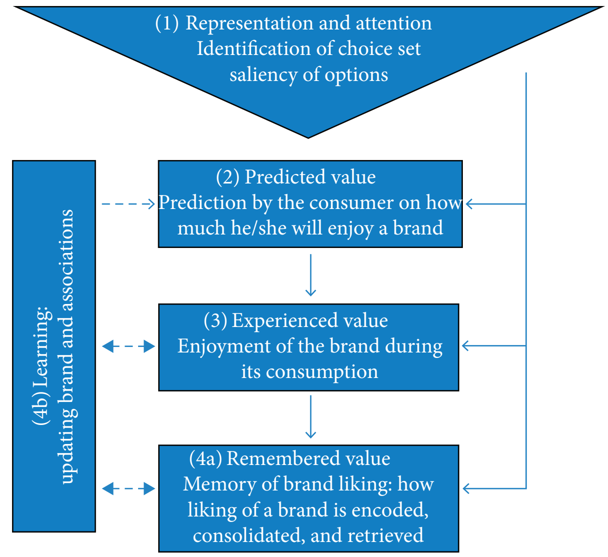

Figure 6: Value signals important for brand decisions. Source: [62].

The company chose to maintain one of the two previous brand names, TIM, but with a new graphic icon refined through traditional marketing research methods combined with a neuromarketing test. The company performed a long process of selection among large numbers of different logo ideas, over more than two years. Ultimately, two alternative symbols made the short list. A final-stage research study with two different methods was planned: quantitative surveys with a predefined questionnaire (web-based interview) and a neuromarketing test (ET, GSR, HR, and EEG). Combining the results of quantitative surveys with a neuromarketing test, the latter provided the insight to aesthetically refine and strengthen the impact of the final version which in the final decision-making process has been firmly endorsed by top management and become the logo selected for the renewed TIM brand [308].

7.7. Web Usability and Apps. During the last twenty years, the Internet has grown quickly in usage and penetration: this has led to changes in the behaviour of people, business, and organizations. Nowadays, it is almost ordinary to use the web daily, to look for any sorts of information, to get products and services, and to socially interact through different platforms and websites. Hence, companies and organizations make their best to obtain a position within this network in order to attract and retain users and customers. To achieve this objective, it is necessary to have an interesting and effective presence online, by having more engaging websites than the competitor ones. To do this, it is very important to have specific knowledge about the needs of potential users and customers, alongside with the ability to establish personalized services that satisfy these needs [309]. This is directly related to how people interact with the websites, how they behave in browsing the Internet, what their preferences are, and what areas drive their attention: these concepts are encompassed by the notion of web usage mining [310, 311].

Researchers and website developers, since the birth of the web, have kept always in mind a focal question: What are the optimum structure and content of a website for attracting the web users' interest and preferences? [312]. The answer is not easy, and many efforts have been developed over the years. Traditionally, web user behaviour on the web has been studied by using web usage mining techniques [313, 314], where the web log files, which contain records of web user activities, are processed to extract information and knowledge about their navigation and content preferences. This information is used for improving the site structure and content with the aim to provide online navigation recommendations through an automatic recommendation system [315].

The adoption of new technologies, like ET, EEG, HR, and GSR, also in the web area, is aimed at better understanding what kind of people look at and pay attention to the website and the characteristics of the user experience.

There is a large set of studies aimed to link a web user choice with different variables or behaviours. For example, in 2006, Chandon et al. [316] (for more details, read a review of eye-tracking research in marketing [317]), performed an eye-tracking experiment that analysed object choice situations associated with brands. They concluded that visual attention is relevant in a user's choice process, suggesting that those objects with low choice probability could be enhanced if they were placed next to the objects with high choice probability. Another study was performed by Krajbich et al. [318] with the objective of relating choice process with gaze position.

To study the effect of faces for the visual appeal, efficiency, and trustworthiness on the website, Djamasbi et al. [319] conducted an ET study, and they discovered that users believe that pages containing images of people's faces are more appealing and that it is easier to perform tasks in them, as opposed to those that do not contain them. Furthermore, the analysis revealed a strong positive correlation between trusting the informational content of a page and its visual appeal. In 2010, Lee and Seo performed a usability study in which typical techniques were mixed with biosignal analysis [320] finding that using new technologies (EEG and ECG), it is possible to obtain a reasonable and valuable method for web evaluation, since they obtained 70% precision with respect to traditional methods (user performance measurements, keystroke analysis, satisfaction questionnaires, and interviews). In 2011, Reutskaja et al. [321] using the ET tool studied the user's behaviour when choosing between objects under conditions of time pressure and overload. The results highlighted that objects placed in the centre of the screen have a higher probability of being chosen than objects with similar characteristics placed in other screen zones. Khushaba et al. [322, 323], using EEG and ET, studied the user's preferences to find interdependencies among the EEG signals from cortical regions in a decision-making environment and also a way to quantify the importance of different product features such as shape, colour, or texture in these decisions. The results have shown there is a clear and significant change in the EEG power spectral activities that take place mainly in the frontal, temporal, and occipital regions, occurring when participants indicate their preferences.

Using pupil dilation and EEG, Slanzi et al. [311] explored the user's behaviour from a physiological perspective, to assess the choice represented as a click intention. They found the when people choose and click, they have greater pupil size. These results show that it is possible to create a classifier for web user click-intention behaviour based on merging features extracted from pupil dilation and EEG responses.

Moreover, in recent years, smartphone APP design gets more attention from both industrial companies and academic researchers, which brings us not only great surprise but also abundant convenience to our daily life [324, 325]. An increasing amount of research has been conducted to determine what business opportunities a mobile presents as an added channel for driving revenues by e-commerce. The advantages and disadvantages of APP design affect the user experience actually directly, and smartphone apps' large commercial interests encourage firms to continually improve the performance of apps [326] with regard to benefits and obstacles to their user experience and their engagement. Recently, the evaluation of the user experience of smartphone apps was mainly based on the perspective of a relatively simple, objective evidence-less evidence-based questionnaire [327–329]. Quing-Xing Qu et al. [330] in their study proposed that eye-tracking data could be used as objective criteria to evaluate user experience for smartphone apps. A correlation model between smartphone APP design variables and user experience was built based on Quantification Theory I [330, 331]. The app's performance, in terms of emotional engagement and attentional activation, drew attention as early as 2013, when in a study Adhami [332] used neuromarketing technology to evaluate three different apps, for determining what drives users when browsing, selecting, and purchasing items. He discovered the following: (1) apps have a significant impact on overall brand perception, (2) user experience impact on whether or not the user makes a mobile transaction, and (3) there are some elements that make a difference to the user in a mobile transaction.

Finally, the use of web advertising to promote brands, products, and services is another important aspect. Often, an enormous problem with online advertisements is that Internet users tend to avoid them, leading to ineffective branding campaigns and a significant waste of money for advertisers. In response, more advertisers use technology to measure the visibility of advertising campaigns on the website of publishers [333]. Programmatic advertising and the ability to collect data on consumer and ad impressions allow advertisers to automate the buying and selling of ads and to achieve an effective personalized targeting of audiences. In such a case, online advertisements are considered in a better position with respect to the TV and print media to estimate how successful a particular ad is in driving a purchase decision or in raising brand awareness over time. However, the promises rest on the assumption that the served ad impressions are viewable by Internet users; that is, "*contained in the viewable space of the browser window, on an in-focus browser tab, based on pre-established criteria such as* *the percent of ad pixels within viewable space and the length of time the ad is in the viewable space of the browser*" [334]. Viewable in this context refers to the user's opportunity to see an advertisement, regardless of whether they have seen it. This simple assumption is however challenged by companies such as Google, Comscore, and Nielsen that daily analyse billions of impressions from campaigns over thousands of publishers and observe that most of the served impressions are actually never seen by Internet users. A well-known commented statistic released by Comscore in 2013 indicates, for instance, that half of the publishers' list is not seen by users. In 2016, the percentage of ads being seen by people in most of the countries around the world is still relatively low, between 40% and 50%. Also, Facebook, the most popular social network, that attracts a large part of ad investments is also criticized: according to the Business Insider article, "*Facebook ads are far less viewable than advertisers were expecting*" [333].

For these reasons, in the last years, a new way to make advertising has gained attention: the *native advertising or sponsored content*, which is considered a means for advertisers to cut through the clutter and for online publishers to boost their diminishing ad revenues [335]. It refers to any paid advertising that takes the specific form and appearance of editorial content from the publisher itself, and compared to display ads, which users avoid or ignore, it has more opportunity to be noticed [336–338].

Native advertisements offer a higher level of reader attention to marketers. The visual focus is more on banners than on native advertisements, especially on the text. This direct focus on the advertisement can help the reader form associative networks of words and brand assets that influence and strengthen brand perceptions subconsciously. The main problem is that there is an almost endless amount of content, but only a limited amount of time to consume everything. A marketing research conducted by Nielsen in 2014 revealed that mobile users are less open to ads. Only 13% of Americans using mobile devices say they are willing to receive ads on their phones in exchange for services. And yet, mobile advertising can often be a great advantage for advertisers. Studies have shown that exposure to mobile ads can produce a 45% lift in intent [339].

The most recent research by Neurons Inc. has revealed that mobile advertisements trigger customer reactions in less than a second (i.e., 400 milliseconds) [340, 341]. Thus, data suggest that desktop advertisements take 2-3 seconds in comparison with 400 milliseconds for mobile advertisements. Therefore, these findings reveal that companies should rearrange their strategies in order to gauge customer attention. Indeed, winning customer and mobile users attention can be valuable prospects.

But how does an advertiser get his audience to pay attention to their advertisements on mobiles? And how can that attention be measured? The click-through rate (CTR, or the ratio of clicks to impressions) only tells a fraction of the story. Even the highest-performing mobile advertisements—those with click-through rates above 1%—still fail to convert the other 99%, which could amount to millions of unconverted impressions over the course of a campaign. Very little is being done to understand the value of these impressions because there are very few options to measure it.

Therefore, the modern mobile marketers face a dilemma: How can they ensure that their advertising receives customer attention it deserves and maximizes the value of each impression?

In 2015, Nielsen conducted a study for Sharethrough, a software company that enables leading websites and apps to manage their in-feed, native ads. To understand the effectiveness of mobile advertising, the study compared native advertising and banners, both placed in feed. Using a combination of EEG and ET, Nielsen quantified where and how participants' focus was being directed. The main findings were that (1) native advertisements appear to receive two times more visual attention than banners, (2) banners are processed peripherally, (3) native advertisements are being read, (4) headlines of native advertisements can be optimized to trigger associations, and (5) brand assets impact brand resonance lift.

In conclusion, as mobile adoption and usage grow, consumers' attention will become increasingly elusive. Native advertisements command focus and attention. They can be an effective method for marketers to share their brand's stories and narrative to the highly distracted mobile consumer [339], and the use of the new technologies could be considered very useful to measure the impact of these advertisements.

7.8. In-Store Retail. The consumer perceives the store environment by all five sensory organs. Solomon and colleagues [342] describe this perception as the process in which people collect, organize, and interpret information from the outside world. In a store, several elements such as light, sound, smell, and merchandising influenced the consumer behaviour during shopping. Specifically, these elements impact on the retail atmosphere and have an influence on consumers' emotional involvement. They are considered important marketing tools due to the fact that they increase retail space and enable easier orientation for the customers, making them feel comfortable in the store. Otherwise, it is possible that the customers would be discouraged from buying goods that they would be interested in a different situation [343]. Many facets are overlaid in the overall creation of the atmosphere, which affects both subconsciousness through senses and a specific state of mind for customers [344]. The moment when customers make their decisions is significantly affected by what they see, hear, smell, and touch in their surroundings because these are immediate signals for the creation of emotions [345]. For the consumer decision system, emotions and feelings are the primary medium [346].

Importantly, retail market is changing at an incredible speed, and therefore, every retailer is trying to adopt innovative ideas that can help differentiate them from competitors [347].

The most critical requirement in modern retail stores is a high quality of lighting, which increases the image of these stores, attracts the potential customers, points their attention to products being offered, and finally raises the sales [348]. By using correct lighting (intensity, colour temperature, and illumination angle), it is possible to attract customers' attention, create a unique in-store environment, and encourage customers to stay longer and come back to these stores. Moreover, light is a tool that can be precisely controlled and measured. The consumer's interest for visual stimuli is due to the fact the visual sense is the most developed and predominant in the human brain. Almost a quarter of the human brain is involved in visual processing, much more than in case of any other sense. Indeed, the human eyes contain approximately 70% of body sensory receptors. The simplest and the most successful way to reach customer attention in the food selection process is through visual (products) illuminated in an eye-catching way. In the case where visual and musical stimuli are presented simultaneously, the brain puts more credibility and impact on the visual part.

In 1994, Areni and Kim [349] conducted a study in which they found out that brighter indoor lighting of the store makes a more positive impression on consumer perception reflected in time spent looking at the goods. Total preferences of lighting and colour temperature (chromaticity temperature) which is produced can be changed depending on weather and moods of customers [350].

A significant attribute of marketing tools in neuroscience research and visual merchandising is that 50–80 percent of unplanned purchases are influenced by initial (positive) neural excitement during shopping in-store units. Thanks to the innovative interdisciplinary approach with the use of neuromarketing, efficient marketing strategies can be developed and human emotions can be stimulated by managing a higher number of closed contracts, increasing incomes and improving the ability to buy [351]. Understanding the needs, purchasing behaviour, and changing lifestyle of today's shopper is critical in being able to deliver on their immediate and future needs. While it is true that shoppers' decisions are no longer limited to the in-store ones, POPAI's 2012 Shopper Engagement Study found that nowadays more than ever, shoppers are making an overwhelming number of their purchasing decisions in stores. In fact, the in-store decision rate has climbed from 70% in 1995 to 76% in 2012. With the advent of smartphones, shopping apps, mobile coupons, and other innovations, the shoppers' path to purchase is considerably different today in comparison with the past. Usually, the decision-making process of shoppers does not occur until they see a product in the store. Therefore, how a product is displayed in a store and is supported by in-store marketing materials can often be instrumental in leveraging sales. In the study conducted by POPAI in collaboration with Sands Research, the EEG brain signals and ET fixations have been recorded, during the shopping experience in a store. The main findings were the following ones:

(1) The items placed in the cart by a shopper produce a positive emotional brain response, thus demonstrating that there is a brain response capable of predicting a purchase.

(2) Subsequent eye fixations to the to-be-purchased item show the purchase intent effect, but it is diminished. This means that the biggest reward comes earlier in the discovery process [352].

Cherubino and colleagues in 2017 [77] investigated the brain activity (through the EEG) and the eye gaze (through the ET) of some individuals who were experimenting a visit to specific areas of a supermarket; they were focused particularly on the purchase of some products in the fruit and vegetables department. The results show how neurophysiological tools could be used to get kinds of information that would not be obtainable otherwise with the verbal interviews. The main findings demonstrated that the elements that made the individuals' shopping experience more enjoyable are the following:

(1) An innovative packaging and countless graphic customizations

(2) A better organization of the shelf (allowing an easier customer experience with a low value of the mental effort index)

(3) The presence of the farmer outside the store

These elements returned higher neurometric values of pleasantness in the experimental participants.

7.9. Neuropolitics. Since the last decades, the emergence of political neuroscience has meant "*before*" and "*after*" in the way of developing and analysing the approach between neuroscience and politics, in the realization of new research studies which allow to understand the impact of the electoral messages of each of the parties and candidates in the population, in order to predict the outcomes of the electoral process and success. Neuropolitics is defined by Antoni Gutiérrez-Rubí, a political consultant, as a "*new discipline capable of understanding the brain of people in their capacity as citizens, voters or activists that allows knowing and understanding how it works, how it articulates images, values, feelings and channels its decisions*" [353]. That is, neuropolitics includes a set of techniques aimed at knowing the electorate so as to predict its behaviour, as well as the design and elaboration of communication campaigns meant to seduce it [354]. With regard to the "*political brain*," a series of studies highlighted that political information is recorded at different brain levels.

Kanai [355] conducted a study in which it was discovered that, at a physical level, there are differences in the brain of conservatives and liberals and, therefore, a difference between cognitive systems. Using fMRI and according to different tests, the researcher found that the more liberal people had more volume of grey mass in the cortex of the anterior cingulate, while the more conservative people had more volume of grey mass in the right amygdala of the brain [355]. Therefore, the liberals presented more brain activity in the region than conflicting process information, and 10% of the participants with this orientation were more predisposed to rectify a response incorrect than the conservatives [356] (Braidot stated "*What happens in the brain of the electorate,* *what happens in the brain of the candidates?*" (p. 7 in [357]). According to the theory of affective intelligence, the most important emotions for political behaviour are enthusiasm (the opposite of depression) and fear (the opposite of calm). Thanks to different tools of neuromarketing, it is possible to analyse how effective a political campaign is and how it can influence votes for candidates from an unconscious level. Neuroscientists are familiar with the established research evidence of more than 50 years that personality variables accompany differences in political opinion [358].

A brain imaging study of swing voters, in the summer of 2007, was analysed by a group of researchers who published it in The New York Times on November 11, 2007 [359].

Politicians use many different techniques to hold and extend their appeal to their traditional voters. It is not surprising that political campaigners also try to benefit from this knowledge as we learn more about how the human brain works.

Westen [360] in a study based on brain scanning found that "*the political brain is an emotional brain. It is not a dispassionate calculating machine, objectively searching for the right facts, figures and policies to make a reasoned decision.*" He built this formulation by analysing political TV advertisements that, whilst banned in the UK, were widely used in the US. Indeed, these advertisements represent the items that received most of the campaign budget of the candidates (about some millions of dollars). Westen concluded that "*Republicans understand what the philosopher, David Hume, recognized three centuries ago: that reason is a slave to emotion, not the other way around. Except for the Clinton era, Democratic strategists for the last three decades have instead clung tenaciously to the dispassionate view of the mind and to the campaign strategy that logically follows from it, namely one that focuses on facts, figures, policy statements, cost and benefits, and appeals to intellect and expertise*" [361].

Vecchiato et al. [362] used EEG technology to assess the Italian Prime Minister's TV speech in 2009. The brain activity was observed in two groups of people divided into swing voters and Italian Prime Minister's "*supporters.*" The results showed a different brain activity between two groups: for the supporters, a greater power spectral activity was observed throughout the speech than the swing voters, who were less attracted by the speech.

7.10. Neurotaste. Neuromarketing has been widely used in the food and beverage sector. In recent years, researchers have focused their attention on applying the neuroscientific methods not only to the extrinsic features of the food and beverage sector products (i.e., packaging, price, shape, colour, and texture) but also to their intrinsic values: flavour/taste and scent/aroma. This kind of study named "*neurotasting*" includes the concepts such as "*neurogastronomy*" [363] and "*neuroenology*" [364]. The taste is a vital sense in humans because of its active role in regulating nutrition or avoiding harmful substances [90]. Information conveyed via the gustatory system aids in identifying edible and nutritious foods, makes the humans able to avoid toxic substances, and drives the hedonic evaluation of nutrition, which can take place before, during, or after ingestion. For such a reason, the interest in understanding the cognitive processing related to the human sense of taste grew up during the last decades, not only for basic research on food and nutrition but also for the clinical applications and consumer industries. Perception of the basic tastes of sweet, salty, umami, sour, and bitter as well as the oral sensation of fat plays a vital role in determining food acceptance, preference, and choice. Our subconscious state associates certain foods with pleasure and happiness, and certain others with fear [365]. The pleasure we derive from eating, termed "hedonics," provides us with the drive to consume a food. Taste is not simply defined by our genetics but can be modulated by a variety of biological and environmental factors, including body mass index and the consumption of certain foods [366, 367], smoking and alcohol consumption [368–370], aging [371, 372], gender [372], and exposure to pathogens [372].

There are numerous neuroscientific studies investigating the relationships among communication, perception, and satisfaction experienced by consumers [373].

Using fMRI and MEG, it has been possible to determine the dynamics of the human brain processing of information coming out from the gustatory system. In particular, the human insula has been associated with the initial sensory processing of taste [374]. It is hence commonly considered the primary taste area. The orbitofrontal cortex (OFC) and prefrontal cortex (PFC) have been linked to the processing of hedonic aspects of taste [375] and are often regarded as the secondary taste area. Several studies based on less invasive technologies, in particular fNIRS and EEG, confirmed the theory about the important role of PFC in decoding information related to the taste [376, 377]. These findings couple with the widely accepted theory about the relationship between the human PFC activity and the motivational processes towards sensorial stimuli based on which an increasing left hemisphere activity is associated with approach attitude, while an increasing right hemisphere activity is associated with withdrawal attitude [188]. It is important to remember that the first neuromarketing study conducted by Read Montague (and described in the previous part of this paper) was based on the taste perception, which is important in order to understand consumers' preferences about common beverage products such as Coca-Cola and Pepsi [99]. In Plassmann and colleagues' study [47], participants have been scanned with an fMRI while they were performing a wine tasting and preference rating task. Various food products and beverages, such as chocolates, wine, and cola, have been administered in the fMRI scanner. These products are particularly easy to administer through a computer-controlled pump attached to a tube that delivers controlled amounts of fluid into the participant's mouth.

An important application of the neuroscientific methods could be to better understand how the smells influence the consumers in the food choice [90]. In fact, odours and tastes can lead to specific memories: some people may have particular odours associated with friends, family members, or other loved ones, and these memories can be automatically triggered by a brief exposure to the same odour [340]. The importance of the variable "*olfaction*" during the tasting experience had already been naturally demonstrated when people are recommended not to drink wine when they have cold (the closed nose decreases the pleasure of drinking). This has also been empirically demonstrated in a couple of studies [197, 198] with an experimental protocol taking into account an EEG index, assumed as an indicator of approach or withdrawal (AW) motivation [188], and an autonomic index (emotional index (EI)), deriving from the matching of the heart rate and galvanic skin response activity [61]. The experiments have provided the degustation of two types of Italian wines, and the process has been divided into two phases as well: smell and tasting. For the tasting phase, two different conditions were considered: "*with open nose*" and "*with closed nose*." The results of both research studies showed an impact of the smelling phase on the emotional index in comparison with the other two phases of tasting (with and without olfactory component) and a trend of major approach attitude in correspondence of wine tasting with the olfactory component (in comparison with the other two conditions).

To conclude, these techniques could be applied not to encourage junk-food addiction but to make healthy food more attractive, appealing, and thus more consumed.

7.11. Neuroaesthetics. As Santayana [378] observed, "*Humans are drawn to the aesthetic features of objects and the environment around them*." Such features are not mere inconsequential adornments; they influence people's affective responses, decisions, and behaviour. In fact, aesthetics plays a central role in consumers' choice of products [264, 379], in judgments of artificial [380, 381] and natural environments [382, 383], and in attitudes, judgments, and behaviour toward other people [384–386]. Some of the questions that neuroaesthetics aims to answer are related to the understanding of which neural processes of aesthetic features influence people's attitudes, decisions, and behaviour and, in general, what are the neural underpinnings of aesthetic appreciation [387].

Neuroaesthetics is an emerging discipline, within cognitive neuroscience, that investigates the biological foundations of the aesthetic experiences [388]. The discipline merges empirical aesthetics with cognitive and affective neuroscience [389]. "Neuroaesthetics" is a term coined by Zeki [390] and refers to the study of the neural bases of beauty perception in art [391].

At its core, neuroaesthetics is a certain way of doing aesthetics, using neuroscience as a method of investigation where other aesthetic approaches have used philosophical analysis or psychological models. Neuroaesthetics, therefore, studies how the brain processes support the aesthetic behaviour. Although the real experimental work on this issue has only begun in the last 20 years or so, the conceptual inclination to investigate the neural mechanisms underlying the aesthetic behaviour can be traced back to the eighteenth and nineteenth centuries [392].

Neuroaesthetic studies are usually performed recording the cerebral hemodynamic responses, with fMRI for the observation of computer screen reproductions of paintings or sculptures (reviewed in [391]). Neuroelectrical and neuromagnetic correlates of such brain activity were also addressed by few authors by using MEG [393] and EEG [394, 395] brain imaging modalities. However, in all the published scientific reports related to the study of brain activity with fMRI, MEG, or EEG modalities, the fruition of the paintings or the sculptures was made possible to the subjects through a presentation of a series of images of such fine art works on a screen. This was due to the fact that both fMRI and MEG are not portable. On the contrary, modern EEG technologies allow to record the brain activity in different environment and mobile conditions, for example, during the fruition of real masterpieces in a fine art gallery environment, where they are usually observed by visitors [193].

The study of neuroaesthetics has mostly dealt with aesthetic appraisal: in this context, participants are usually asked to explicitly judge a visual stimulus as either beautiful or ugly. Kawabata and Zeki [396] used fMRI to investigate the neural correlates of beauty perception during the observation of different categories of paintings (landscapes, portraits, etc.) that were judged by participants as beautiful, neutral, or ugly. The core imaging results revealed different brain activations for judged-beautiful stimuli versus both judged-neutral and judged-ugly images in the medial orbitofrontal cortex (OFC). The differential activation observed in the OFC consisted of decreased activity with respect to baseline, with judged-ugly stimuli evoking the lowest level of activation. Using a similar methodological approach, Vartanian and Goel [397] carried out an event-related fMRI study, in which explicit aesthetic preference for representational versus abstract paintings was investigated in three stimulus versions: original, altered, and filtered. Participants indicated their preference with a button press at each stimulus presentation. Representational paintings evoked higher preference than abstract paintings. In both categories, original paintings elicited the highest preference. In 2009, Cela-Conde et al. [393] investigated gender-related similarities and differences in the neural correlates of beauty by using a set of images of either artistic paintings or natural objects, divided into five groups. Through MEG, it was possible to detect an enhanced activation for "*judged-beautiful versus judged-ugly*" stimuli in several parietal foci (bilaterally for women and mainly in the right hemisphere for men) with a latency of 300 ms after stimulus offset. The activation of parietal areas during aesthetic experience was also shown in an fMRI study by Cupchik et al. [398], in which participants viewed various categories of representational paintings that were classified as the "*hard edge*" (containing well-defined forms) and as the "*soft edge*" (containing ill-defined forms). Enhanced activation of the left superior parietal lobe was observed for the "*soft-edge*" paintings, particularly during the "*aesthetic*" condition. Involvement of parietal and premotor areas in aesthetic experience was observed in the fMRI study of Jacobsen et al. [399]. Participants had to make an aesthetic assessment of abstract geometric shapes, the symmetry and complexity of which had been manipulated. Behaviourally, symmetry has been shown to have a strong effect on aesthetic judgment and aesthetic judgment tasks compared to the control condition (observation of the arrow), and activation in areas that serve visuomotor processes, including the intraparietal sulcus and ventral premotor cortex, has been enhanced under both conditions. In 2007, Di Dio et al. [400] carried out a study in which two versions of Classical and Renaissance sculptures were presented: original and proportional. The image results showed that some lateral and medial cortical areas (lateral occipital gyrus, precuneus, and prefrontal areas) and, importantly, the right anterior insula were activated by the observation of original sculptures related to the modified ones. Activation of the insula was particularly strong during simple observation condition, in which the brain could be said to respond most spontaneously to the presented images, and support for this finding comes from the study of Cupchik et al. [398] in which the observation of representational paintings under the "*aesthetic*" condition versus baseline condition elicited bilateral activation of the insula. It is interesting to note that, in this study, no explicit behavioural responses were required in the scanner and that implicit "*aesthetic attitude*" was induced in the participants by specific instructions provided prior to the scanning [391].

As previously said, through the portable technologies, it is possible to conduct the research in different real environment and in mobile conditions. Babiloni et al. [193] conducted a study during a visit to a real fine art gallery, in which they examined how motivational factors as indexed by EEG asymmetry over the prefrontal cortex (relative activity of the left and right hemispheres) could be related to the experience of viewing a series of figurative paintings. The results suggested a strict correlation of the estimated EEG asymmetry with the verbal pleasantness scores reported by the subjects and an inverse correlation of the perceived pleasantness with the observed painting's surface dimensions.

In 2014, Babiloni et al. [401] conducted a study in which they collected the neuroelectrical brain activity, heart rate, and galvanic skin response correlated with the observation of the real sculpture of Michelangelo's Moses within a church in Rome. The group observed the Moses sculpture from three different perspectives, each revealing different sculpture details. In addition, the light conditions related to the sculpture's specific observation were explicitly changed at each location. The results showed that the subjects' cerebral activity varied significantly across three different views and did not have a light condition. In addition, the estimated emotional involvement of the entire population has been higher for the point of observation in which the face of Moses was directed to the observers' eyes. Finally, the cerebral appreciation of the investigated group was found to be maximum from a perspective in which all the details of the sculpture could be easily seen.

Babiloni et al. [192, 402] measured the neuroelectrical and eye movement activities in a group of participants during their visit to a fine art gallery where a series of masterpieces of the Italian painter Tiziano Vecellio were shown. A mobile EEG device with an eye tracker was used for this experiment. The results showed that, in the examined group, the approach-withdrawal (AW) index was significantly higher during the observation of portraits rather than during the observation of the religious subjects. Interestingly, the average AW index estimated in the first 20 seconds of the observation of the pictures remained highly correlated with the AW index evaluated for the second part of the data for all the pictures examined. In addition, the number of eye fixations performed by the subjects in the first 5 or 10 seconds of observation of the most appreciated pictures is significantly higher than the number of eye fixations performed on the pictures that subjects did not like. But such a difference vanishes if the entire period of observation of the pictures becomes one minute.

Importantly, Cartocci and colleagues [403] conducted a pilot study using the neurometric index during the listening of selected pieces of Dante's Divina Commedia in 2016. Half of the participants had a literary formation, while the other half of them were attending other kinds of university courses. The findings revealed that the "*humanist*" group reported higher approach-withdrawal and emotional index values when compared to the "*nonhumanist*" group sample.

Finally, in 2017, Maglione et al. [196] estimated the cortical activity correlated with the perception and appreciation of different sets of pictures by using the neuroelectrical brain activity and graph theory methodologies in a group of original pictures of Titian's and a contemporary artist's paintings (Orig dataset) plus two sets of additional pictures. These additional datasets were obtained from previous paintings by removing all but the colours or the shapes employed (Colour and Style datasets, respectively). The results suggest that the verbal appreciation of the Orig dataset when compared to Colour and Style ones was mainly correlated with the neuroelectric indexes estimated during the first 10 s of observation of the pictures.

8. Ethical Issues

As we have seen in the previous sections, neuromarketing is a new field in consumer research that is rapidly emerging. For some observers, the mysteries of consumer choice and behaviour in the human brain are finally unlocked by the "*Holy Grail*" of research technologies. For others, the root of all evil will ultimately give marketers and advertisers ultimate control over our minds and wallets. The truth lies somewhere in the middle, as with most exaggerations. Neuromarketing does bring some quite powerful insights and techniques into the consumer research domain. Actually, the neuromarketing research is not a discipline for turning people into "*zombie consumers*," but it is a marketing or market research activity that uses the methods and techniques of brain science to better understand the consumer behaviour. It is a distinctive approach to market research because it is based on new knowledge from the brain science and it does not represent a tool to identify the consumer's "*buy button*", as it has been stated in some contexts. In many cases, neuromarketing is not well understood, but it is controversial [404].

For all these reasons, researchers should be aware and careful with ethical aspects when using brain scans and neuroscience advances to understand consumers' decisions. So, the ethics of neuromarketing is also an issue. Of course, the use of scientific technology to promote commercial interest is not inherently problematic. However, the use of technology that tests the inner workings of the human brain, especially beyond what can be disclosed in traditional behavioural tests, raises significant ethical problems. These problems fall into two main categories: (1) protection of different parties that may be harmed or exploited by neuromarketing and (2) consumer autonomy protection [405]. In someone's mind, neuromarketing raises disturbing questions about the extent to which advertising agencies, market researchers, and their corporate clients should be allowed to invade consumers' privacy and the supposed power that will give them the possibility of manipulating consumers' purchase decisions [406]. A question of whether neuromarketing is just a benign method to help companies better understand customers' true desires while giving customers the power to influence companies should be addressed, as well as determining whether this method is a way of unconsciously suggesting the purchase of an otherwise unwanted item [407]. Moreover, neuromarketing by companies producing tobacco, alcohol, junk food, or quick food might be harmful to public health [408]. This also raises significant ethical problems for children and adults [409, 410]. The protection of vulnerable populations is also part of the neuromarketing concerns [64, 67, 266, 405, 410]. Murphy et al. [405] suggested the need to regulate the use of neuromarketing techniques on children and other vulnerable groups, such as people with neurological diseases or pathological disorders, people sensitive to advertisements, and legally protected groups. Lee et al. [62] cite shopping addiction and overconsumption as problems associated with neuromarketing because its techniques may have the ability to read consumers' minds [63–65, 405, 410, 411]. Thus, companies would be able to identify and easily trigger mechanisms that induce consumer purchasing behaviour [38, 63, 410, 412]. Consumers, therefore, would become transparent to the companies, which, at any moment, could invade their private thoughts [65, 413]. Another ethical question of neuromarketing lies in the use of the technique for commercial purpose [38, 49, 64, 65, 67]. In examining the cognitive processes related to individuals' consumption preferences, companies acquire great power to influence the purchase decision [51, 405]. Many texts cite the lack of ethics related to the possibility of neuromarketing creating irresistible ads and products [38, 51, 65]. Neuromarketing would then represent a major threat to the autonomy of consumers because it would remove their defensive mechanisms [38, 51, 64, 65, 67, 405].

There are also reasons for criticism from the institutions for the use of neuromarketing, how it is applied, and the audience that is examined. Four of the texts analysed indicated the existence of ethical dilemmas involving the application of neuromarketing by academicians and physicians or the conduct of neuromarketing studies in universities [51, 65, 410, 414]. Other authors also say that neuromarketing has raised criticism because physicians and academicians are working in marketing research companies [51, 65]. According to Dinu et al. [414], possible damage to the health of participants or negative aspects of marketing research can be hidden, and therefore, the results would be biased. Some authors argue that companies should disclose the procedures and results of their research to avoid accusations of irresponsible behaviour [51, 64, 405]. Consent from participants should also be obtained before studies are conducted [64]. Ariely and Berns [46] also discussed other ethical issues [52].

Murphy et al. [405] have addressed ethics and neuromarketing considering the following five different areas:

(1) Protection of research subjects
(2) Protection of vulnerable niche populations from marketing exploitation
(3) Full disclosure of goals, risks, and benefits
(4) Accurate media and marketing representation
(5) Internal and external validity

Trettel et al. [415], in their work, wrote about the transparency and reliability issues in the practice of the applications of neuroscience-based methodologies on relevant marketing stimuli. It is assumed that the lack of transparency in the methodologies used by neuromarketing companies is one of the reasons for the public opinion and mass media's misperception and overestimation of the actual capacity of neuromarketing to inform marketing researchers. In fact, different neuromarketing companies provide services, based on proprietary computational methods, which are not fully validated or disclosed to the scientific community via science publications: this opacity in the methodologies employed by some companies makes it difficult for scientists to classify supported and unsupported claims of validity of the services offered by those companies. These confusions are associated with an often-misplaced communication towards the public opinion and the final users of these methodologies about the effective capability of such an approach to capture the generation of the decision-making of the persons in front of marketing stimuli.

On the contrary, the application of neuroscience to marketing forms a basis for understanding how human beings create, store, recall, and relate to information such as brand messages in everyday life. Then, it may be possible to discover whether certain aspects of advertisements and marketing activities are able to trigger negative effects, such as overconsumption. Exploring why certain individuals become compulsive credit-card users could provide outcomes of considerable social utility.

In the face of all of the ethical issues involving neuromarketing, a solution proposed by various authors for better regulating and making the technique more accepted by the community has been the adoption of an ethical code for neuromarketing [49, 63, 102, 405].

In 2013, for the first time, the Neuromarketing Science and Business Association has drawn up the first code of ethics that suggests a series of good practices to neuromarketing companies. The code may be revised from time to time to ensure that it adequately reflects the highest and up-to-date ethical standards for the neuromarketing research industry. The NMSBA code accepts the principles enshrined in the ICC/ESOMAR Code.

If, therefore, neuromarketing complied with an ethical code like other methodologies did and is used (as mentioned above) for marketing purposes, there should not be any ethical or moral problems: on the contrary, neuromarketing could actually help marketers understand consumer behaviour and as well help companies find business solutions that precisely respond to their needs.

9. Conclusions and Future Trends

During the last decade, the advancements achieved in the field of neuroscience regarding technology, i.e., the possibility to record a user's biosignals with wearable, ergonomic, and reliable devices, have encouraged the scientific community to investigate the use of neurophysiological measures, not only for research purposes but also for daily life applications [90]. In other words, it is now possible to record, even in real time and in a real environment, a person's actual mental and emotional reactions, without asking anything to the user or interfering with the ongoing task. With respect to the standard methods to evaluate the mental and emotional states of the user, such as behavioural (i.e., performances and reaction times) and subjective (i.e., questionnaires) measures, neurophysiological signals demonstrate several additional advantages [92]. For example, subjective measures, although providing a direct (i.e., self-reported) measure of the mental or emotional state under investigation, cannot collect information in real time (i.e., the subject must explicitly state their perceived state). Thus, the reliability of the measurement may be affected by the nature of the measurement itself or by the interviewer biases. Instead, neurophysiological actions overcome all the above-mentioned problems, allowing a measure of the user's actual mental and emotional condition, which is objective, non-intrusive, and even continuous [10, 416] and which paves the way for a range of applications. This paper highlighted several applications of neuromarketing, published in the last two decades: with most probability, the number of these will increase in the next years. However, there are still a lot of challenges that need to be addressed.

In particular, from the academic point of view, Plassmann et al. [83] in 2015 identified three major challenges faced by the field: First, consumer neuroscience studies often face the criticism that they provide correlational evidence but not causal evidence, so the first challenge is related to the fact that consumer neuroscience research informs the understanding of consumers' brain, not consumer behaviour. In order to meet this challenge, marketing researchers should see consumer neuroscience not as a way to replace traditional behavioural measurements, but as an addition to improve the way behavioural measures are obtained and interpreted. The second challenge is the interpretation of findings that is often based on the assumption that a brain region is united on the basis of previous studies. In other words, researchers conclude that participants must have engaged in a specific psychological process (i.e., a reverse inference) based on previous activations in a particular brain region. Reverse inference is problematic for any research linking neuroscience to behaviour—including consumer neuroscience research—but its problems can be addressed by using a theory-driven approach for designing studies and by applying meta-analytic statistical tools for improving interpretations of results. The third and the last challenge is the perceived lack of reliability due to the considerably smaller sample sizes than those used in traditional psychological research studies. The use of small samples raises some important concerns: the reliability of the neuroscience findings, the generalizability of the findings from neuroscience experiments to the population, and the increased possibility of opportunistic findings. If we consider behavioural research articles published in journals such as the *Journal of Consumer Research*, *Journal of Marketing Research*, and *Journal of Cognitive Neuroscience*, these typically feature several studies, each consisting of approximately 25–30 participants in each condition across several between-participant conditions, providing converging evidence toward a specific hypothesis while ruling out alternative explanations [417].

Instead, from the business point of view, in a survey conducted for the NMSBA at the beginning of 2019 (for more details, visit https://bit.ly/2UbeWzz), respondents were asked what they believed were the biggest challenges faced by the neuromarketing field today, and what they were doing to address these challenges. Two clear themes arouse: one focusing on the readiness of clients to embrace neuromarketing and one focusing on the reputational risk created by inexperienced or underqualified vendors, mainly revolving around the negative effects of overpromising and underdelivering. In terms of readiness, the major challenges vendors cite as inhibiting the growth of neuromarketing are lack of knowledge on the part of clients, inadequate client training and education, and general resistance and distrust regarding neuromarketing claims and principles.

In terms of reputational risk, vendors report that "*snake oil*" promises and underwhelming results continue to plague the field. Several responses mention "*bad vendors*" as a source of problem for the industry. Generally, "*bad vendors*" are described as those who overpromise on results, offer technologies and metrics that are neither validated nor transparent, fail to follow scientifically rigorous protocols and procedures, or fail to make a persuasive case for the business benefits of their offerings. Once a bad vendor has disappointed a client, it is hard for other vendors to convince those clients that not all the vendors in the field are like the previous ones.

Taken together, these concerns about clients who lack basic knowledge and vendors who fail to provide adequate services combine to create a kind of feedback loop that inhibits the penetration of neuromarketing into more cautious and conservative segments of the research-buying market.

Despite these challenges and concerns, the application of neuromarketing will grow. A clear and promising direction for the future is the bridge between the measurements of the internal states of the persons in relation to the perception of marketing messages and the data science related to the effective behaviour of hundreds of thousands of them (e.g., big data). This link is a hot direction of research, and it is related to the anticipation of the outcome of the market on the base of the neurometric measurement of the person's internal states. Several attempts have been performed in the past by different research groups [45, 418, 419].

In this specific area of investigation, however, we must develop a comprehensive theory that combines individual internal states with the general social processes (as measured by neuromarketing techniques, such as word of mouth, imitation, and other social phenomena) on the basis of the dissemination of information across multiple groups. Such a theory is clearly lacking and, from the theoretical and empirical point of view, could represent the most promising direction of research. The coming years will see stricter cooperation between more different groups of scientists from different disciplines such as neuroscientists, economists, marketers, and sociologists. All of them will collaborate in order to fully describe the subtle and elusive concept of our decision-making in real contexts.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

A LightGBM-Based EEG Analysis Method for Driver Mental States Classification

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Fatigue driving can easily lead to road traffic accidents and bring great harm to individuals and families. Recently, electroencephalography- (EEG-) based physiological and brain activities for fatigue detection have been increasingly investigated. However, how to find an effective method or model to timely and efficiently detect the mental states of drivers still remains a challenge. In this paper, we combine common spatial pattern (CSP) and propose a light-weighted classifier, LightFD, which is based on gradient boosting framework for EEG mental states identification. The comparable results with traditional classifiers, such as support vector machine (SVM), convolutional neural network (CNN), gated recurrent unit (GRU), and large margin nearest neighbor (LMNN), show that the proposed model could achieve better classification performance, as well as the decision efficiency. Furthermore, we also test and validate that LightFD has better transfer learning performance in EEG classification of driver mental states. In summary, our proposed LightFD classifier has better performance in real-time EEG mental state prediction, and it is expected to have broad application prospects in practical brain-computer interaction (BCI).

1. Introduction

Fatigue driving is an important cause of traffic accidents. According to data from U. S. National Transportation Safety Board, the annual economic losses caused by driving accidents in the United States are more than $12.5 billion [1]. Fatigue has no obvious symptoms but usually manifests as lethargy, fatigue, or weakness [2]. Therefore, developing technologies to monitor and predict driver' mental state or the ability to safely drive the vehicle will have significant social and economic benefits [3].

At present, for fatigue driving detection, the academic community has carried out a lot of research work. To sum up, it mainly lies in the following aspects: (1) mental activity testing using response time and accuracy by passive BCIs [4, 5], which mainly perform an assessment of a subject's cognitive states [6, 7], (2) detection of eye movement parameters, such as eye squint movement, percentage closure of eyes (PERCLOS) [8], and so on, (3) active detection by means of questionnaires, (4) sensor-based methods to find some fatigue indicators by steering force (steering grip pressure), skin conductance, blood volume pulse (BVP), and so on [9, 10], and (5) performing fatigue state detection by bioelectrical signals, such as EEG, EOG (electrooculogram), EMG (electromyogram), and ECG (electrocardiogram) [11–16].

For physiological-electric-based detection, researches have shown that these signals have a strong correlation with the driver's mental state, so these signals can be more accurate to detect driving fatigue. Among the above various researches of fatigue detection, EEG analysis methods are considered to be most convenient and effective for its good time resolution and sufficient spatial resolution. It is known that EEG represents the brain activity by the electrical voltage fluctuations along the scalp [17]. As an effective tool for the indirect measurement of neural activity, EEG is widely used in neuroscience, cognitive science, cognitive psychology, and psychophysiology research, etc. On the other hand, driving behavior involves a variety of behaviors, such as motions, reasoning, audiovisual processing, decision making, perception, and recognition, which is also affected by emotions, attention [18], and many other psychological factors. These physical and mental activities related to driving are reflected in EEG signals.

In recent years, a number of methods for fatigue detection using EEG have been proposed; for example, Kar et al. [2] investigated a number of fatigue-indicating parameters based on higher-order entropy measures of EEG signals in the wavelet domain. In particular, they present a method based on a kind of entropy measures on the EEG signals of the subjects for the relative quantification of fatigue during driving. Charbonnier et al. [19] proposed an online innovative EEG index and proved that the proposed index can be used based on the alpha activity to effectively assess the operator's mental fatigue status. Roy et al. [20] applied a Fisher's linear discriminant analysis (FLDA) to detect and classify EEG-based mental fatigue. In [21], the authors used a KPCA-SVM classifier to distinguish between normal and fatigue mental state, with an accuracy rate of 98.7%. Maglione et al. [22] used high-resolution EEG and neurophysiological variables to analyze the increase in cerebral workload and the insurgence of drowsiness during car driving and acquired a workload index. In 2014, Zhang et al. [23]presented a real-time method with various entropy and complexity measures for the detection and identification of driving fatigue from EEG, EMG, and EOG signals, and the accuracy of estimation is about 96.5%–99.5%. Appriou et al. [24] presented a comparison of 4 modern machine learning algorithms in order to compare EEG-based workload level classification performances and found that CNN can obtain better performance (mean = 72.7% ± 9.1) than a LDA classifier with CSP spatial filters in classifying two workload levels (low vs. high) for both user-specific and user-independent studies. In [25], the authors developed an adaptive stacked denoising auto encoder (SDAE) to tackle cross-session mental workload (MW) classification task, and the adaptive SDAE is also demonstrated to be acceptable for online implementation. All together, these articles support the knowledge that mental fatigue can be efficiently detected by EEG with classification performances varying between 75% and 98%.

Other feature extraction and analysis methods are also used in mental state detection, such as EEG and fNIRS joint analysis [26], discrete wavelet transform [27], wavelet-packets transform (WPT) [28], integrating feature selection, and fusion on high-level EEG features from different models [29]. In recent years, deep learning-based models have also been used in mental state classification, for instance, deep convolutional neural networks [29], long short-term memory network (LSTM) [30], and switching deep belief networks with adaptive weights (SDBN) [31].

Although these methods have achieved excellent performance, how to design appropriate models to obtain robust, real-time, and high-accuracy classification performance of driving mental states by EEG still remains a challenge for a series of reasons. First, EEG shows the characteristics of instability and randomness, EEG signals collected by the single subject (intrasubject) or between two different subjects (intersubject) tend to have large differences over time [32]. Second, the low signal-to-noise (SNR) ratio of EEG often affects the accuracy of detection. Third, with the continuous improvement in EEG acquisition equipment, EEG signals gradually show multidimensional and complex features with a large time and space consumption during processing.

LightGBM [33] is a gradient boosting framework that uses a decision tree-based learning algorithms. It is distributed, efficient with faster training efficiency, and can handle a large amount of applications, but there also exists deficiencies when dealing with high-dimensional features for EEG signals, like lower accuracy, as well as time consumption. Therefore, in this article, we improve and design a LightGBM-based model, LightFD, which adopts the histogram-based decision tree algorithm and the leafwise leaf growth strategy with depth limitation to solve the problem of excessive xgboost memory consumption, which is more suitable for practical EEG clinical applications. Now, LightGBM has been applied to EEG signal classification and has achieved certain results in practical problems, such as emotion recognition [34, 35], epilepsy prediction [36], and so on.

Transfer learning methods have been widely used for EEG signal classification in recent years [37–40], which could transfer the previous extracting features in one kind of trained samples to another sample for some specific decision tasks. Due to its great advantages of lower time consumption, transfer learning can bring more practical application possibilities for EEG analysis.

Motivated by the advantages of LightGBM and following our previous work [41], where only a CNN-based model was investigated to realize the EEG-based binary classification of mental states, and the model is time consuming, moreover, the transfer learning capability of the model is not analyzed. Thus, in this article, we aim to design a LightGBM-based classifier, LightFD, to implement the light-weighted analysis of triclassification identification of EEG mental states, and furthermore, we will also test and validate the efficiency and robustness of LightFD in the aspect of transfer learning and compare them with those of manifold embedded distribution alignment (MEDA) [42] and metric transfer learning (MTLF) [43].

2. Materials

2.1. Subjects. We recruited 10 healthy subjects for EEG data collection. All of them were within 23 and 25 years old and possess Chinese manual driver C1 license. They were informed in advance of the entire experimental process and instructions and also required to keep calm without drinking irritating beverage, like coffee, alcohol, and so on before the experiment. All participants provided their written consents, and the research was approved by the ethics committee of our university.

2.2. Experimental Setup. To collect EEG data during driving, we constructed a simulation platform, as shown in Figure 1,

Figure 1: Driving simulation experiment platform.

which consisted of a racing seat cushion, steering wheel, liquid crystal display (LCD), speaker, video camera, and projector. A 16-channel gUSBamp amplifier (g.Tec Medical Engineering GmbH) was used to record EEG signal. Besides, two more computers were employed for (1) simulating the track with the special "Speed-Shift 2 Unleashed (NFS-S2U)" software, recording all the parameters during driving with "WorldRecord" software, and (2) collecting the video and sound stimuli, dealing with EEG signals, respectively [12, 41].

2.3. Experimental Protocol. The whole experiments lasted for two days and were conducted between 18 : 00 and 21 : 00 in a quiet and isolated environment. The first day was considered the practice stage for familiarizing with the track and stimulating software and experimental operations, and the second day was the formal experimental stage for collecting EEG data. The heart rate and blink were simultaneously collected with EEG by corresponding sensors, such as ECG electrode attached on the subject's wrist and video camera placed in front of the subjects, which were used to aid judgment in the level of mental states. According to previous studies [44, 45], the numbers of blink and heart rate in the situation of awake would be higher than those in the situation of drowsiness. Moreover, we counted the average number of blink and heart rate of all the subjects throughout the whole experiments. We found that at the beginning stages, when the subjects were only asked to drive a car at a predefined speed without any video or sound stimuli, the average number of blinks is above 20 times/min, up to 24 times/min, and the average heart rate was close to 90 times/min. As the stimuli were introduced into the experiments, the average number of blinks changed to 12–20 times/min, and the heart rate was 78–85 time/min. At the last stage, the subjects were not given any stimuli, the average number of blinks increased to 22 times/min, and the average heart rate was 73 times/min. Therefore, we divided the mental states into 8 stages: WUP, PERFO, TAV3, TAV1, TAV5, TAV2, TAV4, and DROWS [12, 41]; the detailed introduction of these eight stages is shown in Table 1.

The flowchart of the experiments is shown in Figure 2. There were two kinds of driving tasks during the experiments: one was a simple driving task, which only required the subject to drive like the practice stage and did not exert any sound and video stimuli. This kind of driving tasks included three stages: WUP, PERFO, and DROWS. WUP was the beginning of the experiment with a baseline driving speed, and PERFO was similar to WUP but required the subjects to drive at a speed of 2% faster than WUP. DROWS was the last stage of the experiments with a fixed driving speed of 60 km/h. The other stages introduced additional video ("alert") and sound stimuli ("vigilance") to simulate situations such as red lights and traffic jams that might occur in real driving, which include five TAV stages: TAV1–5. All TAV stages were exerted with different stimulus frequencies of sound ("vigilance") and video ("alert") stimuli that appeared on the LCD screen 1 m ahead of the subjects, and the corresponding buttons were pressed by the subjects: LEFT button for "vigilance," and RIGHT button for "alert." Five TAV stages: TAV3, TAV5, TAV1, TAV2, and TAV4 were executed in sequence.

Because TAV3 is the first stage with video and sound stimuli, the subjects were bound to drive very carefully and complete the corresponding operations as quickly and accurately as possible, so they were in the most awake state. DROWS was the last stage without any stimuli. It just required the subjects drive with a fixed speed of 60 km/h. It seemed monotonous and boring, especially after about 2 h of driving; therefore, the subjects were extremely prone to fatigue in this stage. In addition, the obvious differences in blink and heart rate between TAV3 and DROWS further

Table 1: Eight experimental stages.

Stages	Durations (min)	Description
WUP	8–10	Also called "warm-up," collecting baseline of EEG, ECG, and EOG when driving a car at a predetermined speed.
PERFO	7–9	Also called "performance," similar to WUP, just has a higher driving speed than that of WUP.
TAV3	7–9	These 5 stages are concurrently exerted task of attention (sound) and video stimuli with different frequency levels. The stages from low to high stimulus frequency are TAV1, TAV2, TAV3, TAV4, TAV5.
TAV1	7–9	
TAV5	6–9	
TAV2	7–9	
TAV4	7–8	
DROWS	12–18	At the stage, the subject falls into drowsiness and feels tired and fatigue.

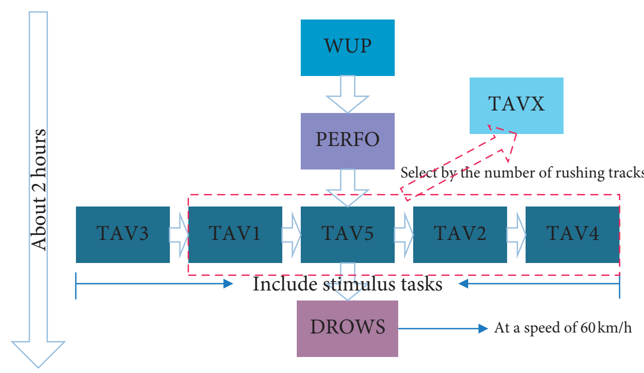

Figure 2: The schematic diagram of experiment procedure.

confirmed the correctness of the design of this experiment. Moreover, we defined a "neutral" stage as TAVX, which was neither fatigue nor awake. However, the time required for each subject to enter the fatigue state may be different, and TAVX is one of those 4 stages: TAV1, TAV2, TAV4, and TAV5, at which the number of rushing out of the track is closest to the average of rushing out of the track during the experiment. Accordingly, the collected data at TAVX were then used for analysis.

2.4. EEG Recording. EEG was recorded by a gUSBamp amplifier with a sampling frequency of 256 Hz and impedance of below 5 kΩ. Of 16 channel electrodes, 15 were used to sample EEG, except for ECG sampling heart rate. All the electrodes were referenced to the left earlobe. After removing the artifacts, EEG signals of 15 channels were divided as Fz, Pz, Oz, Fp1, Fp2, F7, F3, F4, F8, C3, C4, P7, P3, P4, and P8, with a time window of 0.5 s, and then a certain number of epochs of each stage were obtained. According to Kar et al. [2], the EEG recording was filtered between 1 and 40 Hz with a band-pass filter, and independent component analysis (ICA) [46] was then adopted for eye movement artifacts rejection. With ICA, the source signal can be separated or approximately separated without knowing the source signalS, noise, and mixing mechanism. After that, according to the method we proposed in [41], EEG recording was converted into SP ∗ CH ∗ TR format, where SP is the sampling frequency, CH is the corresponding channel, and TR is the event. For the segmentation of EEG data, we adopted 0.5 s-interval time window to split EEG data of 15 channels into different number of epochs. Due to the sampling frequency of 256 Hz, we then expressed every epoch as a 15 ∗ 128 matrix. At the same time, we used the flag "0" for DROWS, "1" for TAV3, and "2" for TAVX, respectively. Thus, we obtained a total of 37,168 epochs, including 18,672 DOWNS epochs, 9,504 TAV3 epochs, and 8,992 TAVX epochs, as shown in Figure 3. In this way, LightFD can be trained by these epochs, and the classification performance of LightFD for mental states prediction could be tested simultaneously as well.

3. Method

3.1. EEG Feature Extraction by Improved CSP. The core of CSP is to find the optimal spatial projection to maximize the power of the two types of signals, so it can estimate two spatial filters to extract the task-related signal components and remove the task-independent components and noise. The method used by CSP is based on the simultaneous diagonalization of two covariance matrices.

For EEG data we extracted, each trail can be represented as a matrix W of $X \times S$, where X is the number of channels and S is the number of sampling points for each channel. The regularized spatial covariance is shown in the following equation:

$$C = \frac{WW^T}{\mathrm{trace}\left(WW^T\right)}, \tag{1}$$

where trace(·) represents the sum of the diagonal elements of the matrix. In order to separate the two types of variances, we averaged the sum of the covariances of the two types of samples in the training data to achieve the respective average covariances C_d and C_t and then obtained the mixed spatial covariance as $C_c = C_d + C_t$. C_c, which was decomposed into the form $C_c = E_c \lambda_c E_c$, where E_c is the eigenvector of the matrix and λ_c is the diagonal matrix formed by the eigenvalues. The eigenvalues were arranged in descending order, and the whitening transformation was performed according to the following equation:

$$P = \sqrt{\lambda_c^{-1}} E_c^T. \tag{2}$$

The eigenvalue corresponding to PC_cP^T is 1, so C_d and C_t were transformed as follows: $S_d = PC_dP^T$, $S_t = PC_tP^T$. Then, S_d and S_t share common feature vectors; when $S_d = B\lambda_d B^T$, there are $S_t = B\lambda_t B^T$ and $\lambda d + \lambda t = I$, where I is the unit vector matrix. Because the sum of the corresponding two eigenvalues is always 1, when eigenvector B has the largest eigenvalue for S_d, it has the smallest eigenvalue for S_t. Thus, the projection matrix obtained was

$$P_N = \left(B^T P\right)^T. \tag{3}$$

Because three states were used in the experiment, we designed a feature extraction method for the three categories by CSP. For the awake state that was easier to distinguish; we projected the fatigue state data and the neutral state data separately and obtained the projection matrices P_A and P_B. Our final projection matrix was

$$P_N = P_A + P_B. \tag{4}$$

All experimental samples (including training and testing) were decomposed according to equation (4) to obtain the required EEG characteristics:

$$F = P_N W. \tag{5}$$

The process of EEG feature extraction is shown in Figure 4. In addition, the high dimensionality of EEG data increased the time and space consumption in deep learning models. But through our experimental tests, we found that LightGBM did not rely on high-dimensional data features as deep learning models. After feature reduction, the training speed was faster, memory consumption was reduced, and the final accuracy did not change much.

Traditional CSP usually uses log variance for feature normalization in the binary-classification problem. While in our proposed improved CSP for EEG-based triclassification problem, after obtaining the feature matrix through the projection matrix W, instead of using the conventional method, we used the channel variance of the feature matrix to achieve the purpose of dimensionality reduction. At last, the variance function: var, for each sample, was used to calculate the variance of the data in each channel and reduced the dimensionality of EEG data. Based on this improved CSP, we designed and implemented a LightGBM-based model, LightFD, for the triclassification of driver mental states.

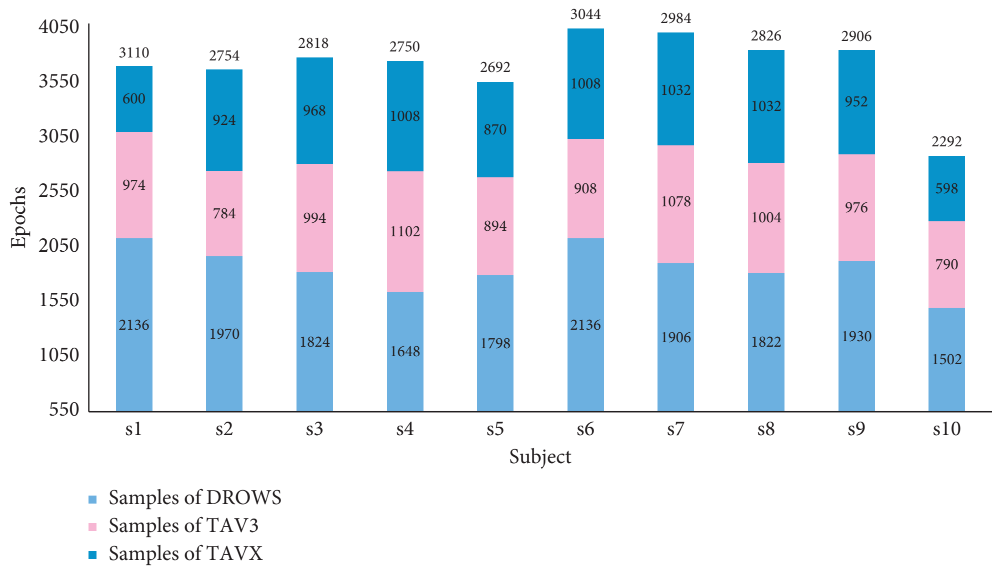

Figure 3: Epoch number of DROWS, TAV3, and TAVX for the subjects.

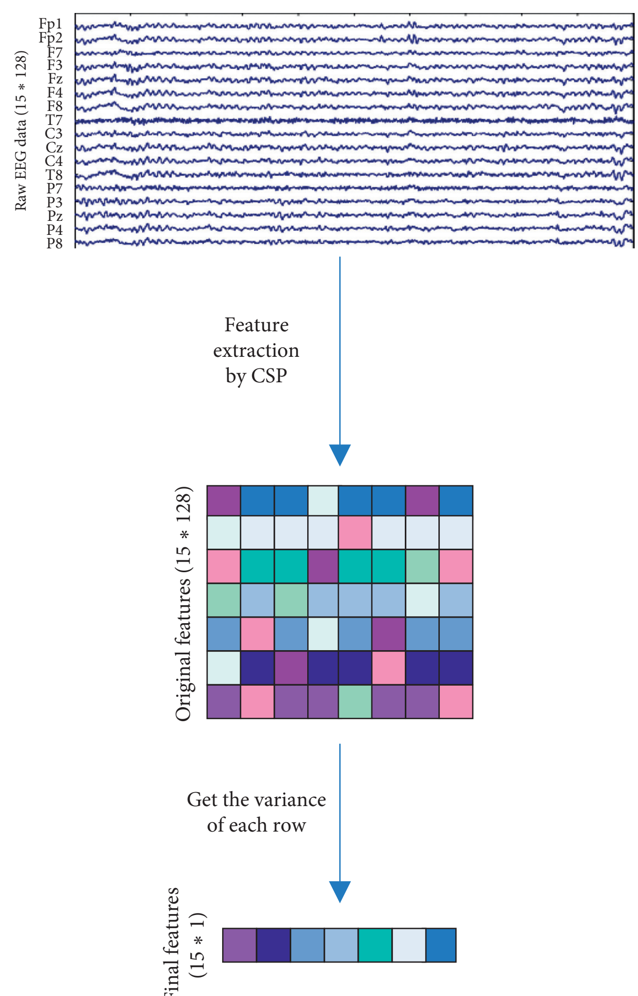

Figure 4: EEG data feature extraction process.

3.2. Training of LightFD Classifier. LightGBM is an algorithm for classification that relies on the gradient hoist, and it is known for its light computational burden [33]. In particular, in the tree-based boosting family of algorithms, many of them (such as xgboost) use the presorting algorithm to select and split features. However, this presorting algorithm can accurately find the splitting point, but it has a large overhead in time and memory consumption. The proposed LightFD model adopts histogram algorithm and leaf growth strategy of leafwise with depth limitation, as shown in Figure 5, which can increase computing efficiency, decrease memory occupancy, improve classification accuracy, and prevent overfitting efficiently (please refer to [33, 47] for more detail). The detailed procedure of LightFD is listed as follows.

3.2.1. Histogram Algorithm. The basic idea of the histogram algorithm is to discretize successive floating-point eigenvalues into k integers and construct a histogram of width k. When traversing the data, the statistic is accumulated in the histogram according to the discretized value as an index. After traversing the data once, the histogram accumulates the required statistic and then traverses to find the optimal segmentation point according to the discrete value of the histogram.

3.2.2. Leafwise Leaf Growth Strategy with Depth Limitation. Levelwise data can split the leaves of the same layer at the same time, easy to multithread optimization, control model complexity. But levelwise is actually an inefficient algorithm because it treats the leaves of the same layer indiscriminately, which brings a lot of unnecessary overhead, and is difficult to prevent overfitting, due to the lower split gain of many leaves, which does not need to be searched and split.

Leafwise strategy is more efficient. It is just to find the leaf that has the highest split gain from the current layer to split. Therefore, compared with levelwise method, leafwise strategy can obtain better performance at the situation with the same number of split. But leafwise strategy may cause deeper decision tree and then be overfitting. So to avoid the situation of overfitting and ensure higher efficiency, we then make a maximum depth limitation in LightFD model.

3.3. Parameters of LightFD. The parameters in lightFD include num_leaves, num_trees, and learning_rate, where num_trees represents the total number of spanning trees and num_leaves represents the number of leaves on per spanning tree. Smaller learning_rate and larger num_trees can improve the final accuracy to a certain extent, but it increases the time and space overhead.

4. Results and Discussion

As traditional machine learning methods, SVM [48] and LMNN [49] are classical methods for the classification of samples. Deep learning (DL) [50] has been successfully applied in many fields such as computer vision, speech recognition, and natural language processing. LSTM is proposed to overcome the fact that the recurrent neural network (RNN) does not handle long-range dependencies well, although GRU is a variant of LSTM. GRU maintains the effects of LSTM with a simpler structure and plays its own advantages in more and more fields. CNN is a neural network designed to process data similar to grid structures, such as time series data and image data, which has become one of the most important representatives of DL because of its excellent classification performance in many challenging applications [51–53].

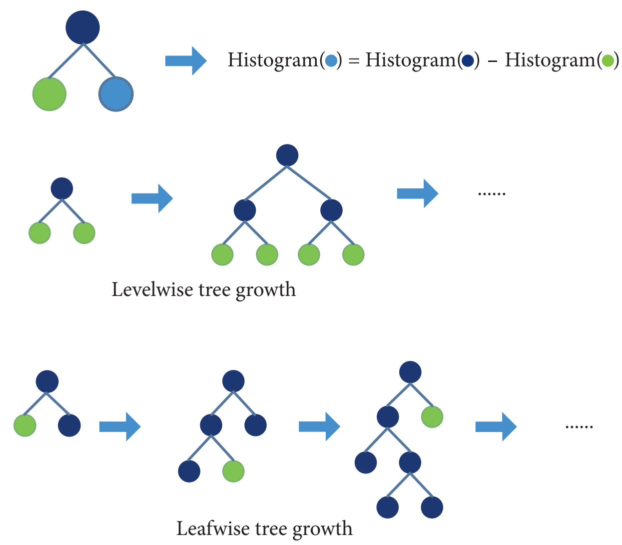

Figure 5: Learning process of LightGBM.

In this section, we compare LightFD with SVM, LMNN, GRU, and CNN from both aspects of intrasubject and intersubject. Particularly, because GRU and CNN rely on high-dimensional features, we do not perform dimensionality reduction after CSP but directly use those high-dimensional features as input to GRU and CNN models for training and testing.

For SVM, the kernel type is used with a Gaussian kernel function, the penalty parameter is set to 1.5, and probability estimation is set as "not enabled." For LMNN, we chose the Euclidean distance as the distance metric, and the nearest neighbor is set to 3. For GRU, we used a single-layer structure with a time step of 128, a learning rate of 0.001, and the RMSprop model as the gradient descent method. For CNN, the model structure contains a 5×5 convolutional layer (output number is 32) and a 3×3 convolutional layer (output number is 32 as well), followed by a maximum pooling layer with a step size of 2, and a learning rate of 0.01.

4.1. Intrasubject Classification Performance. For each subject, we randomly extracted 80% of EEG signals as a training set, denoted as Train_i, and the remaining 20% as a test set, denoted as Test_i, where $i = 1, 2, \ldots, 10$, indicating the i-th subject, the ratio of the training set to the test set is strictly 4 : 1; both Train_i and Test_i were the data sets after dimensional reduction by our improved CSP.

When comparing LightFD with SVM and LMNN, we adopted Train_i and Test_i as the training set and test set, respectively, for the analysis of classification performance. Although comparing LightFD with GRU and CNN, due to the high-dimensional feature correlation of GRU and CNN, we did not adopt those features processed by the improved CSP as input but the original data after preprocessing.

The test results are shown in Figure 6. For the mental state detection of the same subject (intrasubject), SVM and LMNN models have similar classification performance, and their average classification accuracy are 90.10% and 88.10%, respectively; however, LightFD reaches the average accuracy of 95.31%, which is much higher than others. GRU and CNN only surpass LightFD in the classification performance of subject s4, whereas the classification accuracy of the other 9 subjects is inferior to that of LightFD.

In addition, we also counted the average classification accuracy of those 5 models for intrasubject, as shown in Table 2. We found that LightFD has the best classification performance among these models.

To evaluate the stability performance of LightFD, we then calculated the variance of the accuracy of LightFD, SVM, LMNN, GRU, and CNN, respectively, as shown in Table 3.

From Table 3, it is clear that SVM and LMNN have some extent of similar stability and better than GRU and CNN, but the variance of LightFD is significantly lower than those of all others, which shows that LightFD has better robustness in EEG signal processing and further lays the foundation for its real application.

Moreover, to validate the applicability of LightFD, we randomly divided the existing data sets for 5 times and obtained 5 groups of data containing different test sets and training sets, then tested the performance of LightFD by the 5 groups of training and test sets. The acquired results are shown in Figure 7. From Figure 7, it is clear that the different data set has a certain impact on the classification result, for example, the average accuracy of subject s4 decreases to about 88%, but in a whole, LightFD keeps a much higher classification accuracy under different test data sets.

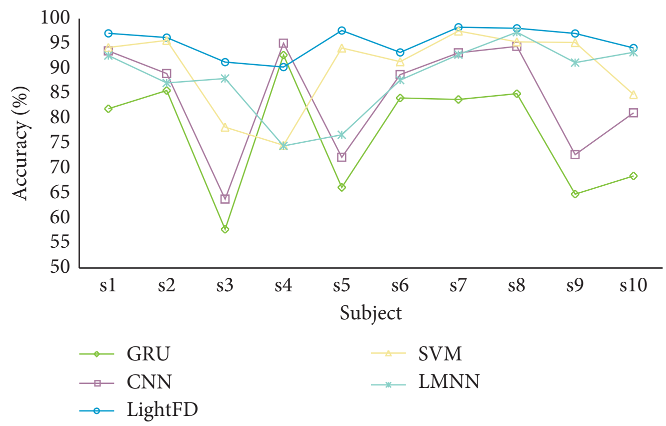

Figure 6: Accuracy comparison of SVM, LMNN, CNN, GRU, and lightFD for intrasubject classification.

Table 2: Average classification accuracy of SVM, LMNN, GRU, CNN, and LightFD for intrasubject.

Model	SVM	LMNN	LightFD	GRU	CNN
Average accuracy (%)	90.10	88.10	95.31	77.01	84.37

Table 3: Variance analysis of SVM, LMNN, GRU, CNN, and LightFD for intrasubject.

Model	SVM	LMNN	LightFD	GRU	CNN
Variance	0.0065	0.0053	0.00084	0.0135	0.0126

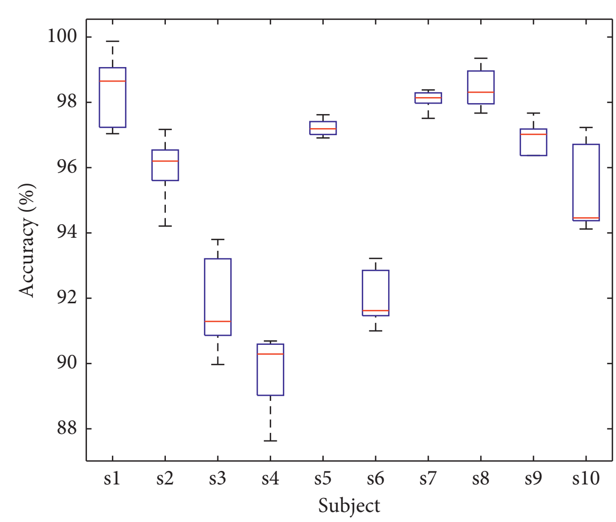

Figure 7: Classification accuracy statistics of 10 subjects under the condition of different testing sets.

4.2. Intersubject Classification Performance. EEG signals vary widely among subjects, and these differences can affect the final classification results. To further test the performance of LightFD, in this section, we made a classification performance analysis of intersubject.

Similarly, we mixed all the EEG data of 10 subjects and randomly selected 80% of them as training sets, the remaining 20% as test sets. We also conducted the classification performance analysis and comparison for intersubject analysis between SVM, LMNN, GRU, CNN, and LightFD. To satisfy the input need of GRU and CNN, we do not yet carry out the operation of dimensionality reduction for the two models.

As shown in Figure 8, LightFD has a classification accuracy of 91.67%, which is significantly higher than SVM with 74.54%, LMNN with 57.59%, GRU with 73.19%, and CNN with 77.89%. The comprehensive performance of CNN for intersubject analysis is slightly better than SVM but much lower than LightFD. Also from the intersubject classification results, it was found that, compared with intrasubject test, LightFD could maintain more stable performance for intrasubject analysis, although the individual differences of EEG have a greater impact on the classification of the other four models. Therefore, we conclude that LightFD can learn more features and can be better extended to the mental state detection of intersubject.

In addition, similar operation with intrasubject analysis, we could get 5 groups of data with different training sets and test sets, then we also calculated and acquired the average accuracy of each of the three states using these 5 groups of data sets, which are TAV3 95.58%, DROWS 93.97%, and

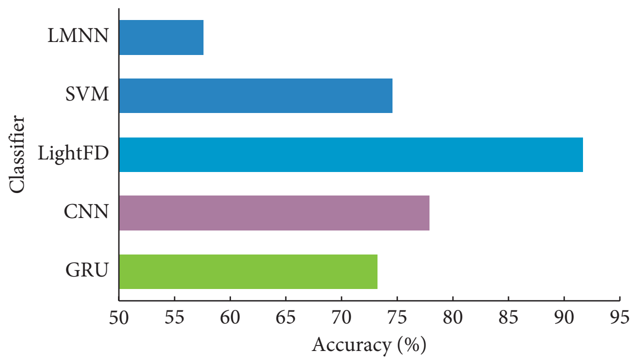

Figure 8: Classification accuracy of SVM, LMNN, and lightFD for intersubject.

TAVX 83.71%. We found that the classification accuracy of TAVX is low. The reason may be that, according to statistics, the TAVX state is more likely to be misclassified into the state of DROWS.

4.3. Transfer Learning Capabilities Analysis of LightFD. Mathematically, transfer learning is defined as below [54].

Given a source domain $D_s = \{X_S, f_S(x)\}$ and learning task T_S, a target domain $D_T = \{X_T, f_T(X)\}$ and learning task T_T, transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S, where $D_S \neq D_T$, or $T_S \neq T_T$.

Transfer learning emphasizes on the ability of a system to recognize and apply knowledge and skills learned in previous source tasks transferring to a target prediction tasks.

In this section, we try to evaluate the capabilities of transfer learning of LightFD. In particular, we wanted to measure the performance of LightFD as a general model for real time and efficient driver fatigue detection, which could be directly used for mental states identification without any additional training process. Such last feature could be very important for promoting clinical application of such EEG analysis.

As we know, there exists significant differences of EEG signals between different subjects. Therefore, it is difficult to evaluate the situation of mental states of the other subjects just from EEG characteristics of some known subjects, which means it needs to enhance the transfer learning capabilities in EEG analysis.

First, we selected EEG data from subject s1 to s9 as the training set and that of subject s10 as the test set, then we used CSP to find the projection matrix, and the rest of the operations were consistent with those mentioned in 3.1. Based on the above experimental results, we compared and analyzed the transfer learning performance of LightFD, SVM, and LMNN models, respectively.

For the identification of three mental states, namely, TAV3, TAVX, and DROWS, SVM and LMNN have the classification accuracy of 54.95% and 53.04%, respectively, whereas LightFD could reach the promising classification accuracy of 70.28%, which proves the potential of LightFD in the field of EEG analysis for transfer learning.

Furthermore, to verify the transfer learning robustness of LightFD, we conducted 10 cross-validations. Of all the ten subjects, we randomly selected two as the test set each time, and the rest as the training set. MEDA and MTLF were used for comparison with LightFD. The randomly selected testing sets for 10 cross-validations are (s5, s7), (s1, s3), (s3, s5), (s3, s7), (s6, s7), (s4, s9), (s7, s9), (s4, s8), (s5, s6), and (s6, s10), respectively, and the results are shown in Figure 9.

In the future, combining with transfer learning will be a major development trend in EEG signal processing. We believe that LightFD, a LightGBM-based model with good performance of EEG transfer learning capabilities, will bring new opportunities and progress for EEG classification and identification analysis.

4.4. Time Complexity Analysis of LightFD. In this section, to explore the feasibility of lightFD in practical applications, we analyzed and compared the time complexity of LightFD with the abovementioned 4 typical models: SVM, LMNN, CNN, and GRU.

The obvious benefit of using histogram in lightFD is that the time consumption of calculating the split gain drops from $O(N)$ to $O(bins)$. LightGBM usually adopts feature parallelism by vertical segmentation of samples, whereas lightFD adopts sample parallelism, namely, horizontal segmentation, to build local histogram that is then merged into full-range histogram to find the best segmentation. The communication transmission cost is further optimized from $O(2{*}\#\text{feature}{*}\#\text{bin})$ to $O(0.5{*}\#\text{feature}{*}\#\text{bin})$.

The time complexity of SVM is between $O(\text{Nsv}^3 + L\text{Nsv}^2 + dL\text{Nsv})$ and $O(dL^2)$, where Nsv is the number of support vectors, L is the number of training set samples, and d is the dimension of each sample (the original dimension without mapping to the high-dimensional space). In short, its time consumption depends on the matrix inversion, and the time complexity is about $O(N^3)$, where N is the number of samples. In the case of small samples, SVM can achieve the similar performance as lightFD. But as the number of samples increases, the time consumption of SVM is much higher than that of lightFD.

As a kind of distance metric learning, LMNN needs to calculate the distance between each sample and all other samples during the training process. As the number of samples increases and that of individual sample dimensions grows, it will greatly augment the time consumption of LMNN.

Deep learning models, CNN and GRU, are a kind of high-level abstraction of data by multiple processing layers composed of multiple nonlinear transformations. The complex structure determines that the time complexity is much higher than that of SVM and LMNN, although CNN and GRU tend to perform better when the sample size gets larger and the sample feature dimension becomes higher.

In CNN, the time complexity of single convolutional layer is $O(M^2 * K^2 * \text{Cin} * \text{Cout})$, where M is the size of the output feature map, which is determined by four parameters such as input size X, convolution kernel size K, padding, and stride. Expressed as follows: $M = ((X - K + 2 * \text{Padding})/\text{Stride}) + 1$. K is the size of the convolution kernel, Cin is the number of input

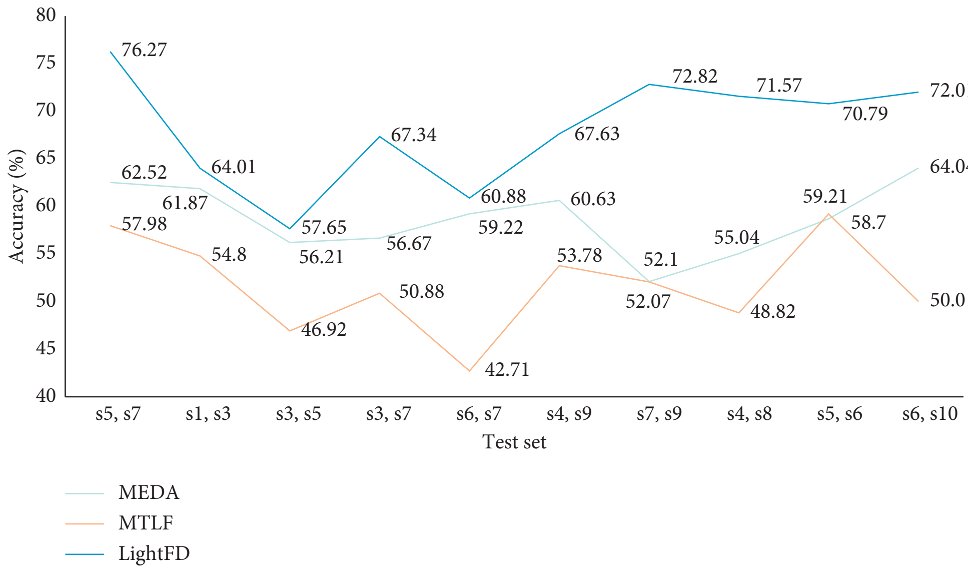

Figure 9: Classification accuracy of MEDA, MTLF, and LightFD for intersubject.

channels, and Cout is the number of output channels. It is shown that CNN runs slower and depends heavily on the configuration of the computer under the situation of larger samples.

For GRU, the computational complexity for each update is $O(KH + KCS + HI + CSI) = O(W)$, where K is the number of output units, C is the number of memory element blocks, S represents the size of the memory element block, H is the number of hidden units, I is the number of units that are forward connected to the memory element, the gate unit, and the hidden unit, and $W = KH + KCS + CSI + 2CI + HI = O(KKH + KCS + CSI + HI)$ is the number of weights. GRU is much simpler than CNN and performs better than CNN in case of time consumption. Furthermore, it is faster than SVM and LMNN under the situation of large samples but is still inferior in time consumption than lightFD.

In summary, LightFD has a faster running speed than other traditional models on average up to 30%, which shows more outstanding performance, especially in the case of large samples, and lays the foundation for its application in real-time EEG analysis systems.

5. Conclusion

As one kind of light-weighted machine learning methods, LightFD has excellent performance in the aspects of multiclassification of EEG analysis, as well as lower time consumption, which show profound significance for practical applications. In addition, LightFD could also achieve better classification effect in the intersubject EEG classification, which suggests its potential transfer learning capability in the classification of mental states during driving by using cerebral measurements.

Data Availability

The EEG data used to support the findings of this study are restricted by the Ethics Committee of Hangzhou Dianzi University (HDU), in order to protect subject privacy. Data are available from the corresponding author for researchers who meet the criteria for access to confidential data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

EEG Alpha Power Is Modulated by Attentional Changes during Cognitive Tasks and Virtual Reality Immersion

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Variations in alpha rhythm have a significant role in perception and attention. Recently, alpha decrease has been associated with externally directed attention, especially in the visual domain, whereas alpha increase has been related to internal processing such as mental arithmetic. However, the role of alpha oscillations and how the different components of a task (processing of external stimuli, internal manipulation/representation, and task demand) interact to affect alpha power are still unclear. Here, we investigate how alpha power is differently modulated by attentional tasks depending both on task difficulty (less/more demanding task) and direction of attention (internal/external). To this aim, we designed two experiments that differently manipulated these aspects. Experiment 1, outside Virtual Reality (VR), involved two tasks both requiring internal and external attentional components (intake of visual items for their internal manipulation) but with different internal task demands (arithmetic vs. reading). Experiment 2 took advantage of the VR (mimicking an aircraft cabin interior) to manipulate attention direction: it included a condition of VR immersion only, characterized by visual external attention, and a condition of a purely mental arithmetic task during VR immersion, requiring neglect of sensory stimuli. Results show that: (1) In line with previous studies, visual external attention caused a significant alpha decrease, especially in parieto-occipital regions; (2) Alpha decrease was significantly larger during the more demanding arithmetic task, when the task was driven by external visual stimuli; (3) Alpha dramatically increased during the purely mental task in VR immersion, whereby the external stimuli had no relation with the task. Our results suggest that alpha power is crucial to isolate a subject from the environment, and move attention from external to internal cues. Moreover, they emphasize that the emerging use of VR associated with EEG may have important implications to study brain rhythms and support the design of artificial systems.

1. Introduction

The preeminent oscillatory phenomenon in brain neurodynamics is represented by the alpha rhythm (approximately 8–12 Hz), which is the dominant frequency in the human scalp EEG [1]. It is well known that EEG activity in the alpha band exhibits a significant change in a variety of conditions; depending on the kind of stimulus or task demand, a brain region responds either with a decrease in alpha power (Event-Related Desynchronization, ERD) or an alpha power increase (Event-Related Synchronization, ERS) [2, 3]. More particularly, a large body of the literature suggests that regions activated during a task exhibit ERD, whereas ERS occurs in regions irrelevant for the task, or regions which process distractors or potentially interfering cues [4–7].

Furthermore, recent studies propose an interpretation of human alpha rhythm in terms of a distinction between internally and externally directed attention.

For what concerns external attention, it is well known that alpha power decreases over occipital sites during visual stimulation [8] and over sensorimotor areas during sensorimotor tasks or movements [3]. Various studies relate the level of visual attention to the strength of oscillatory α activity, observing that greater external attention causes a decrease in alpha power, or a shift in the alpha rhythm toward the attended locations [9–11]. Alpha desynchronization has been associated to tasks requiring processing of relevant information in a variety of cognitive domains, but especially associated with visual perception [12–14]. It was thus hypothesized that the suppression of alpha activity is related to the strength of attention to external objects or stimuli required by the task [15].

Different results, however, have been recently observed in the auditory domain, where an increase of alpha has been linked to increased effort and/or processing [16–19]. Hence, the role of a task on the alpha-band power, even during processing of external inputs is still strongly debated, with possible significant differences in auditory and visual domains and in different tasks.

Conversely, a-band oscillations have been observed to increase during internal tasks, such as visual imagery or arithmetic operations [20–23]. An old influential hypothesis by Ray and Cole [24] assumes that alpha power increases during rejection tasks (internally directed attention), to reflect inhibition or rejection of incoming sensory information. Since an inward shift of attention is accompanied by an increase in alpha power, some authors suggested that ERS may be working to inhibit sensory processing and suppress distractors or potentially interfering cues [4–7, 25, 26] or more generally to implement a general inhibitory mechanism in the brain [26, 27].

Consequent to the previous observations is the idea that α-power modulation is strictly related with working memory (WM). During WM tests, selective attention may be operating to enhance the efficient use of limited memory resources, by enabling the encoding of relevant information and avoiding that memory capacity is degraded by interfering cues [28]. Indeed, several studies have shown a significant α-synchronization associated with memory load in experiments in which participants were presented items to be remembered for a short period [25, 29, 30]. An influential hypothesis is that alpha oscillations work as a filter mechanism able to inhibit an increasing number of distractors via a progressive α-power increase [31]. However, divergent results have been reported on this point. While Sauseng et al. [32] found that alpha activity increases with the number of distractors, other failed to report these changes [33, 34].

From the previous literature, we can conclude that while the relationship between alpha activity and attention mechanisms is well documented today, both when attention is directed toward external stimuli (ERD) and remembered items (ERS), the exact role played by alpha oscillations and its modulation by the task is still unclear. In particular, the alpha-inhibition hypothesis and the role of alpha activity during internal memory tasks continue to be questioned (for a recent review, see [35]). At least three important elements are involved in these procedures: maintenance of internal memory, processing of external stimuli, and task load requirements. As pointed out by van Moorselaar et al. [36], it is still unclear whether these aspects cooperate or are in conflict, and how they interact at the frontal and occipital level to ensure the better behavioural performance. Does alpha activity reflect an internal cognitive process, under the influence of top-down mechanisms which work to focus attention on the essential items, i.e., a shift between "bottom-up" and "top-down" requirements, as suggested by von Stein et al. [37, 38]? Or does it simply reflect the disengagement of attention from external stimuli? Does alpha desynchronization signal a major role of external sensory representation, whereas alpha synchronization emphasizes a major role of internal mental processing?

In order to examine these aspects, we need experiments which manipulate both external stimulation, cognitive processing requirements (i.e., task difficulty), and direction of attention (external vs. internal). In particular, we wish to investigate in which terms alpha power can be reduced by tasks which require an attentional focus to external items, how this desynchronization is affected by the task demand, and how it is affected by strong external stimulation in absence of specific tasks and finally by a mental process which requires isolation from the environment.

To reach our objective, the study comprises two subsequent but strictly related experiments: (i) changes in alpha-band power (i.e., ERD or ERS) were measured in laboratory, using a 13-electrode system, during two tasks which differently recruited visual and cognitive mechanisms (the first is a reading numbers task, the second a visual + arithmetic operation task). The results are used to assess ERD during attentive tasks that require external attention, and its modulation by the level of attention/involvement required. (ii) Changes in alpha-band power were quantified when participants interact with a business aircraft cabin in a Virtual Reality (VR) setting, to mimic conditions experienced by a passenger during an airplane travel. In this case, the EEG was obtained while the participant was immersed in a VR environment, conceived to simulate the main visual and acoustic characteristics of a cabin interior, ad hoc designed during the project. We assume that this condition strongly solicits the external visual/acoustic attention, even in the absence of a specific task. Finally, in the same condition (VR immersion), we asked the participants to perform a mental arithmetic task (internal attention) and to investigate the conflict between the external virtual immersion and the internal focus and its effect on alpha rhythm power.

In all cases, alpha rhythm was investigated both at the parieto-occipital and frontal regions, to point out differences.

Finally, we wish to stress that a novel aspect of this work is the analysis of alpha rhythm in VR environment. The study was designed within the framework of the Horizon 2020 project CASTLE (CAbin Systems design Toward passenger welLbEing), aimed at optimizing the design of innovative interiors of aircraft cabins for Business Jet Industry, also exploiting VR for the collection of users' feedback. Indeed, the present availability of sophisticate VR instruments now allows changes in brain rhythms to be studied when the subject is immersed in a complex realistic scenario and mimicked in a controlled repeatable condition. This idea opens new perspectives not only in the design of artificial systems, but also in the study of the human interaction with the external world.

2. Materials and Methods

Two experiments were carried out in the present study. They served to differently manipulate the task load (more/less demanding task) and direction of attention (internally/externally directed attention). The first experiment (Experiment 1) was performed in a controlled laboratory environment outside the VR setting; a classical monitor screen was used for stimuli presentation to participants and a wired EEG device was used for signal collection. Experiment 1 included two tasks that both required external and internal attentional components (intake of visual items for their internal manipulation) but with different task loads, one task being more demanding than the other. In the second experiment (Experiment 2), we took advantage of the VR technology to strongly manipulate the direction of attention. This experiment was conducted in a VR laboratory where participants were exposed to and interacted with a VR environment (aircraft business cabin interior), and a wireless EEG device was used for data collection. Experiment 2 involved a condition consisting in purely VR immersion whereby the rich sensory stimulation elicited external attention and a condition consisting in performing a mental task during the VR immersion; at variance with purely VR immersion, the latter condition required internal attention and neglect of external environment to perform the mental operations.

2.1. Participants. Thirty healthy volunteers (10 females), aged 20–42 years (mean ± std = 25.4 ± 4.8 years), took part in Experiment 1. Forty-one healthy volunteers (9 females), aged 19–29 years (mean ± std = 22.1 ± 2.6 years), took part in Experiment 2. Participants in the two experiments were different; this avoided that the participants were subjected to a long recording involving several sessions and conditions (of both experiments), that may have induced tiredness and boredom. Each participant had normal or corrected to normal vision and reported no medical or psychiatric illness. The study was approved by the local ethical committee (file number: 187339, year: 2018), and all participants gave written informed consent before the beginning of the experiment. All data were analyzed and reported anonymously.

2.2. Experiment 1: Cognitive Tasks Driven by External Stimuli and with Different Demand

2.2.1. Experimental Protocol. The participants comfortably seated facing a computer monitor at about 50 cm far, in a dedicated laboratory. They underwent two experimental sessions, each lasting 15 minutes, separated by a break of about 10 minutes (Figure 1(a)). Each experimental session consisted of three phases: a 5 min *initial relaxation* phase (named r1), a 5 min *central task* phase (named T), and a 5 min *final relaxation* phase (named r2). The two relaxation phases, preceding (r1) and following (r2) each task, were identical in both sessions: a gray screen with the word "relax" was continuously displayed (Figure 1(b)), and participants were instructed to relax during such phases maintaining the eyes open. The experimental sessions differed only in the type of the task executed during the central phase, namely, an *arithmetic task* and a *reading numbers task* (Figure 1). The order of the tasks was counterbalanced across participants. Both the implemented tasks involved exploration and intake of visual items (symbols and numbers) and their internal manipulation; thus, they involved both visual-spatial processes (external attentional component) and cognitive processes (internal attentional component), but the arithmetic task required higher level of sensory attention and cognitive effort.

(1) The Arithmetic Task. During this task, the participants had to solve the arithmetic operations displayed on the screen, consisting in the addition/subtraction of four one-digit numbers, and had to compare the result with a given displayed target. They provided their response by selecting one of the three displayed button-items (black boxes with symbols < = >, see Figure 1(b)) using the mouse. Each operation was displayed on the computer monitor continuously until the participant responded; immediately after, the screen was updated displaying a new operation together with the target and the three response items (Figure 1(b)). Participants were instructed to answer not only as accurately as possible but also as quickly as possible, motivated by a timer that signaled the time left at each screen update (Figure 1(b)). For each arithmetic operation, the four one-digit numbers and the three operators (+ or −) were generated randomly; the comparison target was generated as a random integer close to the correct result of the arithmetic operation in order to avoid trivial solutions (the absolute difference between the comparison target and the correct result was ≤3).

(2) The Reading Numbers Task. During this task, the screen displayed the arithmetic operation, the comparison target, and the timer in order to provide similar visual items as in the arithmetic task, but the participants were clearly instructed to just mentally read the numbers presented on the screen, without performing any operation (response buttons were not displayed). The screen was updated every 5 seconds (Figure 1(b)). At each screen update, the numbers and operators in the arithmetic operation and the comparison target were generated randomly as in the arithmetic task.

Tasks similar to the ones implemented here were previously adopted in other studies to investigate attentional-related EEG rhythms modifications [39–41].

Before the onset of each experimental session, the participants received the instructions about the task of that session. During each session, participants were asked to reduce body and head movements at minimum (except finger movement for mouse use in the arithmetic task) and not to speak.

It is worth noticing that, in each session, the relaxation phase r1 was considered as the reference state within that session, and the alpha power modifications induced by the task in the following phases T and r2 were evaluated with

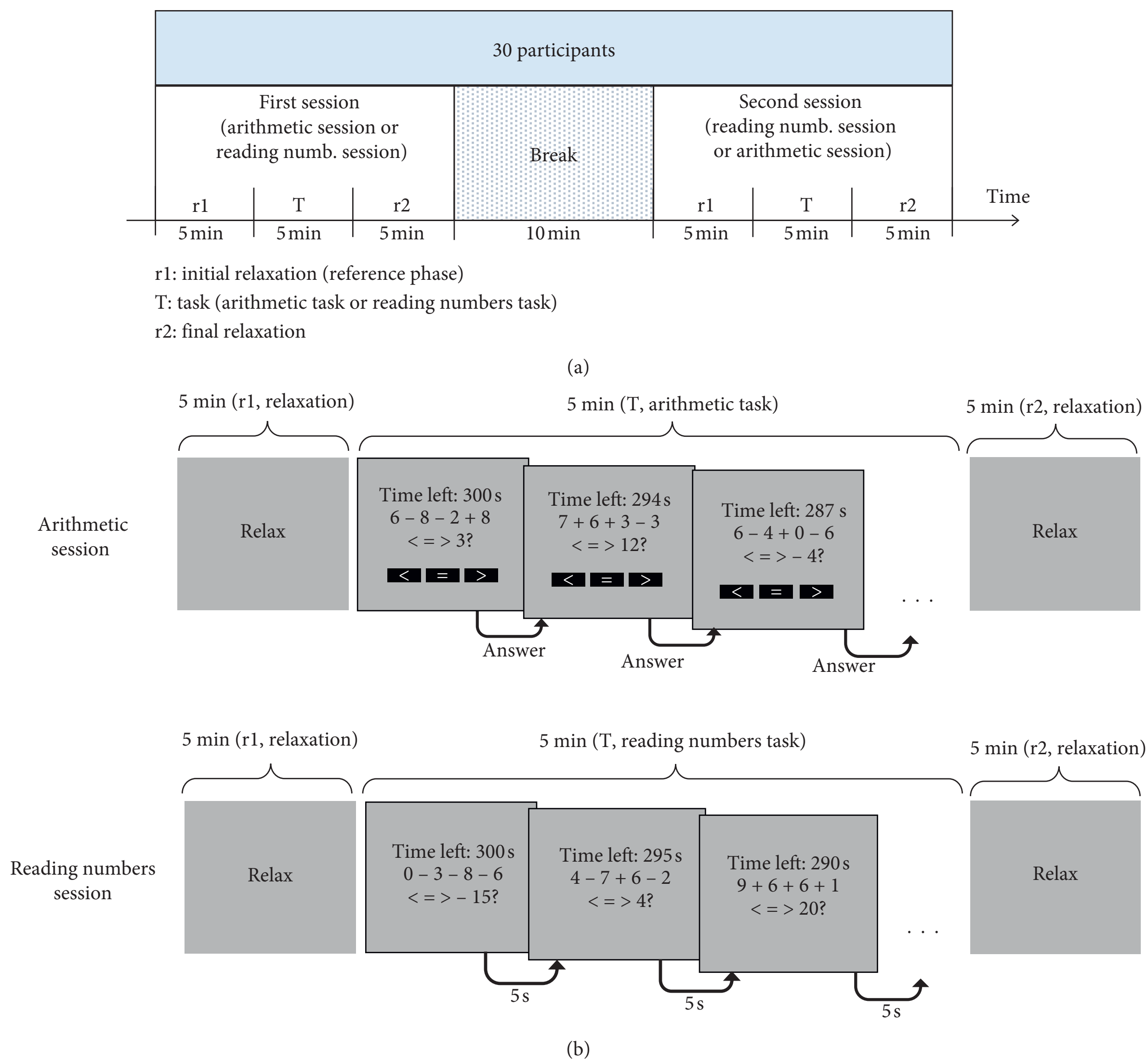


Figure 1: (a) Timeline of Experiment 1. The experiment included two sessions, i.e., an arithmetic session and a reading numbers session, separated by a 10 min break, performed by all participants. Each session lasted fifteen minutes and included an initial (r1) 5-minute relaxation phase, a final (r2) 5-minute relaxation phase, and a central 5-minute task phase (T) consisting in an arithmetic task (arithmetic session) or a reading numbers task (reading numbers session). The order of the tasks was counterbalanced across the participants. (b) Design of each session. In both sessions, the relaxation phases (r1 and r2) consisted in the presentation of a gray screen with the world "relax." In the arithmetic session, during the task phase, the participant had to provide the response to the arithmetic operation (by selecting one of the black button-items with the mouse); after the response selection, a new screen with a new operation appeared. In the reading numbers session, during the task phase, the participant had just to mentally read the numbers appearing on the screen (e.g., 300, 0, 3, 8, . . .), and the screen updated every 5 seconds.

respect to this reference state (see also Section 2.2.3). This was done to focus only on the changes induced by the specific task, ruling out other possible confounding effects (e.g., participant's fatigue due to execution of the previous session).

2.2.2. EEG Recording and Preprocessing. During each experimental session, thirteen EEG signals were recorded via a wired, laboratory-grade device (Brainbox® EEG-1166 amplifier, Braintronics, The Netherlands and Neurowave Acquisition Software, Khymeia, Italy), using wet Ag/AgCl scalp electrodes (embedded in an elastic cap). Electrodes were located at positions F3, F4, T7, C3, Cz, C4, T8, PO7, PO3, PO8, PO4, O1, and O2; the reference electrode was placed on the right earlobe, and the ground electrode was located on the forehead. The number and positions of the electrodes were chosen as a trade-off between the following requirements. (i) Use of a restricted number of electrodes in an effort to outline a system characterized by ease of use, reduced setup time, and low cost, prospectively aimed at real-world practical applications. (ii) Allow coverage of both the frontocentral and parieto-occipital regions, the latter known to be more involved in visual-spatial (and computational) processing than the first [21, 39, 42, 43]. This may be useful to detect potential differences among scalp regions.

During each experimental session, the EEG signals were digitized at a sample frequency of 128 Hz and 16 bit resolution, and with the inclusion of a hardware notch filter eliminating line noise at 50 Hz. Then, for each participant, the two 15-minute EEG recordings, each relative to one of the two different sessions, were converted in a Matlab-compatible format for further offline processing (Matlab R2016a, The MathWorks Inc., Natick MA). First, each 15-minute recording was high-pass filtered at 0.75 Hz to eliminate the DC offset and slow drifts. Subsequently, we applied the Independent Component Analysis (ICA), an effective method largely employed for removal of artefacts from EEG [44–46]. For this purpose, each recording was entered into the "infomax" ICA algorithm (implemented by the EEGLAB toolbox) [47, 48]; artefactual Independent Components were visually identified and removed. An average of 3.87 ± 0.8 Independent Components were rejected across all participants and sessions. In particular, three rejected components were common across all recordings and separated three independent artefact activities inevitably present, i.e., eye blink, lateral eye movements, and heartbeat; one or two additional artefact components were occasionally present extracting EMG-related activity or single-channel noise.

2.2.3. Alpha Power Computation. For each participant and each session, the preprocessed EEG signals were subdivided into three parts of 5 minutes each, corresponding to the three phases of the session (r1, T, and r2). The Power Spectrum Density (PSD) of each channel over each phase was obtained by applying Welch's periodogram method, by using a Hamming window of 5 seconds at 50% overlap, zeropadded to 10 s to obtain 0.1 Hz frequency resolution. Then, for each channel, the power in the alpha band 8–12 Hz was computed for each phase r1, T, and r2. Moreover, a normalization procedure was adopted. Specifically, in each session, the alpha power value of a single channel in the r1 phase was used as reference value for that channel, and the alpha power in each phase of the same session was divided by this reference value, to obtain the normalized alpha powers for that channel.

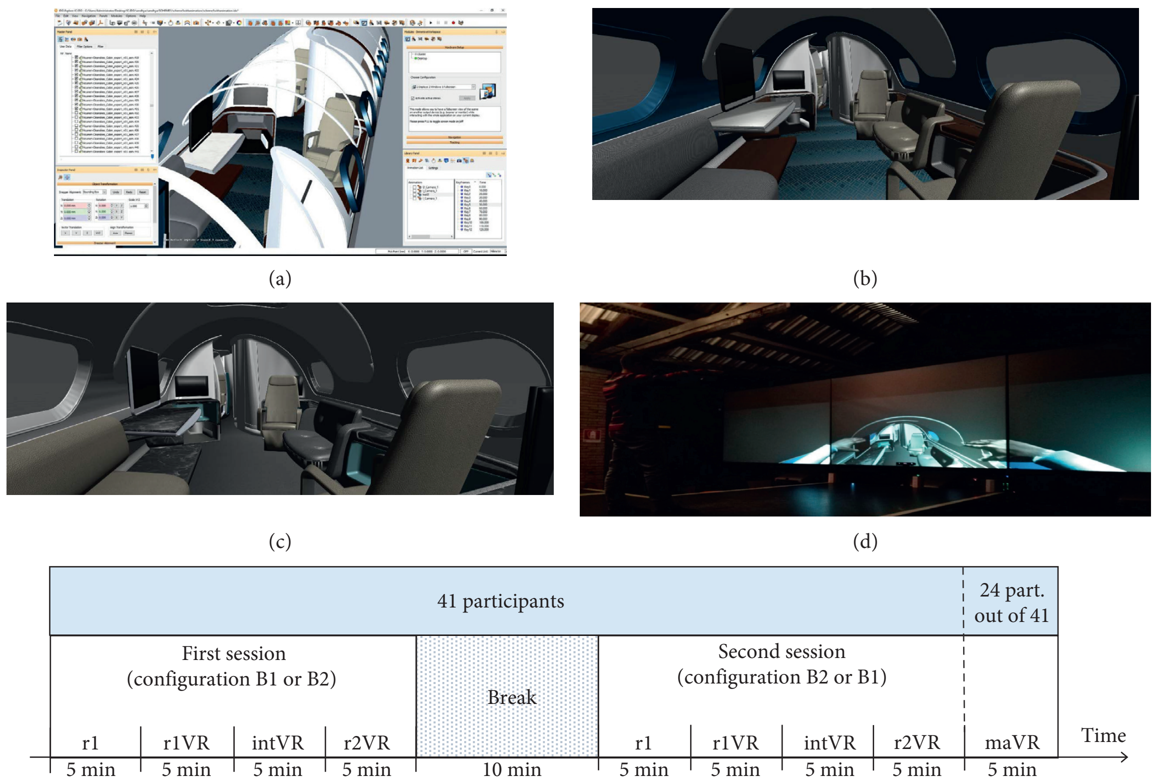
In addition to the analysis at single-channel level, we performed an analysis at scalp-region level, by aggregating the channels into two regions of interest: a region (fronto-central-temporal, *FCT region*) including the anterocentral channels (F3, F4, T7, C3, Cz, C4, and T8) and a region (Parieto-occipital, *PO region*) including the posterior channels (PO7, PO3, PO8, PO4, O1, and O2). To this aim, for each participant and each session, the mean PSD over the FCT and PO regions were computed by averaging the PSD across the corresponding channels, separately for each phase r1, T, and r2. Then, similarly to the single-channel analysis, the power in the alpha band 8–12 Hz was computed over each region and for each phase r1, T, and r2. Finally, the normalized alpha powers at the scalp-region level were computed: the alpha power in the r1 phase over a region was used as the reference value for that region, and the alpha power value in each phase over the same region was divided by this reference value. Of course, the normalized alpha powers assumed value 1 in the r1 phase, both at single-channel level and at scalp-region level.

2.3. Experiment 2: VR Immersion and Mental Task in VR Immersion

2.3.1. Virtual Reality Instrumentation and the Aircraft Virtual Cabin Interiors. The concept and the CAD (Computer Aided) model of the cabin interiors of a business jet were provided by ACUMEN (https://acumen-da.com/). The model design is based on a modular layout of the cabin that is divided into five zones, and for each zone, different functional requirements have been defined by Dassault Aviation. There is a flexible area for informal and formal activities. Moreover, there is a rear cabin area designed with enough privacy and discretion as main targets. The central lavatory is between the two flexible zones and is expected to be easy to access to and safe to use. Finally, the galley and the crew rest areas are provided, all referenced in the fuselage model. The surface CAD model was processed in IC.IDO (Industrial Grade Immersive VR Solutions) Software to create the digital mock up of the entire cabin with the proper color, material and finishing properties for each visible surface. IC.IDO® is a 3D immersive VR software, provided by ESI® Group, supporting industrial decision making processes and digital mock-up verifications (Figure 2(a)). Then, two different CMF (color, material, and finishing) configurations of this cabin model were prepared for test (Figures 2(b)–2(c)), namely, configurations B1 and B2.

The cabin model files, properly converted and refined, were deployed on the CAVE (Cave Automatic Virtual Environment) at the Virtual Reality Laboratory of the University of Bologna. The CAVE is a multiple screens stereoscopic visualization system that immerses the user in a virtual environment [49]. The CAVE is developed on top of Commercial of The Shelf (COTS) components and is based on three 2.5×1.9 m rear-projected screens and a floor. The active stereoscopy was enabled through shutter glasses. To allow the cabin environment to be navigated from a first-person perspective by a user moving on the CAVE floor, face and body tracking was implemented by capturing and filtering data provided by a Microsoft Kinect sensor placed in front of the user at the bottom of the CAVE central screen. Tracking of the face was used to update the VR camera's point of view with the actual user's point of view [50]. Body tracking allows the longitudinal navigation of the cabin, implemented through the amplification of the user's step distance in the main axis direction. In addition, an avatar representing the user was introduced in the cabin virtual environment, and the avatar's joints and face position and orientation were linked to the user's ones captured by Kinect, so that the avatar replicated user's movements and gestures (Figure 2(d)). Finally, to simulate interaction with objects of the virtual environment, a sound was produced by the system whenever the avatar hurt or touched them, to fake collision.

2.3.2. Experimental Protocol. The participants underwent two experimental sessions within the VR laboratory, one for



r1: initial relaxation no VR (reference phase)
r1VR: static immersion in VR
intVR: immersion in VR and interactive exploration
r2VR: static immersion in VR
maVR: immersion in VR and mental arithmetic task

(e)

Figure 2: (a) CAD model processed in IC.IDO (Industrial Grade Immersive VR Solutions) Software creating the digital mock-up of the entire cabin with the proper color, material, and finishing properties of each surface. (b, c) The two different configurations of the cabin interior, namely, configuration B1 (b) and B2 (c), characterized by different color, material, and finishing properties, when projected on the CAVE screens. (d) Example of the avatar within the cabin virtual environment. (e) Timeline of Experiment 2. The experiment included two sessions corresponding to the cabin configurations B1 and B2. The order of the presentation of the two configurations was counterbalanced across participants. All participants executed the phases r1 (relaxation without VR), r1VR (first static immersion in the VR), intVR (interactive exploration of VR), and r2VR (second static immersion in the VR) in both sessions. Only a subset of participants (24 out of 41) executed an additional phase in the second session (phase maVR), consisting in performing a mental arithmetic task (mental serial subtractions) while immersed in the VR.

each virtual cabin configuration, B1 and B2, separated by a break of about 10 minutes (Figure 2(e)). The order of the presentation of the two configurations was counterbalanced across participants. It is worth noticing that the replication of the session using two virtual configurations of the same environment served to test the robustness of the adopted EEG measure (alpha power) and of its extraction procedure. Indeed, as the two configurations differed in subtle details (color and finishing), we expected similar sensory stimulation to be elicited by immersion in them and therefore similar effects on alpha power to be observed across the sessions (see also Sections 2.3.4 and 3.2.1).

Throughout each session, lights were kept off to improve clearness and contrast of the images projected on the CAVE screens and favor participants' immersion within the VR environment; moreover, a background airplane sound was played continuously. All participants were required to not speak throughout the sessions.

Each session was structured into 5-minute phases. The two sessions shared the same structure with the exception that 24 out of the 41 participants performed an additional phase (maVR) in the second session (with either the B1 or B2 virtual configuration, see Figure 2(e)). This additional phase served to test the effects of an internal task (mental arithmetic) requiring isolation from the realistic external context. The remaining phases were common across the two sessions for all participants (Figure 2(e)). The first 5-minute phase, named r1, consisted in an *initial VR-off relaxation phase* without VR stimulation (and only the background sound on); during this phase, the participants were seated centrally in front of the black screens at a distance of about 2 meters and were instructed to relax with eyes open, while the VR environment was kept off. Immediately at the end of this phase, the VR environment was turned on and was kept on until the end of the session. The second 5-minute phase, named r1VR, consisted in a *first still (static) VR immersion*: during this phase, the participants remained seated while being immersed in a static VR scenario, showing the cabin lounge and conference room (flexible area), and were solicited by the rich sensory stimuli and free to visually explore the virtual scenario (via eye and head movements). The third 5-minute phase, named intVR, consisted in *an interactive VR exploration*: during this phase, the participant stood up, walked, moved, and interacted through the virtual cabin interior, trying to explore all the zones. The fourth 5-minute phase, named r2VR, consisted in a *second still (static) VR immersion,* following the interaction phase: during this phase, the same conditions as in the r1VR phase were replicated, with the participants seating again immersed in the same static scenario shown previously. The additional phase maVR performed by the subset of participants consisted in a mental arithmetic task executed during the VR immersion: during this phase, the participant remained seated immersed in the same scenario as in r1VR and r2VR and performed mental serial subtractions in steps of seventeen starting from 1000.

In this study, we did not employ a realistic seat (i.e., similar to the ones present in a real cabin) during the phases in which participants remained seated; of course, this improvement could be implemented in future studies to further enhance the VR experience.

The relaxation phase r1 in each experimental session was considered as the reference condition within that session, and the modifications induced by the VR immersion as well as by the mental arithmetic task (phases r1VR, r2VR, and maVR) were evaluated with respect to this reference state (see also Section 2.3.4), to exclude possible bias due to execution of the previous session. It is worth noticing that, for each session, the interactive exploration phase, intVR, was excluded from the analysis (see also Section 2.3.3). Indeed, this phase mainly included motor aspects which fall outside the focus of the present study (moreover, this analysis would be particularly complex as removing locomotion-induced mechanical artifacts from EEG signals in a reliable way is still a critical problem). Rather, the interaction phase might be useful to assess whether alpha power was modified before and after an active exploration of the VR environment, possibly reflecting a modification of external attention level.

2.3.3. EEG Recording and Preprocessing. In this experiment, a wireless consumer-grade EEG device was used to acquire the EEG signals. Specifically, we employed the OpenBCI Cyton board complemented with the OpenBCI Daisy Module (OpenBCI, https://openbci.com/) that allows up to 16 differential EEG channels to be acquired wirelessly via the OpenBCI USB transmitter/receiver using RFduino radio module. The use of a wireless device was fundamental for EEG recording in the VR laboratory, eliminating restrictions on positioning the participants inside the laboratory and allowing free movements and mobility of the participant when immersed in the VR scenario.

Twelve wet Ag/AgCl electrodes (F3, F4, T7, C3, C4, T8, PO7, PO3, PO8, PO4, O1, and O2) of an electrode cap were plugged into the differential channels of the OpenBCI Cyton + Daisy Board, and the board was secured over the cap in the central position, so as to realize a wireless and wearable system. The same electrodes as in Experiment 1 were used, except electrode Cz skipped for board fixing. The reference electrode was placed on the right earlobe and the ground (bias) electrode was placed on the left earlobe.

For each participant and during each experimental session, the twelve EEG signals were online digitized at a sample frequency of 125 Hz and 24 bit resolution and stored in a Matlab-compatible format. Then, each recording was offline preprocessed. First, each recording was high-pass filtered at 0.75 Hz to eliminate the DC offset and slow frequency drifts and filtered by a 50 Hz notch filter to eliminate line-power interferences. Then, the portion of the signals corresponding to the interaction phase (intVR, from minute 10 to minute 15) was excluded from any further analysis, and the signals in the remaining phases (r1, r1VR, r2VR, and the additional phase maVR for the subset of participants) were examined for artefacts reduction. At variance with Experiment 1, ICA applied to signals acquired in Experiment 2 was in general unable to separate artefactual activities. The reason was due to the different recording modality and device (wireless vs. wired and consumer-grade vs. laboratory grade) and different experimental conditions (participants free to move head, neck, and possibly even trunk to explore the wide facing screens vs. participants facing 15 inches monitor and instructed to reduce their movements to a minimum). As a consequence, several nonstereotypic types of noise, such as complex movement artifacts, electrode pops, transient reduction, and loss of signal transmission, affected signals in Experiment 2, besides more stereotypical artefacts (such as blinking or heartbeat related artefacts). Since only twelve ICs were returned as output, the manifold single-artefactual activities were spread over several (or even all) components, mixing with the useful signal components. Therefore, to reduce artefact effects (especially those induced by less stationary activities), we opted for a direct visual inspection of each EEG recording, removing those fragments containing muscle activities, movement artefacts, electrode artefacts, and transient lost/decreased transmission (removal was obtained by just concatenating the preserved portions). The average number of removed fragments was 2.12 ± 3.1 with a mean duration of 32 s, across participants and sessions. While the ineffectiveness of ICA may be considered a limit, this also hints practical implications. Indeed, this suggests that other procedures for artefact removal are more apt to be used in a low-density, wireless, and wearable system (and in real-world applications) and more susceptible to an online implementation, rather than ICA that requires training using sufficiently long and stationary signals.

2.3.4. Alpha Power Computation. We implemented alpha power computation for the entire set of participants (41) over the two sessions and an additional computation over the second session for the subset of participants (24) who performed the additional maVR phase.

(1) Alpha Power Computation over the Entire Set of Participants (41) and the Two Sessions (Phases r1, r1VR, and r2VR). This analysis served to assess the effect of purely VR immersion on alpha power. For each participant and each session, the preprocessed EEG signals were subdivided into three parts, corresponding to the three phases r1, r1VR, and r2VR (each part lasted approximately 5 minutes depending on the removed fragments), which were the phases performed by all participants in both sessions. Hence, the PSD of each channel over each phase was obtained by applying Welch's periodogram method, adopting the same parameters as in Experiment 1. The power in the alpha band 8–12 Hz was computed both at single-channel level and scalp-region level, according to the same procedure as in Experiment 1. Here, the fronto-central-temporal region was obtained by aggregating six (F3, F4, T7, C3, C4, and T8) rather than seven electrodes, as the Cz electrode was not used (see Section 2.3.3). As in Experiment 1, for each participant and for each experimental session, the alpha power values of each single channel/region in the three phases (r1, r1VR, and r2VR) were divided by the corresponding reference value (i.e., the alpha power in the r1 phase), to obtain the normalized alpha powers and to assess the alpha power modifications with respect to the reference state (r1).

Moreover, across all 41 participants, we included a further analysis to evaluate alpha power modifications at a finer time resolution. To this aim, for each participant and session, the first 10 minutes of the session (comprising the consecutive phases r1 and r1VR) were subdivided into 1-minute segments, and the alpha power over the FCT and PO scalp regions was computed with 1-minute time resolution. In this analysis, we still adopted a normalization by division using the alpha power value obtained in the first minute of the session (i.e., the first minute of the r1 phase) as the reference value.

It is important to note that the computations above were performed separately over each session obtaining separated values of normalized alpha powers for the B1 configuration and B2 configuration. In a preliminary analysis, we did not found significant differences in the B1 vs. B2 normalized alpha powers at any phase and region, in line with our expectations based on the limited dissimilarities between the two configurations. Therefore, the normalized alpha powers for the B1 and B2 configurations were collapsed together; to this aim, we computed the average alpha power across the two configurations for each participant. The collapsed values are shown in Results and used for subsequent statistical analyses (see Section 2.4).

(2) Alpha Power Computation over the Subset of Participants (24) in the Second Session (Phases r1, r1VR, r2VR, and maVR). For these participants, we added a further analysis limited to the second session that included the phase maVR. This analysis served to assess how alpha power was modulated when a mental process required inward shift of attention and isolation from the environment. For each participant, the power in the alpha band 8–12 Hz was computed at scalp-region level in the four phases r1, r1VR, r2VR, and maVR of the second session. Then, for each participant and region, the alpha powers in these phases were divided by the corresponding reference value (i.e., the alpha power in phase r1), to obtain the normalized alpha powers.

2.4. Statistical Analyses. In both Experiments, the variable under statistical tests was the normalized alpha power obtained at the scalp-region level. For each experiment, the differences between the reference value (1) and the other phases (or times, in case of the analysis at 1 min time resolution) were tested via multiple one-sample t-tests, separately within each region, using Bonferroni correction (significance threshold = $0.05/n$, where n was the number of comparisons). Moreover, the normalized alpha power was analyzed via repeated measures two-way Analysis of Variance (ANOVA). In Experiment 1, we analyzed the variable at the phase T and the within subject factors were: Task Type (arithmetic/reading numbers) and Region (FCT/PO). In Experiment 2, the within subject factors were: Phase (r1VR/r2VR for the variable computed on the entire set of participants; r1VR/r2VR/maVR for the variable computed on the subset of participants) and Region (FCT/PO). Post hoc comparisons were performed via pairwise t-tests with Bonferroni correction (significance threshold = $0.05/n$, where n was the number of comparisons). For clarity, in one-sample and paired t-tests uncorrected p values were reported, together with the adjusted significance threshold.

3. Results

3.1. Experiment 1: Effect of Cognitive Tasks Driven by External Stimuli and Different Task Demands. Figure 3 shows the topographical scalp maps of the alpha power (not normalized) averaged across participants as a function of the experimental session (arithmetic and reading numbers session) and of the phase (r1, T, r2) within the session. In both sessions, the pretask relaxation phase (r1) was characterized by a large predominance of alpha power over the posterior area and a gradual decline towards the frontal-central regions (Figures 3(a) and 3(d)). During the task phase (T), the alpha power exhibited a widespread reduction, larger over the posterior area than over the frontocentral area; moreover, the arithmetic task (Figure 3(b)) induced a stronger alpha power decrease than the reading numbers task (Figure 3(e)). Finally, during the posttask relaxation phase (r2), the alpha power distribution resumed a similar pattern as in the r1 phase, with the alpha power increasing up to values slightly above the pretask phase (see Figures 3(c) and 3(f)).

A straightforward quantification of the task-induced alpha power changes across the electrodes was obtained via the normalized alpha power at the single-channel level. Figure 4 displays the normalized alpha power at each electrode, averaged across participants (mean ± sem), plotted during the task (T), and after the task (r2) in the

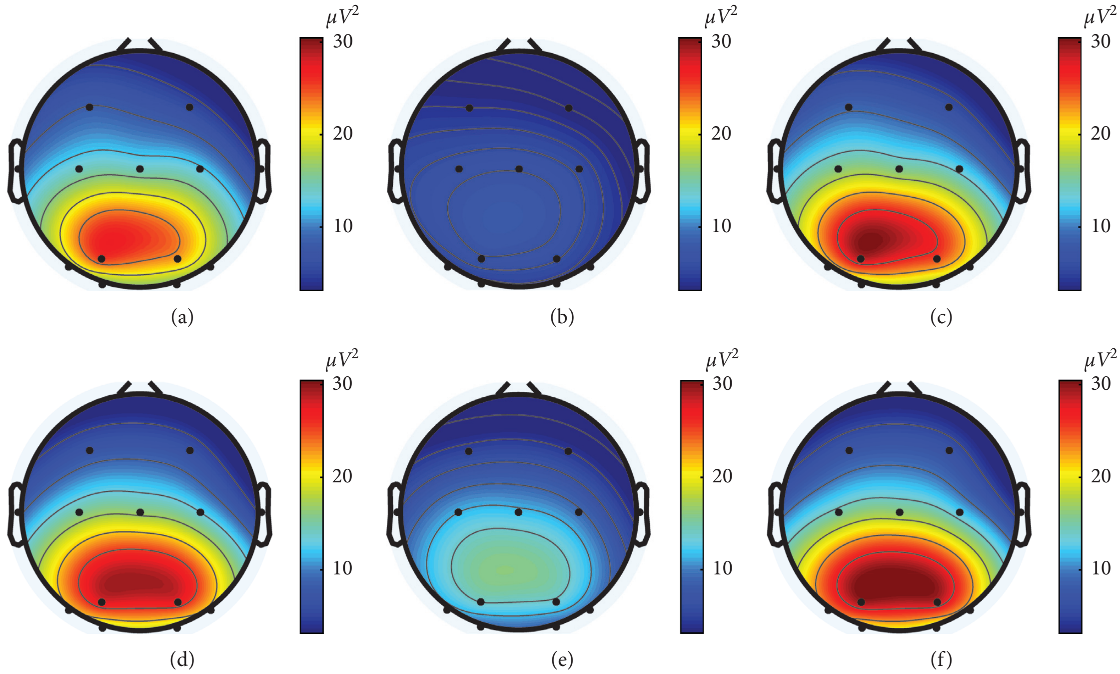


FIGURE 3: Scalp maps of alpha power (μV^2) averaged across all participants in Experiment 1, as a function of the experimental session (arithmetic session: first row; reading numbers session: second row) and of the phase within the session (relaxation pretask r1: first column; task T: second column; relaxation posttask r2: third column). Each scalp map was obtained via the EEGLAB Matlab Toolbox, by color coding the average alpha power value at each electrode position in a 2D circular view (top view of the head, nose at the top) and using interpolation on a fine 67×67 grid. (a) Arithmetic session (r1 phase). (b) Arithmetic session (T phase). (c) Arithmetic session (r2 phase). (d) Reading numbers session (r1 phase). (e) Reading numbers session (T phase). (f) Reading numbers session (r2 phase).

arithmetic and reading numbers sessions. Thus, in this plot value 1 represents the pretask reference value for each electrode. The alpha power exhibited a larger decrease (by about 0.15 points) during the arithmetic task than that during the reading numbers task across all electrodes (solid red and blue lines). Furthermore, in the task phase (both for arithmetic and reading numbers), an abrupt reduction in the normalized alpha power was evident at the transition from the fronto-central-temporal electrodes to the parieto-occipital electrodes. During the posttask relaxation phase (r2 and dotted red and blue lines), the normalized alpha power assumed similar values across the electrodes and sessions, slightly overcoming the pretask value.

The analysis at scalp-region level is presented in Figure 5 that depicts the normalized alpha power computed over the two scalp regions (FCT: Figure 5(a); PO: Figure 5(b)), in the three phases of the two experimental sessions (arithmetic/reading numbers). The values at phase T emphasize the stronger effect of the arithmetic task compared to the reading numbers task in reducing the alpha power within each region and the larger alpha power decrease in the PO region (Figure 5(b)) than that in the FCT region (Figure 5(a)) during each task. Multiple one-sample t-tests (Figure 5) confirmed that the normalized alpha power significantly deviated from the r1 reference value (1) during the task phase (both the arithmetic and reading numbers task), but not during the r2 phase, within each region. The 2×2 repeated measures ANOVA conducted on the normalized alpha power in T (factors: Task Type = arithmetic/reading and Region = FCT/PO) revealed that there was a main effect of Region ($F(1,29) = 23.9$, $p < 0.0001$), showing that the alpha power decreased more posteriorly than anteriorly during the tasks. Moreover, there was a main effect of Task Type ($F(1,29) = 24.1$, $p < 0.0001$) showing that the arithmetic task induced a larger alpha desynchronization than the reading numbers task.

3.2. Experiment 2: VR Immersion and Mental Task in VR Immersion

3.2.1. Effect of the VR Immersion. This section presents the results obtained across the entire set of 41 participants, on phases r1, r1VR, and r2VR, showing the effects of the VR immersion in absence of any specific task. It is worth noticing that the displayed results concern the alpha power values over the two VR cabin sessions aggregated together (see Section 2.3.4 in Materials and Methods): indeed, the two virtual experiences turned out to be characterized by highly similar patterns of alpha powers (not shown results). This was an important preliminary outcome as it proved robustness of the adopted EEG measure and of its extraction procedure, attesting that similar VR configurations (hence similar visuospatial stimulations) induced similar alpha power changes.

The analysis at single-channel level is shown in Figure 6; it plots the normalized alpha power at each electrode (mean ± sem across participants), during the phases of pure VR immersion (r1VR and r2VR). The following main

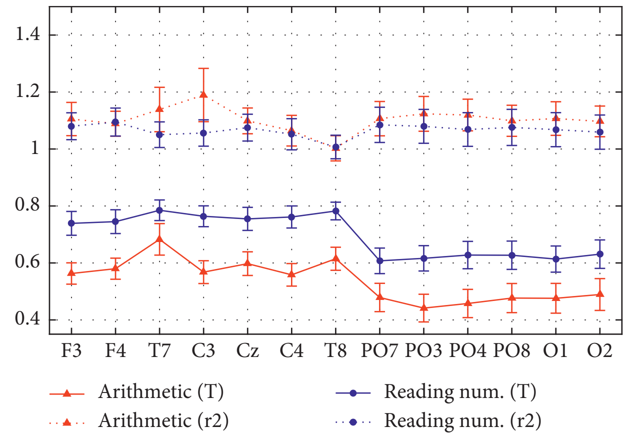


Figure 4: Normalized alpha power, averaged across participants (mean ± sem), at each single electrode in Experiment 1, distinguishing between session (arithmetic session: red lines; reading numbers session: blue lines) and phase (phase T: continuous lines; phase r2: dotted lines). Value 1 represents the pretask reference value (at phase r1) for each electrode; thus, values below 1 indicate alpha power decrease (desynchronization) while values above 1 indicate alpha power increase (synchronization) compared to the pretask phase, at single-channel level.

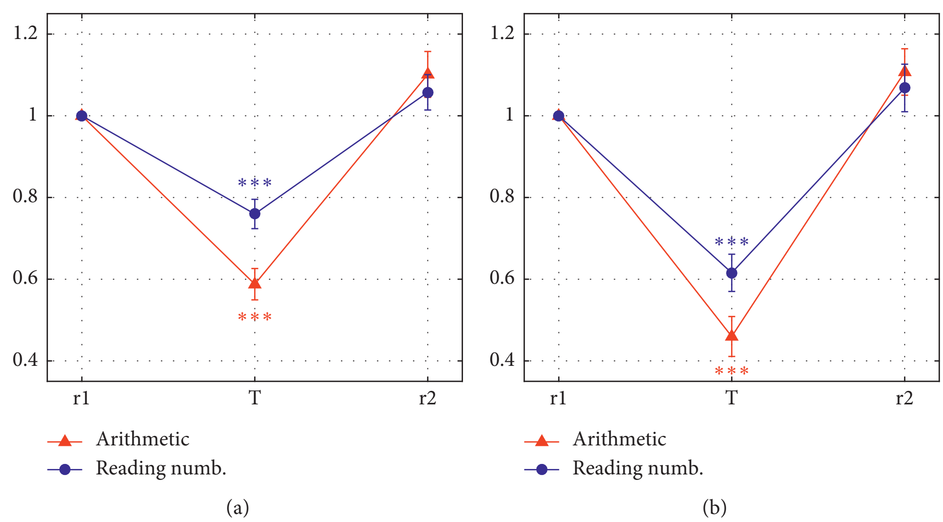


Figure 5: Normalized alpha power, averaged across participants (mean ± sem), over the two scalp regions (front-central-temporal FCT (a); parietal-occipital PO (b)) at each of the three phases (r1, T, and r2) of the arithmetic session and of the reading numbers session. Asterisks denote the results of multiple one-sample t-tests comparing the normalized alpha power in the phases T and r2 of each session with the reference value (1), separately within each region (significance cut-off = 0.05/4 = 0.0125). In both regions, significant deviation from the reference value was found during the task phases T ($p < 0.0001$ for both arithmetic and reading numbers) but not during the r2 phases (FCT: $p = 0.082$ arithmetic; $p = 0.195$ reading numbers; PO: $p = 0.07$ arithmetic; $p = 0.25$ reading numbers) (a) Normalized alpha power-FCT. (b) Normalized alpha power-PO.

observations can be drawn. First, the alpha power during the first visual exploration (r1VR, preinteraction) exhibited larger decrease than during the second visual exploration (r2VR, postinteraction) across all electrodes. Moreover, an abrupt decrease in the normalized alpha power occurred at the transition from the fronto-central-temporal to the parieto-occipital channels, both in r1VR and r2VR, while the electrodes within each set exhibited close values, similarly to what observed in Experiment 1 (Figure 4).

Motivated by the previous differences, an analysis at scalp-region level was performed in this case too.

Figure 7 shows the PSD over each scalp region (FCT region: Figure 7(a); PO region: Figure 7(b)) averaged across participants, and computed separately for each phase. The PO region (Figure 7(b)) was characterized by a huge peak in alpha band in the reference state r1 that dramatically decreased during r1VR and r2VR, while the FCT region (Figure 7(a)) presented a lower alpha peak and smaller modulation of its amplitude.

The obtained values of the normalized alpha power (mean ± sem across participants) in the three phases (r1, r1VR, and r2VR) are depicted in Figure 8, for each region separately (FCT: Figure 8(a); PO: Figure 8(b)). The VR immersion was characterized by a larger alpha power modulation over the PO region (Figure 8(b)) than the FCT region (Figure 8(a)). It is interesting to note that by

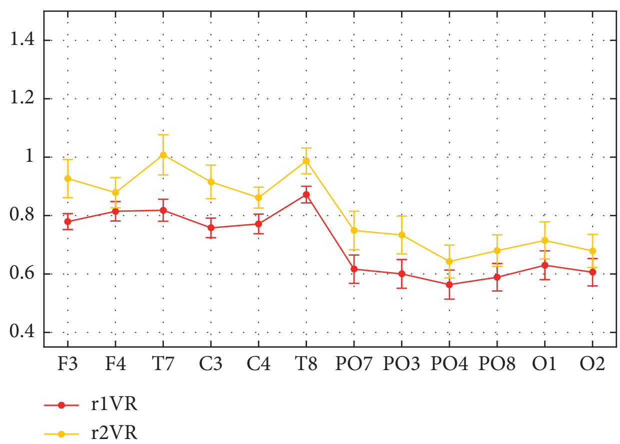


Figure 6: Normalized alpha power, averaged across participants (mean ± sem) and aggregated across the two sessions, at each single electrode in Experiment 2, during the two examined phases of purely VR immersion (r1VR and r2VR).

comparing Figures 8 and 5, the alpha power desynchronization in VR immersion appeared to assume values similar to those observed in the reading numbers task rather than the arithmetic task, over both scalp regions. Multiple one-sample t-tests (Figure 8) confirmed a significant deviation of the normalized alpha power from the reference value (1) in both phases r1VR and r2VR, within each region. The 2×2 repeated measures ANOVA (factors: Phase = r1VR/r2VR and Region = FCT/PO) revealed that there was a main effect of Region ($F(1,40) = 29.32$, $p < 0.0001$) showing that alpha power decreased more posteriorly than anteriorly during the VR immersion. Moreover, there was a main effect of Phase ($F(1,40) = 15.01$, $p = 0.0004$), indicating that alpha exhibited a larger desynchronization in the preinteraction static immersion (r1VR) than that in the postinteraction static immersion (r2VR).

Furthermore, we tested whether the alpha power index was able not only to capture differences among distinct 5-minute phases, but also to monitor trends and variations with a higher temporal resolution (1 minute), to promptly detect a change in the state of the participant at the transition from one phase to another. Figure 9 plots the temporal pattern, at 1 min resolution, of the normalized alpha power (mean ± sem across participants) throughout the first ten minutes of the sessions (comprising phases r1 and r1VR), over each region (FCT: Figure 9(a); PO: Figure 9(b)). An interesting pattern emerged especially in the PO region (Figure 9(b)). In this region, alpha power exhibited an evident secondary increase after the first minute of the r1 phase. This pattern may reflect a progressive relaxation in the very first period of phase r1, when the participants were seated down and got used to the experimental setup. A large and abrupt alpha power decrease (evident also in the FCT region) occurred at minute 6, as soon as the participant got immersed in the VR environment, as an evident marker of visual stimulation and capture of external attention by the immersive sensory inputs. In the following minutes (minutes 7–10), the alpha power tended to moderately increase suggesting a gradual lessening of attention as the immersion in the static VR environment went on. Figure 9 also displays the results of the multiple one-sample t-tests contrasting the normalized alpha power at each minute with the reference value (1), within each region. Almost all time points satisfied the uncorrected significance threshold (0.05, ∗), except minutes 4, 5, and 9 in the FCT region. Interestingly, minutes from 6 to 8 (and even minute 9 in the PO region) survived the Bonferroni corrected threshold (0.05/9, §).

3.2.2. Effect of an Internal Cognitive Task in VR Immersion. This section presents the results obtained across the subset of 24 participants, in the phases r1, r1VR, r2VR, and maVR of the second session, showing how the alpha power was modified when shifting from a condition of external attention to a condition requiring internal attention against the external appealing environment.

Figure 10 displays the normalized alpha power (mean ± sem across the 24 participants) in the four phases, separately for the two regions (FCT: Figure 10(a); PO: Figure 10(b)). As well expected, the alpha power exhibited a decrease in both phases r1VR and r2VR, more evident in the PO region, similarly to the effects previously observed across all participants and sessions (Figure 8). Here, it is remarkable the dramatic increase in the alpha power induced by the execution of the mental arithmetic during the VR immersion. In particular, in this condition, the alpha power assumed values very close to the reference value, i.e., to the initial relaxation condition (r1). Indeed, the one-sample t-tests confirmed that the normalized alpha power during maVR did not deviate from the reference value (1), at variance with the phases r1VR and r2VR (Figure 10). The 3×2 repeated measure ANOVA (factors: Phase = r1VR/r2VR/maVR and Region = FCT/PO) disclosed that there was a significant Phase × Region interaction ($F(2,46) = 10.77$, $p = 0.0001$) and a main effect of Phase ($F(2,46) = 9.299$, $p = 0.0004$). Indeed, post hoc t-tests revealed that the alpha power was lower in the PO region than FCT region in both phases r1VR and r2VR ($p < 0.0001$ in both phases, corrected significance threshold = 0.05/3 = 0.0167), whereas no difference across the two regions emerged in the maVR phase ($p > 0.999$). Moreover, the alpha power in each phase, r1VR and r2VR, was lower than in maVR ($p = 0.0002$ and $p = 0.0017$, respectively; corrected significance threshold = 0.05/3 = 0.0167).

4. Discussion

The present results provide several interesting indications, which not only may contribute to our understanding of the role of alpha oscillations and of the mechanisms driving alpha increase/decrease, but can also have practical perspectives in future studies oriented to the noninvasive assessment of human/environment interaction via scalp EEG.

4.1. Electrodes Position. First, all electrodes in the scalp exhibited a significant ERD in the alpha band, both during the laboratory tasks (Experiment 1) and during the pure VR immersion. However, the level of ERD was significantly

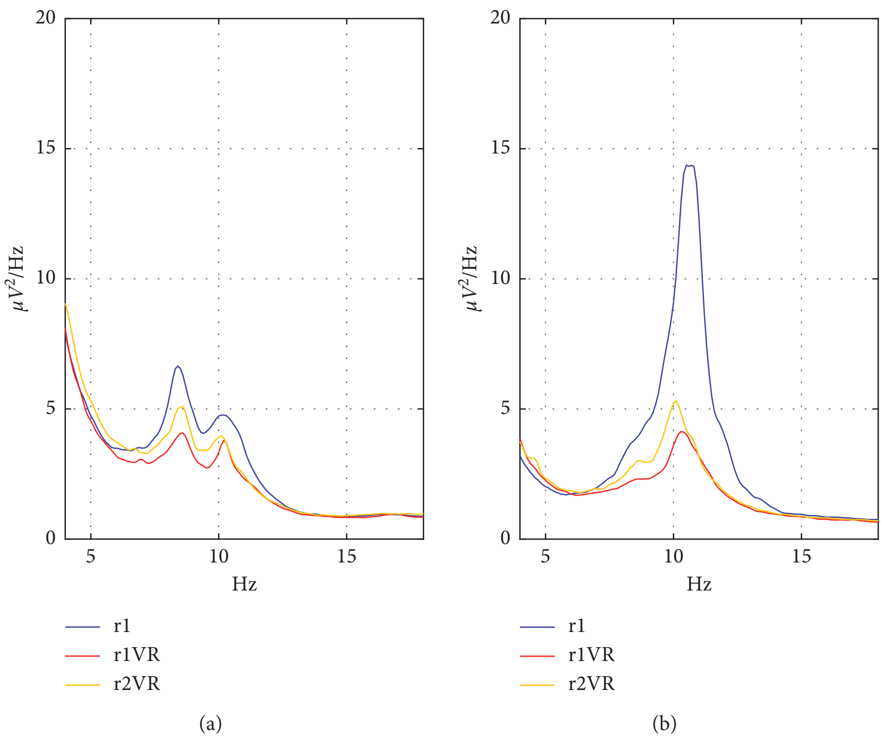


Figure 7: Power Spectrum Density (PSD) over each scalp region (front-central-temporal FCT (a); parietal-occipital PO (b)) computed separately for each phase r1, r1Vr, and r2VR, averaged across participants and across the two sessions (a) PSD-FCT. (b) PSD-PO.

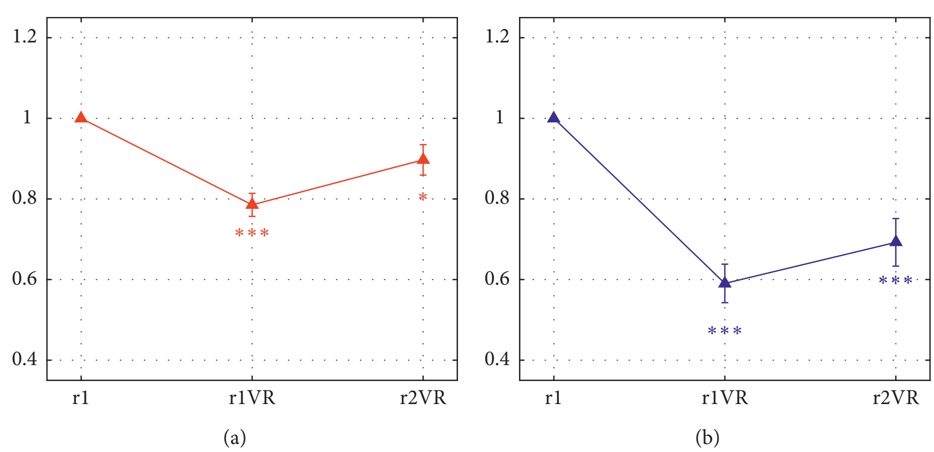


Figure 8: Normalized alpha power, averaged across participants (mean ± sem), over the two scalp regions (front-central-temporal FCT (a); parietal-occipital PO (b)) at each of the three phases (r1, r1VR, and r2VR) of the VR sessions. Asterisks denote the results of multiple one-sample t-tests comparing the normalized α powers in the phases r1VR and r2VR with the reference value (1), separately within each regions (significance cut-off = 0.05/2 = 0.025). In both regions, significant deviation from the reference value was found both in r1VR and r2VR ($^{***}p < 0.0001$; $^{*}p = 0.0096$). (a) Normalized alpha power-FCT. (b) Normalized alpha power-PO.

stronger in the parietal-occipital electrodes compared to the frontal-central ones. In particular, in these experiments, a drastic fall in alpha power was evident passing from the frontal-central to the parietal-occipital electrodes (Figures 4 and 6). This difference was even more evident using absolute values of power instead of normalized ones (Figure 3). This result agrees with results of several neurocognitive works. Indeed, recent EEG studies suggest that parietal and occipital regions are involved in visuospatial processing of stimuli [15, 42], spatial representations of numbers [51], and arithmetic problems [39, 43], at least when the latter involved external attention and visual processing too (such as the arithmetic task of the Experiment 1). It is probable, however, that other kinds of tasks (for instance those requiring motor actions or working memory) rely more on frontal-central regions [25, 52] and on other rhythms such as theta, beta, or gamma [53]. An interesting point is that the same electrodes (PO3 and PO4) were mainly sensitive both in the laboratory cognitive tasks and in the VR immersion (Figures 4 and 6). This provides the indication that, at least in

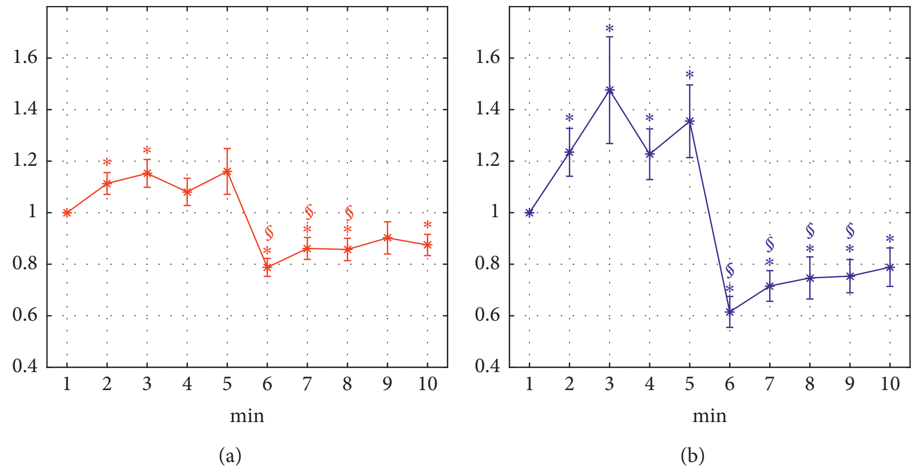


FIGURE 9: Temporal pattern, at 1-minute resolution, of the normalized alpha power (mean ± sem across participants) throughout the first ten minutes of the VR sessions, plotted separately for each scalp region (front-central-temporal FCT (a); parietal-occipital PO (b)). The examined ten minutes included the r1 phase from minute 1 to minute 5 and the r1VR phase from minute 6 to minute 10. For each region, the α power at each minute was normalized with respect to the value obtained at minute 1 (i.e., the first minute of phase r1). Symbols above each point denote the results of multiple one-sample t-tests comparing the normalized α power at each minute (from 2 to 10) with the reference value (1), separately within each region (significance cut-off = 0.05/9 = 0.0056). Symbols $*$ denote points that satisfied the uncorrected significance threshold (0.05), while symbols § denote points that survived the severe Bonferroni correction (0.05/9). Uncorrected p values at each point (subscript indicate the minute at which the p value refer to) are $p_2 = 0.015$, $p_3 = 0.01$, $p_4 = 0.159$, $p_5 = 0.089$, $p_6 = 1.5 \cdot 10^{-6}$, $p_7 = 0.004$, $p_8 = 0.003$; $p_9 = 0.136$, $p_{10} = 0.006$ for the FCT region; $p_2 = 0.021$, $p_3 = 0.032$, $p_4 = 0.036$, $p_5 = 0.019$, $p_6 = 4 \cdot 10^{-7}$, $p_7 = 5 \cdot 10^{-5}$, $p_8 = 0.004$; $p_9 = 6 \cdot 10^{-4}$, $p_{10} = 0.011$ for the PO region. (a) Normalized alpha power-FCT. (b) Normalized alpha power-PO.

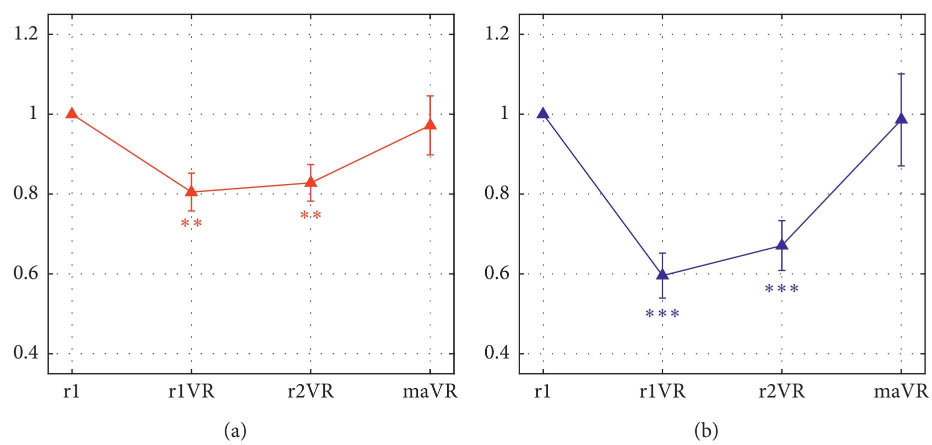


FIGURE 10: Normalized alpha power, averaged across the subset of 24 participants (mean ± sem), over the two scalp regions (front-central-temporal FCT (a); parietal-occipital PO (b)) in the four phases of the second session (r1, r1VR, r2VR, and maVR). Asterisks denote the results of multiple one-sample t-tests comparing the normalized α power in the phases r1VR, r2VR, and maVR with the reference value (1), separately within each region (significance threshold = 0.05/3 = 0.0167). In both regions, significant deviation from the reference value was found in r1VR and r2VR (FCT: $^{**}p = 0.0004$ in r1VR, $^{**}p = 0.001$ in r2VR; PO: $^{***}p < 0.0001$ in r1VR and r2VR), but not in maVR (FCT: $p = 0.71$; PO: $p = 0.9$). (a) Normalized alpha power-FCT. (b) Normalized alpha power-PO.

this kind of problems, the number of electrodes can be significantly reduced without a significant loss in method sensitivity, thus further dropping the complexity of the experimental setup and improving its portability in real scenarios.

4.2. ERD and Attention. As we anticipated above, results of the present study confirm several data in the literature; however, they also introduce some interesting new elements. (1) First, we confirmed that attention to visual stimuli (either in the reading numbers task or in the Virtual Reality immersion) causes a significant ERD compared with a previous relaxation phase, especially accentuated in the parieto-occipital regions. Although various authors observed ERD in response to visual engagements [9–14], this is the first time that visual intake is not produced by specific stimuli, but via a full immersion in a motivating VR environment. This signifies that VR environments can represent a new important tool to study human internal vs. external attention in future work, more similar to conditions occurring in real life. (2) In Experiment 1, we differentiated the effect of a simpler visual task (pure reading numbers) and a more complex task (reading + arithmetic operation) which still involved external attention but a higher internal processing. In fact, from the previous analysis of the literature, it is still not clear whether and in which conditions an increase in the internal task produces ERS or ERD. Our results indicate that ERD was more accentuated during the demanding task (arithmetic operation), i.e., the arithmetic computation (although internal) further reduced alpha power, provided the task was driven by external visual inputs (attention to the digits). This result means that the alpha-band power can be finely modulated by the level of external attention and that external attention (not the task load) is the dominant factor in visual tasks. This result agrees with previous studies [3, 8]. Moreover, Schupp et al. [23] observed lower alpha for perceptual tasks as opposed to purely mental tasks. In agreement with our result, Benedek et al. [54] suggest that task processing under low internal processing demands (i.e., involving bottom-up processing) did not result in alpha synchronization but rather in strong desynchronization, especially in posterior brain regions, which could reflect stronger demands on the visual system. Only during more demanding tasks, involving top-down control and creativity, can ERS be verified. This result apparently disagrees with a result by Cooper et al. [21], who observed an increase in alpha power with the task demand not only during internal, but also during external attention tasks. We think that these differences may depend on the fact that, during Cooper et al. experiments, some items, given in sequence, should be maintained in memory for a certain period, whereas in our experiment, all numbers were simultaneously available and the external input stream dominated the process. In conclusion, our original result is that an internal arithmetic task can produce ERD, if dominated by external attention. (3) At odds with the previous experiment, in the VR experiment (maVR phase), we used an arithmetic task which was merely mental, while the strong visual intake (cabin immersion) had no relation with the task. At the same time, we did not use specific distractors, but the overall full immersion in the cabin environment had a distractor function. In this condition, we demonstrate that alpha power returned to approximately the same level (or in some participants, even to a higher level) as in the initial resting condition. This result agrees with previous studies, showing that alpha activity increases during a purely mental task not driven by sensory inputs [20, 22, 24]. A difference from previous studies, however, is that we started the mental task from a condition in which alpha power was already significantly reduced by attention to the cabin. We are not aware of any similar experiment performed before (i.e., a global environment distractor). It is interesting to observe that alpha power returned toward baseline (i.e., the resting state), suggesting that the participant was trying to completely neglect the VR environment, i.e., to reach a complete isolation state. This result suggests that the alpha power increase has the most important function to isolate a subject from the external world.

4.3. Artefact Removal. EEG signals are commonly affected by artefacts. Hence, artefact removal is an important aspect of any EEG processing method. Today, ICA is probably the most employed method for removal of artefactual activity from EEG cerebral signals [44], being highly effective in separating several stereotyped nonbrain artefacts (eye blinks, eye movement potentials, EMG, and ECG) from the rest of EEG signals, given that they represent independent physical processes. For this reason, we used this classical and consolidated technique to effectively remove artefacts from the EEG recording acquired in the controlled laboratory setting (Experiment 1) via the wired, laboratory-grade device. However, accurate EEG artefact removal in environments outside controlled laboratory settings, in real or realistic scenarios, and/or in online applications, is still a critical open issue. In these less-controlled conditions, indeed, several nonstereotyped and transient artefacts may corrupt the EEG signals, and ICA may result ineffective in separating them if not sufficient stationary time points are provided. Indeed, we encountered this problem in our recordings obtained in the VR environment with the wireless, consumer-grade EEG device: a large number of artefactual elements (including several nonstereotyped activities) were mixed over most or all ICs, making it impossible to separate the useful signal from the spurious noise via a simple IC selection. This problem is further aggravated (as in our recordings) when a limited number of EEG channels is acquired, as the number of estimated ICs, in the basic ICA model, is constrained to be equal to the channel number (thus imposing a superior limit to the number of independent signals that can compose the mixed EEG for their efficient separation). On the other hand, a limited number of electrodes is a desirable feature in real applications reducing the time of preparation and cost. Due to the ineffectiveness of ICA, in case of the VR recordings, we simply eliminated the EEG portions affected by too much noise from the signal processing procedure: portions with too much noise were not examined and did not contribute to the final analysis. Results, however, were still quite robust and reliable as shown in Figures 6–9. Moreover, the robustness of our procedure for EEG processing in VR recordings was further supported by our preliminary analysis performed on the results obtained separately in the B1 and B2 virtual configurations; this analysis (not shown results) verified that the two virtual configurations, pretty similar and thus eliciting similar visuospatial sensory stimulation, induced overlapped patterns of EEG alpha powers. However, our study confirms that EEG artefactual removal is still a crucial problem in real-world or realistic applications. This problem is currently faced by the scientific community and new methods, also more online-capable than ICA, for removal of transient, and nonstereotyped artefacts have been recently suggested [44, 55]. An important development of the present study will concern testing alternative and more recent methods other than ICA for artefact correction of the VR recordings.

4.4. Temporal Aspects. During the VR immersion, the participant experienced a phase in which he/she was fully immersed in the cabin environment (r1VR), simply sitting down as a passenger during a travel, followed by a second phase in which he/she moved along the environment interacting with the objects (intVR). Then, a third phase followed, in which he/she seated again in a relaxed state fully immersed in the visual and acoustic cabin details (r2VR). We did not use the EEG registered during the interaction with the cabin, since the rapid body and head movements produced too much artefact noise on the electrode signals. However, as anticipated above, it is interesting to observe that, in the third phase of the measurement (r2VR), when the participant sat again after the active interaction, alpha ERD was less evident compared with the first phase, and this difference was statistically significant (see Results in Figure 8 and corresponding ANOVA). This may indicate that the attention-grabbing effect that the VR scenario caused on the participant partially declined as the participant became more used to the environment.

Finally, we tested whether the method can detect mental state changes in a rapid temporal basis. To this aim, we computed the alpha power spectral density in one-minute intervals. Results show that rapid ERD can be detected fairly well and that the temporal variations detected have a straightforward interpretation. During the second minute of the initial relaxation, alpha power exhibited an evident increase, denoting that the participant was becoming more used to the experimental setup (and so was more relaxed). A rapid decrease in alpha-power was immediately observable after 5 minutes (Figure 9), i.e., in the first minute (minute 6) when the participant experienced his/her first immersion in the virtual reality. During the subsequent four minutes of immersion, the alpha power remained low, but showed a moderate temporal increase, reflecting a modest progressive reduction in the level of attention, that is a kind of settling. It is worth noticing that the variations captured by the alpha power index at 1 min resolution were statistically significant and especially large and consistent across the participants in the very first minutes following the VR immersion (Figure 9).

4.5. Analysis in the VR and Perspective Implications. An important point of strength of the present study is the specific investigation in the VR immersion. This analysis has evidenced that even a resting immersion in a static VR scenario had profound effect on EEG alpha power, as the rich sensory stimulation probably exerts a strong attention-grabbing influence, and this effect was quantitatively comparable to a high-level cognitive processing such as reading numbers. The assessment of EEG consequences of pure VR immersion is relevant to enhance interpretation of brain rhythms modifications when a subject is immersed in a complex realistic scenario. This may have perspective implications considering the emerging use of VR associated with EEG-based measures in several applications. In particular, the use of VR technology together with objective physiological measures (other than subjective evaluation) is rapidly increasing as a valuable tool to inform design decisions in the early phases of artificial environment projects ([56–59]) and/or to study human/environment interaction [60, 61]. Moreover and in a different context, there is a growing number of studies investing the use and effectiveness of VR-based therapy for psychiatric disorders [60, 62]. Of course, in all these applications, understanding how the simple immersion in a VR scenario (or a task performed in the VR) can modify the subject's physiological parameters, and in particular EEG parameters, is strictly necessary for a correct interpretation of the behavioural data and of the psychophysiological effects.

4.6. Limitations and Future Improvements. While the present study may provide interesting cues on the role of alpha oscillations and its relations with internal/external attentional components and task load, the objective of the present work was not to investigate the neural bases of alpha rhythm changes. In order to investigate the underlying neural mechanisms, more sophisticated methods should be implemented, with the use of high-density EEG recording, source reconstruction in the cortex, and estimation of connectivity changes between regions of interest. This may be the subject of subsequent studies.

Furthermore, in this work, we showed that traditional methods (like the Welch periodogram, computed on a shifting temporal window) can acceptably detect temporal changes of a nonstationary signal. However, time changes can be even better detected using more sophisticated processing methods, such as wavelets (as used, for instance, in [63] to build sensitive indicators of mental workload). This may be implemented and tested in future developments. Indeed, efficient algorithms for wavelet computation do exist, which are even compatible with real-time application.

5. Conclusions

In conclusion, emphasis in the present work is on the possibility to detect changes in attention during human/environment interaction, with the use of a simple unexpansive EEG technique, applicable in an artificial setting and prospectively in real time. The results emphasize that alpha power decreases during tasks which necessitate attention to the external environment, even in conditions when the task requires an increasing mental effort. Conversely, alpha power increases to levels similar to a relaxation state, when a task requires isolation from the external world. These results elucidate some aspects still insufficiently clear in the recent literature, suggesting that one of the main roles for the alpha rhythm is isolation from the external environment and attentional shift toward internal aspects.

A peculiarity of our study is the use of a sophisticate virtual reality environment to mimic the interaction of individuals with an artificial ad hoc designed scenario. In perspective, this may be used in the design of artificial systems, or in neuroengineering applications. Indeed, the possibility to monitor attentional changes from low-resolution EEG is of the greatest value to realize easy-to-use, comfortable, and cheaper systems in practical applications such as neurofeedback, brain computer interfaces, neuroergonomics, and neuromarketing [64–66].

Data Availability

The data used to support the findings of this study are available (in anonymized form) upon request submitted to Elisa Magosso (elisa.magosso@unibo.it) and Francesca De Crescenzio (francesca.decrescenzio@unibo.it).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Antismoking Campaigns' Perception and Gender Differences: A Comparison among EEG Indices

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Human factors' aim is to understand and evaluate the interactions between people and tasks, technologies, and environment. Among human factors, it is possible then to include the subjective reaction to external stimuli, due to individual's characteristics and states of mind. These processes are also involved in the perception of antismoking public service announcements (PSAs), the main tool for governments to contrast the first cause of preventable deaths in the world: tobacco addiction. In the light of that, in the present article, it has been investigated through the comparison of different electroencephalographic (EEG) indices a typical item known to be able of influencing PSA perception, that is gender. In order to investigate the neurophysiological underpinnings of such different perception, we tested two PSAs: one with a female character and one with a male character. Furthermore, the experimental sample was divided into men and women, as well as smokers and nonsmokers. The employed EEG indices were the mental engagement (ME: the ratio between beta activity and the sum of alpha and theta activity); the approach/withdrawal (AW: the frontal alpha asymmetry in the alpha band); and the frontal theta activity and the spectral asymmetry index (SASI: the ratio between beta minus theta and beta plus theta). Results suggested that the ME and the AW presented an opposite trend, with smokers showing higher ME and lower AW than nonsmokers. The ME and the frontal theta also evidenced a statistically significant interaction between the kind of the PSA and the gender of the observers; specifically, women showed higher ME and frontal theta activity for the male character PSA. This study then supports the usefulness of the ME and frontal theta for purposes of PSAs targeting on the basis of gender issues and of the ME and the AW and for purposes of PSAs targeting on the basis of smoking habits.

1. Introduction

Smoking is the first cause of preventable deaths in the world [1]. It has been proved that tobacco companies specifically target women and children through their advertising, marketing, and promotion activities [2]. The main tool that governments can use to contrast such global emergency is constituted by antismoking public service announcements (PSAs). In relation to this, the possible gender differences in the response to antismoking measures, such as antismoking PSAs, are extremely worthy to be investigated. It has been previously highlighted how men and women respond differently to advertising [3, 4] and in particular to antismoking advertising [5–7]. In addition, it was seen a different modulation operated by the transportability within each sex [8] in response to advertising. Focusing on the gender effect in the reaction to smoking cue in antismoking advertisements, fMRI studies identified higher activation in women in several brain regions in comparison to male smokers, male exsmokers, and nonsmokers [6]. Furthermore, other fMRI research studies found a greater bilateral hippocampal/amygdala activation in males exposed to smoking cue in comparison to nonsmoking cues [7].

The mental engagement (ME) index was developed by Pope and colleagues [9] for its application in cognitive tasks, such as a closed-loop system to modulate task allocation. It was based on several evidences that the increases in beta activity would reflect a higher degree of alertness and greater engagement in the task, while increases in alpha and/or theta activity were supposed to reflect less alertness and decreased task engagement/information processing [10–16]. Concerning the ME application, for instance, it has been measured an improvement in performances during a vigilance task when this index was used as a criterion for switching between manual and automated piloting mode [17]. Subsequently, it has been applied to the assessment of the emotional influence on learning in an educational setting, resulting as predictive of the performance [18]. Also due to the emotional content often present in antismoking PSAs, we decided to apply such index to this study.

The approach/withdrawal (AW) index and the frontal theta index have been already applied to the study of antismoking PSAs, in relation to the investigation of neurophysiological correlates of effectiveness in such kind of advertising [19–22]. The AW was based on the theory of the frontal alpha asymmetry introduced by Davidson [23] and further adopted in several studies [24–27]. According to this theory, the prefrontal cortex (PFC) plays a crucial role in the circuitry that mediates both positive and negative motivation. In particular, various studies evidenced a relative increase in the left PFC activation in correspondence of the positive motivation, while an augmented right-sided anterior activation was observed during the negative motivation [28–32]. The application to advertising material of the frontal alpha asymmetry index, defined as the difference between the prefrontal right and left EEG power spectra alpha activity, has been already repeatedly reported [4, 33–36]. The frontal theta index was included among the assessed indices groups since its relation to the processing of the antismoking message of the PSA. In fact, higher values of frontal theta have been connected to higher levels of task difficulty [10, 37]. Moreover, it has been evidenced how the frontal theta activity represents a marker of cognitive processing during a visual task execution [11, 38]. The frontal theta as index of effort and processing has been already applied to a number of studies in different fields of research, such as neuroaesthetics [12, 39, 40]; advertising [40]; avionic [41–46] and car driving [16, 42, 47–49]; different challenging listening conditions both in normal hearing and in hearing impaired participants [50–52]; and human-computer interaction [53, 54] studies.

The spectral asymmetry index (SASI) was introduced by Hinrikus and colleagues with the aim of comparing the sensitivity of different electroencephalographic (EEG) indicators for the detection of depression [54]. Afterwards, it was applied to the reaction to emotional stimuli, providing evidence of the capability of discrimination of negative (SASI increase), positive (SASI decrease), and neutral stimuli [55]. SASI is based on the balance of EEG theta and beta frequency band powers, since evidences found a relation between EEG theta power and emotional activation. For example, Hu and colleagues [56] found evidence of a correlation between global theta power changes and "playfulness" emotions (amusement, interest, and joy) characterizing video stimuli. This evidence was also in accord with a previous study on videos by Aftanas and collaborators [57] who highlighted the major increase in theta power in response to video clips related to joy. On the other hand, beta power has been associated with high anxiety levels, especially in the right hemisphere [58], while decrease in beta activity with relaxation [59]. Therefore, SASI was expected to increase in the case of negatively perceived stimuli and to decrease in the case of positively perceived stimuli while compared to neutral pictures.

It is not clear how the gender and the previous smoking habit issues could interact with the observation of antismoking PSAs. Aim of this study was to compare the sensitivity of different EEG-based indices in detecting first gender issues and secondly smoking habit issues, in the reaction to antismoking PSAs. The final aim is to understand if such eventual cerebral patterns could be different in relation to some features of the employed PSAs in terms of characters and plot and in relation to some features of the experimental sample, that is, gender and tobacco use. If so, it could be explored in the future the possibility to evaluate the PSAs before their broadcast to understand if they could be successful (e.g., effective) or unsuccessful (e.g., ineffective) in generating appropriate healthy responses taking into account the particular gender and the smoking habit issues.

2. Materials and Methods

2.1. Participants. The experimental sample was composed of 46 participants (23 F and 23 M), divided in smokers (participants usually smoking at least 5 cigarettes per day) and nonsmokers. Smokers were 12 F and 11 M, while nonsmokers were 11 F and 12 M (Table 1). Participants were healthy volunteers aged between 25 and 55 years (mean age and standard deviation: F nonsmokers: 36.00 ± 12.05; F smokers: 36.25 ± 9.92; M nonsmokers: 33.50 ± 8.67; M smokers: 38.63 ± 10.58) and received a small compensation for their participation. All participants were given of detailed information about the study and signed informed consent. The experiment was performed in accord to the principles outlined in the Declaration of Helsinki of 1975, as revised in 2000, and it was approved by the Sapienza University of Rome Ethical Committee in charge for the Department of Molecular Medicine.

2.2. Protocol. During the execution of the test, participants were sitting on a comfortable chair in front of a computer screen, and they were not instructed with any particular task, just to be relaxed and to restrict head and body movements as much as possible. Participants were asked to watch a video

Table 1: The table reports the number of cigarettes per week smoked by participants.

Female participants	Cigarettes/week	Male participants	Cigarettes/week
F1	0	M1	0
F2	0	M2	0
F3	0	M3	0
F4	0	M4	0
F5	0	M5	0
F6	0	M6	0
F7	0	M7	0
F8	0	M8	0
F9	0	M9	0
F10	0	M10	0
F11	0	M11	0
F12	42	M12	0
F13	42	M13	40
F14	50	M14	40
F15	50	M15	50
F16	50	M16	55
F17	56	M17	60
F18	85	M18	65
F19	100	M19	75
F20	100	M20	85
F21	100	M21	100
F22	140	M22	100
F23	140	M23	105

Note. Those who smoked zero cigarettes per week were included in the nonsmoker group.

composed by a train of ten randomly delivered antismoking PSAs, with a total length of 9 minutes, preceded and followed by a documentary (neutral in respect to gender; in fact it was about constellations) lasting 1 minute, and already used as baseline [19]. The target stimuli were two of the ten PSAs, and participants were exposed once to each stimulus (both target and distracting stimuli) (Figure 1):

(i) One male character antismoking PSA: CDC Roosevelt (USA, 2012–2015). The video displays a young man telling how he got a heart attack when he was just 45 years old and all the consequences of that event, beginning from the scar on his chest to the limitations in his everyday life, for instance, in climbing the stairs or playing with his son (retrievable at https://www.youtube.com/watch?v=OdmI35elnCQ).

(ii) One female character antismoking PSA: Baby Love (Finland, 2013). The video displays a young pregnant woman at first apparently preparing the room for the baby she is waiting, but as long as the video develops, it turns out that she actually does horrible actions, like hanging knives instead of toys in the carillon over the cradle, or putting a snake into it. The video ends with the young woman lighting a cigarette and smoking with an ashtray placed on her pregnant belly (retrievable at https://www.youtube.com/watch?v=SPBQII5c9fw).

2.3. EEG Recordings and Signal Processing. For the recording of the EEG activity, it has been employed a portable 24-channel system (BEmicro, EBneuro, Italy) and an EEG frontal band with ten electrodes (Fpz, Fp1, Fp2, AFz, AF3, AF4, AF5, AF6, AF7, and AF8). Impedances were kept below 10 kΩ, and signals were acquired at a sampling rate of 256 Hz. EEG traces were digitally bandpass filtered by a 5th order Butterworth filter ($[2 \div 30]$ Hz), so as to reject the continuous component and high-frequency interferences.

At this point, the independent component analysis (ICA) was employed on cleaned EEG data, so as to identify and remove blinks activity contribution. For this purpose, the signal has been decomposed in 10 ICA components (the same number of EEG channels), but only the component related to blinks activity has been selected [60].

Moreover, specific procedures of the EEGLAB toolbox have been adopted [61], in order to remove further sources of artifacts (e.g., muscular activity and bioamplifier saturation). First of all, EEG signal has been segmented in epochs of 1 second, shifted of 0.5 seconds. Three epoch rejection criteria have been applied as follows:

(i) Threshold criterion: when amplitudes in the EEG signal were equal to or greater than 100 μV, the corresponding epoch was labeled as artifact

(ii) Trend criterion: in the aim to check the slope of the trend within the considered epochs, EEG epochs were interpolated, and if the slope of an epoch was higher than 10 μV/s, it was labeled as artifact

(iii) Sample-to-sample difference criterion: cases in which the amplitude difference between consecutive EEG samples was higher than 25 μV, representing an abrupt nonphysiological variation, the corresponding EEG epoch was labeled as artifact

Specifically, all the adopted numeric values just mentioned were chosen accordingly to the guidelines reported in Delorme and Makeig [61].

After the application of the just mentioned epoch rejection criteria, in order to have an artifact-free EEG signal from which estimating the brain variations along the different conditions, all the EEG epochs labeled as artifact were rejected from the EEG dataset.

For each participant, the individual alpha frequency (IAF) was calculated over a 60-second long open eyes segment, recorded before the beginning of the experimental task. IAF was computed in order to define the EEG bands of interest according to the method suggested in the current scientific literature, i.e., each band is defined as "IAF $\pm x$," where IAF is the individual alpha frequency, in Hertz, and x an integer in the frequency domain [37]. Consequently, the EEG activity was divided in three main frequency bands: theta $[\mathrm{IAF}-6 \div \mathrm{IAF}-2\,\mathrm{Hz}]$, alpha $[\mathrm{IAF}-2 \div \mathrm{IAF}+2\,\mathrm{Hz}]$, and beta $[\mathrm{IAF}+2 \div \mathrm{IAF}+14\,\mathrm{Hz}]$. To summarize the activity of the cortical areas of interest in a specific frequency band, the global field power (GFP) [62] was then computed. The GFP summarizes the synchronization level of the brain activity over the scalp surface, and its measure corresponds to the spatial standard deviation. GFP estimates the quantity of activity at each time point in the field, simultaneously considering data from all recording electrodes, resulting in a

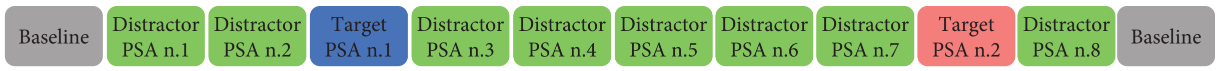

Figure 1: Structure of the protocol employed in the study. Each of the target stimuli could randomly appear in one of the ten possible PSA positions. Distractor stimuli were randomly placed in the remaining positions. At the beginning and at the end of the PSA train, there was the 1-minute baseline video.

reference-independent descriptor of the potential field [63]. The main concept of GFP is that scalp fields presenting high activity reflect the synchronous activation of a large number of intracranial neuronal elements, while fields with few field lines would contain little information. The GFP was already employed in studies of perceptual, attentional, and cognitive processing [64–66] as well as in clinical studies [67–69]. The GFP represents an index for the temporal determination of information from cognitive studies; moreover, it constitutes a parameter for the time-domain analysis of EEG (as in the present work), as it allows the identification of the maps of maximal electric field strength (hilliness).

Specifically, in this study, the GFP was calculated from a specific set of electrodes (the set depends on the investigated brain area, and for each index it will be specified later in the study) by performing the sum of squared values of EEG potential at each electrode, averaged for the number of involved electrodes, resulting in a time-varying waveform related to the increase or decrease of the global power in the analysed EEG. The GFP formula is specified in the following equation:

$$\mathrm{GFP}_{\vartheta,\mathrm{Frontal}} = \frac{1}{N}\sum_{i=1}^{N} x_{\vartheta_i}(t)^2, \tag{1}$$

where ϑ is the considered EEG band, *Frontal* is the considered cortical area, N is the number of electrodes included in the area of interest (in this example the Frontal area), i is the electrodes' index, and x represents the specific EEG sample at time (t), filtered within the related EEG band (i.e., ϑ) and for the specific channel i.

It was calculated then the average GFP value on all the GFP values estimated over 1 second of EEG signal. According to the following paragraphs, EEG indices were calculated and normalized for each second by using the mean and the standard deviation of the same neurometrics calculated on the baseline:

$$\text{normalized index} = \frac{\text{index} - \text{mean}_{\text{baseline}}}{\text{standard deviation}_{\text{baseline}}}. \tag{2}$$

2.4. Mental Engagement. The mental engagement (ME) index has been defined as the ratio between the activity in the beta band and the sum of alpha and theta activity (equation (3)), as defined by Pope and colleagues [9]:

$$\text{mental engagement index} = \frac{\mathrm{GFP}\beta}{\mathrm{GFP}\alpha + \mathrm{GFP}\theta}. \tag{3}$$

2.5. Approach Withdrawal. The approach/withdrawal (AW) index has been defined according to Davidson and colleagues [23] as the frontal alpha asymmetry as reported in the following formula:

$$\text{approach withdrawal index} = \mathrm{GFP}\alpha\_\mathrm{right} - \mathrm{GFP}\alpha\_\mathrm{left}, \tag{4}$$

where the GFPα_right and GFPα_left stand for the GFP calculated among right (Fp2, AF4, and AF8) and left (Fp1, AF3, and AF7) electrodes, respectively, in the alpha (α) band. Higher AW values, reported by the subjects, stood for an approach motivation toward the stimulus, while lower AW values for a withdrawal motivation [70, 71].

2.6. Frontal Theta. The EEG activity in the theta band over all the frontal electrodes has been considered for the estimation of the mental effort/processing processes. An increase in the frontal theta (i.e., mental effort/processing) would imply an increase in the task difficulty [38, 49] and therefore in the attendance to the antismoking content of the PSA, as also already evidenced by studies in which the frontal theta activity has been investigated during the exposure to antismoking advertising [19–22].

2.7. Spectral Asymmetry Index. The spectral asymmetry index (SASI) has been defined by previous studies where it was calculated for each EEG electrode [54] and for groups of electrodes corresponding to cerebral regions [55], and here calculated, over all the frontal electrodes, according to the following equation:

$$\mathrm{SASI} = \frac{\mathrm{GFP}\beta - \mathrm{GFP}\theta}{\mathrm{GFP}\beta + \mathrm{GFP}\theta}. \tag{5}$$

2.8. Statistical Analysis. ANOVA test has been performed on all the considered indices. The first between-variable was the "Smoking Habit," with 2 levels: smokers and nonsmokers; the second between-variable was the participants "Gender," with two levels: men and women; the within variable was the "PSA kind," with two levels: male character PSA and female character PSA. Duncan's post hoc comparisons have been performed on the statistically significant interactions. Logistic regression analysis was also performed on the indices, considering as dichotomic variables the participants' gender. Simple regression analysis has been performed in order to investigate the correlation between the number of smoked cigarettes by participants and the neurophysiological response indexed by the selected indices.

3. Results and Discussion

3.1. Mental Engagement Results. Concerning the mental engagement (ME), results showed a statistically significant increase for ME values in smokers in comparison to nonsmokers ($F(1, 42) = 4.207$, $p = 0.046$) (Figure 2). Furthermore,

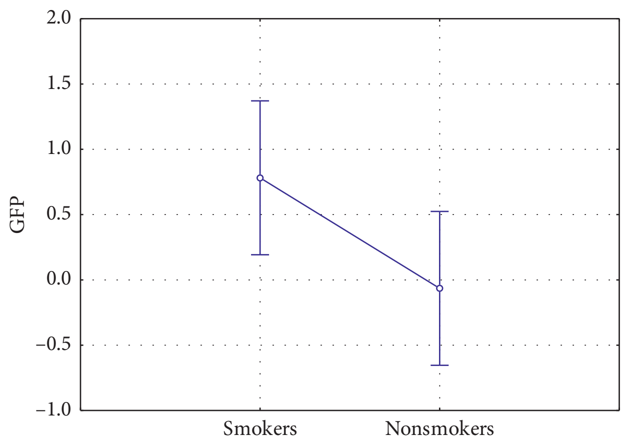

Figure 2: Mental engagement index: comparison among smokers and nonsmokers ($n = 46$). Smokers showed a statistically significant increase in ME values in comparison to nonsmokers ($F(1, 42) = 4.207$, $p = 0.046$). Vertical bars denote 0.95 confidence intervals.

ANOVA test reported a statistically significant interaction between the factor PSA and the factor Gender ($F(1, 42) = 5.225$, $p = 0.027$). Post hoc analysis did not show any statistically significant difference in the pairwise comparisons (Figure 3).

In addition, ME results evidenced a statistical significance in the logistic regression between the values obtained in response to the male character PSA and the Gender of participants ($p = 0.015$) (Figure 4).

Finally, ME results provided evidence of a correlation between the number of cigarettes per week smoked by participants and the ME values obtained in correspondence of the exposure to the male character PSA ($p = 0.044$) (Figure 5).

3.2. Approach/Withdrawal Results. Results evidenced increased AW values for the nonsmokers in comparison to smokers ($F(1, 42) = 4.413$, $p = 0.042$) (Figure 6). It is also interesting to note that nonsmokers presented positive AW values and therefore an approach tendency toward the antismoking PSAs, while smokers showed negative AW values and therefore a withdrawal tendency.

3.3. Frontal Theta Results. Concerning frontal theta activity, it has been found a statistically significant effect for the kind of the PSA ($F(1, 42) = 19.981$, $p < 0.001$). In particular, the male character PSA showed higher frontal theta values (Figure 7). Furthermore, it has been found a statistically significant interaction between the variables PSA kind and Gender of the participants ($F(1, 42) = 5.150$, $p = 0.028$) (Figure 8). The post hoc analysis highlighted also an increase of the frontal theta values reported by women participants in response to the male character PSA in comparison to the response of both women ($p < 0.001$) and men ($p = 0.040$) to the exposure to the female character PSA.

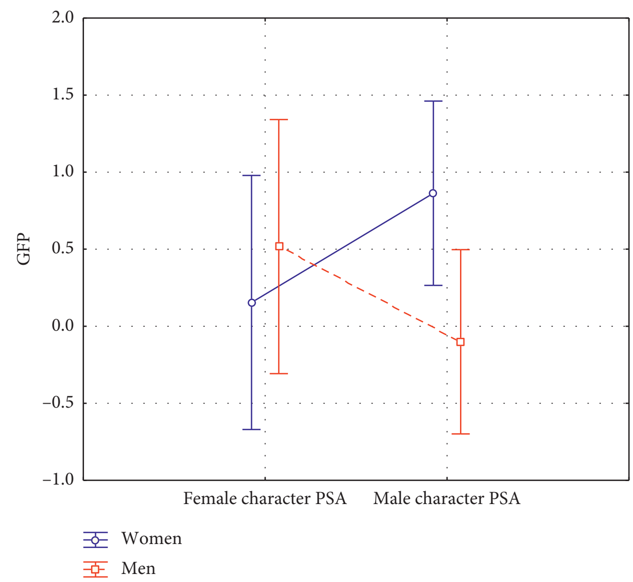

Figure 3: Mental engagement index: interaction between PSA kind and Gender ($n = 46$). The statistical analysis reported a statistically significant interaction between the factor PSA and the factor Gender ($F(1, 42) = 5.225$, $p = 0.027$). Post hoc analysis did not show any statistically significant difference in the pairwise comparisons. Vertical bars denote 0.95 confidence intervals.

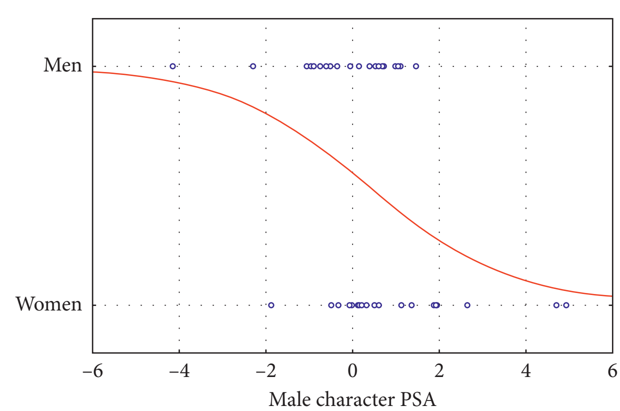

Figure 4: Mental engagement index: plot of the logistic regression between the male character PSA and Gender ($n = 46$). The statistical analysis reported a statistical significance for such correlation ($p = 0.015$) suggesting that men reported lower ME values in comparison to women in correspondence of the exposure to the male character PSA.

3.4. Spectral Asymmetry Index Results. Concerning the SASI, the statistical analysis performed on the collected data did not provide any statistical significance.

4. Discussion

The higher ME values, the logistic regression results, and the higher frontal theta activity showed by women in response to the male character PSA (narrating the story of a man who had an heart attack at a very young age due to smoking)

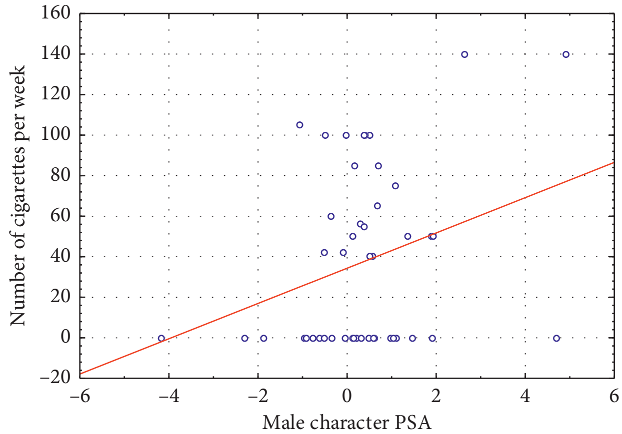

Figure 5: Mental engagement index: plot of the linear regression between the male character PSA and the number of cigarettes per week smoked by participants ($n = 46$). The statistical analysis reported a statistical significance for such correlation ($p = 0.044$) suggesting that heavy smokers reported higher ME values in correspondence of the exposure to the male character PSA.

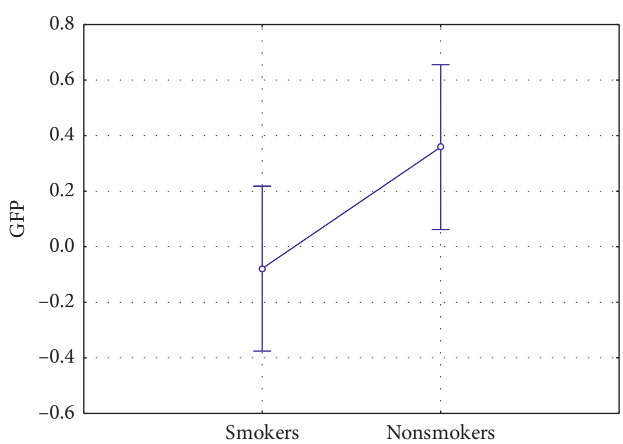

Figure 6: Approach/withdrawal index: comparison among smokers and nonsmokers ($n = 46$). Nonsmokers showed a statistically significant increase in AW values in comparison to smokers ($F(1, 42) = 4.413$, $p = 0.042$). Vertical bars denote 0.95 confidence intervals.

could be explained by the evidence that women in comparison to men have been found to be more influenced by advertisements that emphasize the negative effects of smoking on health [5].

The significant correlation between the number of cigarettes per week smoked by participants and the ME values stated that as long as the number of cigarettes increased, the relative ME values also increased. It is interesting to note that this was true only for the male character PSA, again, the one showing the negative health effects of smoking (heart attack and its consequences on the everyday life). This would be explained by the fact that smokers would feel more involved by such content, possibly resulting in higher ME values.

The tendency of approach showed by nonsmokers during the exposure to the antismoking PSAs could be explained by the perceived higher effectiveness by

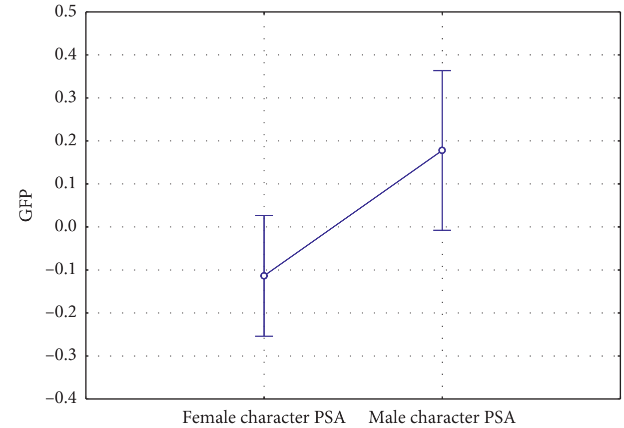

Figure 7: Frontal theta index: comparison between the kind of PSA ($n = 46$). The male character PSA showed higher frontal theta values ($F(1, 42) = 19.981$, $p < 0.001$). Vertical bars denote 0.95 confidence intervals.

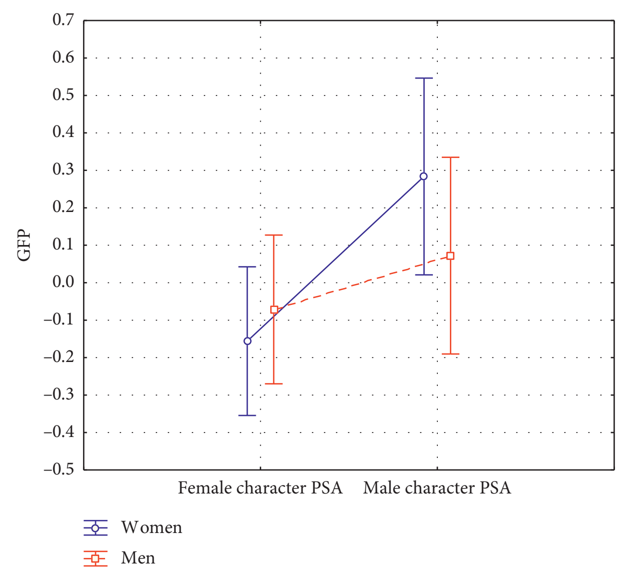

Figure 8: Frontal theta index: interaction between the kind of PSA and the Gender of the participants ($F(1, 42) = 5.150$, $p = 0.028$) ($n = 46$). The male character PSA showed higher frontal theta values in women in comparison to the female character PSA both in men ($p = 0.040$) and women ($p < 0.001$). Vertical bars denote 0.95 confidence intervals.

nonsmokers in response to advertisements eliciting strong negative emotions (sadness and fear) [72], like the PSAs included in this study.

The higher frontal theta levels reported for the male character PSA in comparison to the female character PSA were probably due to the complexity of the narrated story, in accord to a previous study providing evidence that the presence of a narrative structure in video commercials resulted in higher theta power of the left frontal area [73].

The lack of significant results obtained by the analysis employing the SASI could be explained by the fact that both PSAs would be negatively perceived due to the frightening and worrying nature of their content. However, it must also be considered the method of investigating the SASI index at the level of a region in the present article and not at the level of each single electrode or small area (grouping the electrodes by 3), as in previous studies [54, 55].

5. Conclusions

This study, through the comparison among EEG indices, showed the sensitivity of the ME and the frontal theta index in evidencing gender influences (both of the PSA characters and of the participants) on the neurophysiological response. The ME presented also the advantage of pointing out also a difference based on the smoking habit of the participants, an aspect highlighted also by the AW index. The frontal theta on the other hand highlighted the significant effect of the PSA character gender. This study then supports the usefulness of the ME and frontal theta for purposes of PSAs targeting on the basis of gender issues and of the ME and the AW and for purposes of PSAs targeting on the basis of smoking habits.

Data Availability

The data relative to the study could be obtained by sending an e-mail to fabio.babiloni@uniroma1.it. Prof. Babiloni will return directly the excel file related to the data gathered by the study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

Giulia Cartocci, Enrica Modica, and Dario Rossi equally contributed to this article.

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Research Article

Fusion of Motif- and Spectrum-Related Features for Improved EEG-Based Emotion Recognition

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Emotion recognition is a burgeoning field allowing for more natural human-machine interactions and interfaces. Electroencephalography (EEG) has shown to be a useful modality with which user emotional states can be measured and monitored, particularly primitives such as valence and arousal. In this paper, we propose the use of ordinal pattern analysis, also called motifs, for improved EEG-based emotion recognition. Motifs capture recurring structures in time series and are inherently robust to noise, thus are well suited for the task at hand. Several connectivity, asymmetry, and graph-theoretic features are proposed and extracted from the motifs to be used for affective state recognition. Experiments with a widely used public database are conducted, and results show the proposed features outperforming benchmark spectrum-based features, as well as other more recent nonmotif-based graph-theoretic features and amplitude modulation-based connectivity/asymmetry measures. Feature and score-level fusion suggest complementarity between the proposed and benchmark spectrum-based measures. When combined, the fused models can provide up to 9% improvement relative to benchmark features alone and up to 16% to nonmotif-based graph-theoretic features.

1. Introduction

Human-machine interaction can become more natural once machines become aware of their surroundings and their users [1, 2]. These so-called context-aware or affective interfaces can open up new dimensions of device functionality, thus more accurately addressing human needs while keeping the interfaces as natural as possible [3]. For example, affective computing can enable applications in which the machine can learn user preferences based on their reactions to different settings or even become a more effective tutor by assessing the student's emotional/stress states [3]. Automated recommender and tagging systems, in turn, can make use of affect information to better understand user preferences, thus improving system usability [4]. Measuring affective state and engagement levels can also be used by a machine to infer the user's perceived quality of experience [5–9], thus providing the machine with an objective criterion for online optimization.

Human emotions are usually conceived as physiological and physical responses and are part of natural human-human communications. Emotions are able to influence our intelligence, shape our thoughts, and govern our interpersonal relationships [10–13]. Emotion is usually expressed in a multimodal way, either verbally through emotional vocabulary or by expressing nonverbal cues such as intonation of voice, facial expressions, and gestures. As such, audio-visual cues have been widely used for affective state monitoring [14]. Alternately, emotions have also been known to effect neurophysiological signals; thus, biosignal monitoring has been extensively explored. Representative physiological signal modalities have included galvanic skin response (GSR), skin temperature, and breathing and cardiac activity (via electrocardiography (ECG) and photoplethysmography (PPG)) [15–18].

More recently, brain-computer interfaces (BCIs) have emerged as another tool to accurately monitor implicit user information, such as mood, stress level, and/or emotional states [9, 19, 20]. Within BCI-based affective computing methods, electroencephalography (EEG) has remained the most popular modality due to its noninvasiveness, high temporal resolution, and portability [21], though alternative modalities, such as near-infrared spectroscopy (NIRS), are slowly emerging [5, 22, 23]. Typically, with EEG-based systems, spectral power features have been widely used (e.g., [18, 24–26]), including frontal interhemispheric asymmetry features [27–32]. EEG signals, however, are very sensitive to artefacts, such as eye blinks and muscle movement [33]. To overcome such issues, artefact removal algorithms can be used. Alternately, new noise-robust features can be developed and/or multimodal fusion strategies can be explored [34].

In this paper, focus is placed on the latter and motif-based features are proposed and tested alone or alongside alternate complementary features. Motif-based analysis has shown to be useful in the past to recognize sleep states [35], as well as the effects of anesthesia [36], to detect seizures [37, 38], and to measure alertness [39]. Motif-based methods are inherently robust to noise as they deal with the shape of the time series and are unaffected by the magnitude [38, 40, 41]. To the best of our knowledge, they have yet to be explored for affective state monitoring; thus, this paper fills this gap. In particular, we compare the proposed features with spectral power and spectral asymmetry benchmark features. Notwithstanding, one main limitation of motif features concerns the loss of both amplitude and rate-of-change information when time series are converted into motif series [40, 42]. As such, we also explore three different fusion strategies to combine information from the proposed motif features and classical benchmark features. Experimental tests on a publicly available database [18] are performed, which show the advantages of the proposed features over benchmark ones, as well as the benefits of fusion for affective state monitoring.

The remainder of this paper is organized as follows. Section 2 describes the materials and methods used, including the database considered, proposed, and benchmark features, fusion methods used, and performance metrics used. Section 3 then presents and discusses the results obtained, and conclusions are drawn in Section 4.

2. Materials and Methods

Here, we describe the database used, benchmark features, proposed motif features, as well as the feature selection schemes employed, classifiers, and fusion schemes explored.

2.1. DEAP Database. This study relies on the publicly available, widely used DEAP (Dataset for Emotion Analysis using EEG and physiological signals) database. As detailed in [18], thirty-two healthy participants (50% females, average age = 26.9 years) were recruited and consented to participate in the study. Thirty-two channel EEG data were recorded using a Biosemi ActiveTwo system (Amsterdam, Netherlands) at a sampling rate of 512 Hz. Electrodes were placed on the scalp according to the International 10–20 system.

Participants were presented with 40 one-minute long music videos with varying emotional content. These video clips were selected based on a previous analysis of several hundred videos as they were shown to elicit the strongest reactions across the four quadrants in the valence-arousal space (i.e., low valence, low arousal; low valence, high arousal; high valence, low arousal; and high valence, high arousal). The valence-arousal space is a two dimensional scale used to characterize emotions [43]. Valence refers to the (un)pleasantness of an event, whereas arousal refers to the intensity of the event, ranging from very calming to highly exciting. Using this space, various emotions can be mapped, as shown in Figure 1. Prior to each video, there was a baseline period of five seconds where the participants were asked to fixate at a cross in the middle of the screen. Following the presentation of each video, participants were asked to rate the music videos on discrete 9-point scales for valence and arousal using the self-assessment manikins (SAM) [44]. While other dimensional ratings, such as dominance and liking were also collected, these have not been explored herein.

The EEG data are available for public download in raw format or in preprocessed format, which includes common referencing, down-sampling to 128 Hz, bandpass filtering between 4 and 45 Hz, and eye blink artefact removal via independent component analysis. Moreover, only the last three seconds of the five-second baseline are available. Since this is a standard pipeline for EEG processing, the analysis reported herein is done on the preprocessed data. Data per subject were epoched into forty 60 s long trials with a 3 s long prestimulus baseline. The prestimulus baseline was then subtracted from the preprocessed data. The interested reader can refer to [18] for more details on the DEAP database and its data collection process.

2.2. Benchmark Features. As mentioned previously, spectral power features in different EEG bands have been widely used for affective state monitoring, including for the DEAP database [18, 45]. Moreover, an interhemispheric asymmetry in spectral power has also been been reported in the affective state literature [27, 28, 30–32], particularly in frontal brain regions [29, 31]. Typically, EEG signals are band decomposed into theta ($4 < \theta < 8$ Hz), alpha ($8 < \alpha < 13$ Hz), beta ($13 < \beta < 30$ Hz), and gamma ($30 < \gamma < 45$ Hz) bands. Here, 48 asymmetry index (AI) features (12 interhemisphereic electrode pairs × 4 bands) were computed for the following electrodes pairs: Fp2-Fp1, F3-F4, F7-F8, FC1-FC2, FC5-FC6, C3-C4, T7-T8, Cp1-Cp2, Cp5-Cp6, P3-P4, P7-P8, and O1-O2.

Moreover, EEG band ratios have also been explored in the past for tasks such as human mental state monitoring, fatigue, attention control, and negative emotional response monitoring [46–48], thus are also included here as benchmark features. The ratios computed include $\gamma/\beta, \beta/\theta, \alpha/\theta, (\alpha + \beta)/\gamma,$ and $(\gamma + \beta)/\theta$. The ratios are computed individually over each electrode. Lastly, the Shannon entropy [49] has been used as a feature to measure the complexity of the EEG time series. Shannon entropy can be calculated as follows:

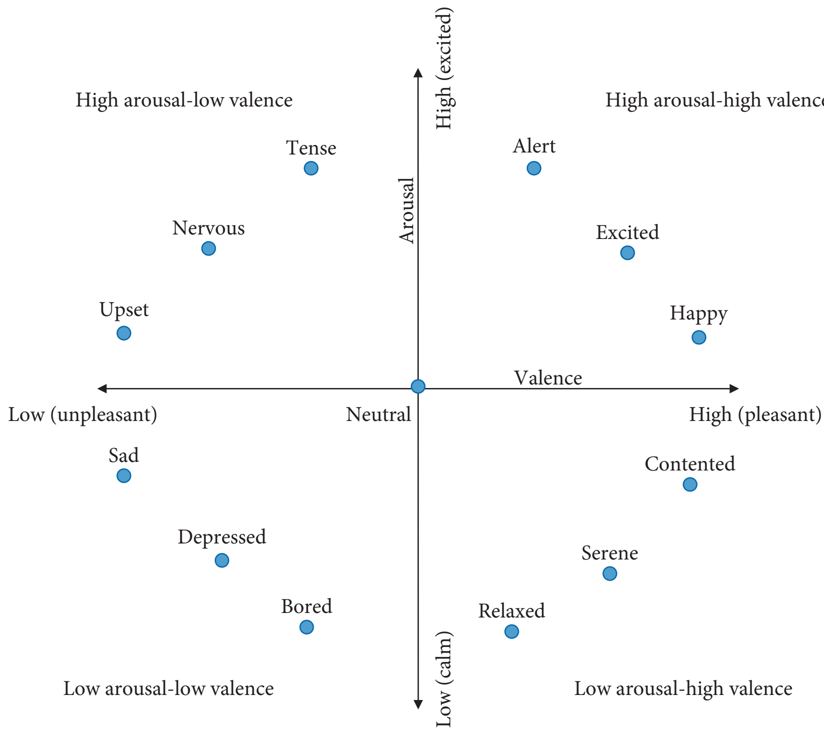

Figure 1: Valence-arousal plot with representative emotions.

$$\mathrm{SE} = -\sum_j P_j \cdot \log\left(P_j\right), \tag{1}$$

where P_j is the power in sub-band j.

2.3. Motif-Based Features. A motif is a pattern or structure characterized by the number of nodes or degree (represented by n) and the connection between them and the number of points used between these nodes (called lag, represented by λ). Each motif can be represented as an alphabet or a number. The robustness of motif features comes from the fact that they only consider the underlying shape of the time series and not the amplitude. Using this definition, any time series $X(i)$ can be converted into a motif series $X_m(i)$ using these given rules (e.g., for degree, $n = 3$):

$$X_m(i) = \begin{cases} 1 & \text{if } X(i) < X(i+\lambda)\; X(i+\lambda) < X(i+2\lambda)\; X(i) < X(i+2\lambda), \\ 2 & \text{if } X(i) < X(i+\lambda)\; X(i+\lambda) > X(i+2\lambda)\; X(i) < X(i+2\lambda), \\ 3 & \text{if } X(i) > X(i+\lambda)\; X(i+\lambda) < X(i+2\lambda)\; X(i) < X(i+2\lambda), \\ 4 & \text{if } X(i) < X(i+\lambda)\; X(i+\lambda) > X(i+2\lambda)\; X(i) > X(i+2\lambda), \\ 5 & \text{if } X(i) > X(i+\lambda)\; X(i+\lambda) > X(i+2\lambda)\; X(i) > X(i+2\lambda), \\ 6 & \text{if } X(i) > X(i+\lambda)\; X(i+\lambda) < X(i+2\lambda)\; X(i) > X(i+2\lambda). \end{cases} \tag{2}$$

Figure 2 shows the different motifs possible for degree $n = 3$ appearing in a particular time series. Once the motif series has been derived, different features can be extracted based on the statistics of recurring patterns within the motif series. The features proposed herein are detailed in the subsections below and only consider motifs of degree $n = 3$ and lag value $\lambda = 1$. These parameters have been suggested in the past for related tasks [39, 50].

2.3.1. Permutation Entropy. Permutation entropy (PE) [41] is a commonly derived motif-based metric and is calculated as

$$\mathrm{PE} = -\sum_j^{n!} p(j) \cdot \log(p(j)), \tag{3}$$

where $p(j)$ is the relative frequency of the motif pattern represented by j.

2.3.2. Ordinal Distance Dissimilarity. Ordinal distance-based dissimilarity [38] is a metric with close parallel to the benchmark asymmetry index and measures the dissimilarity between two motif series for different electrode pairs using

$$D_m(X, Y) = \sqrt{\frac{n!}{n!-1}}\sqrt{\sum_i^{n!}\left(p_x(i) - p_y(i)\right)^2}, \tag{4}$$

where $p_x(i)$ and $p_y(i)$ are the relative frequencies of the motif pattern represented by i in electrodes X and Y, respectively, and n is the degree of the motif. In order to compare against the benchmark asymmetry index, ordinal dissimilarity is calculated for the same electrode pairs reported in Section 2.2.

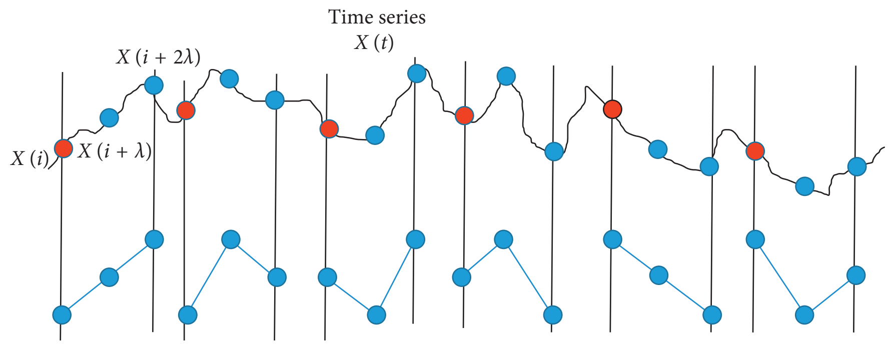

Figure 2: All motifs of degree $n = 3$ appearing in a time series.

2.3.3. Motif Synchronization. Functional connectivity gives insight into the dynamic neural interaction of the different regions of the brain. Recently, motif synchronization has been proposed as a functional connectivity analysis tool [50] and measures the simultaneous appearance of motifs in two time series. For two motif series X_m and Y_m, $c(X_m; Y_m)$ is defined as the highest number of times in which the same motif can appear in Y_m shortly after it appeared in X_m for different delay times, i.e.,

$$c(X_m; Y_m) = c_{XY} = \max\left(\sum_{i=1}^{l_m} J_i^{\tau_0}, \sum_{i=1}^{l_m} J_i^{\tau_1}, \ldots, \sum_{i=1}^{l_m} J_i^{\tau_n}\right), \quad (5)$$

with

$$J_i^{\tau}(i) = \begin{cases} 1, & \text{if } X_{M_i} = Y_{M_{i+\tau}}, \\ 0, & \text{else.} \end{cases} \quad (6)$$

The time delay τ ranges from $\tau_0 = 0$ to τ_n, where τ_n is the maximum value to be considered, and l_m is the size of the time varying window within the time series. Similarly, the opposite measure c_{YX} can be obtained by changing only the order of the time series to $Y_{M_i} = X_{M_{i+\tau}}$. Finally, the degree of synchronization Q_{XY} and the synchronization direction q_{XY} are given by

$$Q_{xy} = \frac{\max(c_{XY}, c_{YX})}{l_m},$$
$$q_{XY} = \begin{cases} 0, & \text{if } c_{XY} = c_{YX}, \\ \operatorname{sign}(c_{XY} - c_{YX}), & \text{else.} \end{cases} \quad (7)$$

The degree of synchronization, Q_{XY}, is scaled between 0 and 1, with 0 representing no interaction and 1 suggesting very high interactions. Feature q_{XY}, in turn, gives the direction of information flow, with 0 indicating no preferred direction, 1 indicating direction from X to Y, and −1 indicating direction from Y to X. For our calculation, τ_n has been chosen as 5 and the window size l_m is chosen as 256.

2.3.4. Graph Features. The different functional connections obtained by motif synchronization analysis can be further extended by means of graph-theoric analysis, where each electrode on the scalp represents a node on the brain network. Weighted graphs have weights that represent the level of interaction between the two nodes. Edges with smaller weights are believed to represent noisy/spurious connections [51], thus a thresholding is done to obtain an unweighted graph. Previously, graph-theoretic features have been explored for affect recognition based on EEG spectral coherence measures [52]. Graph-theoretic analysis based on motifs, however, has yet to be explored, thus both weighted and unweighted graphs (thresholded to the average value of the graph weighted) are tested herein. An advantage of motif synchronization over more popular connectivity approaches is the ability it provides to measure direction of information flow for the different nodes in the brain network. From the weighted and unweighted graphs, several features are extracted, namely,

(i) Degree of connectivity (k): the degree of connectivity is defined as k_i where i is a given node. For the unweighted network, it is calculated as

$$k_i = \sum_{j \epsilon N_e} a_{ij}, \quad (8)$$

where N_e represents the nodes in the network and $a_{ij}, i \neq j$ represents the value of the unweighted adjacency matrix. For the weighted network, the formula is

$$k_i^w = \sum_{j \epsilon N_e} w_{ij}, \quad (9)$$

where instead of a_{ij}, the weights w_{ij} assigned to each edge are used. The average degree of connectivity for the whole network is used as a feature in our analysis.

(ii) Clustering coefficient (C): the mean clustering coefficient for an unweighted network is given by

$$C = \frac{1}{N_e} \sum_{i}^{N_e} \frac{e_i}{k_i(k_i - 1)}, \quad (10)$$

where e_i is the number of existing edges between the neighbors of i and k_i is the degree of connectivity for the unweighted network. For a weighted network, the clustering coefficient value is given by

$$C^w = \frac{1}{N_e}\sum_i^{N_e}\frac{t_i^w}{k_i^w(k_i^w-1)}, \quad (11)$$

where t_i is calculated as

$$t_i = \frac{1}{2}\sum_{j,h\in N_e}\left(w_{ij}w_{jh}w_{hi}\right)^{1/3}, \quad (12)$$

and represents the geometric mean of the triangles constructed from the edges around a particular node i, and k_i^w represents the weighted degree of connectivity.

(iii) Transitivity (Tr): transitivity is defined as the ratio of "triangles to triplets" in a network and is defined as

$$\mathrm{Tr} = \frac{3\lambda}{k(k-1)}, \quad (13)$$

where λ represents the number of triangles in network, while k is the average degree of connectivity (weighted or unweighted) of a network. Transitivity is a global measure of the clustering coefficient and is equal to it when the degree of connectivity of all nodes is equal to one another.

(iv) Characteristic path length (L): for an unweighted network, L is given by

$$L = \frac{1}{N_e(N_e-1)}\sum_{j=1 i\neq j}^{N_e} d_{ij}, \quad (14)$$

with d_{ij} being the minimum amount of edges required to connect nodes i and j and is replaced by the shortest weighted path length d_{ij}^w for the weighted characteristic path length L^w.

(v) Global efficiency (G): this is calculated using the inverse of the shortest weighted or unweighted path for the network, i.e.,

$$G = \frac{1}{N_e(N_e-1)}\sum_{j=1 i\neq j}^{N_e} d_{ij}^{-1}, \quad (15)$$

where $d_i j$ is replaced by the shortest weighted path length d_{ij}^w for weighted global efficiency measure.

(vi) Small-world features: the work in [53] has shown that human brain networks exhibit small-world characteristics. A small-world network is characterized by a high clustering coefficient and a small average path length from one node to another [54]. Here, three small-world features are computed, namely, (i) the small-world characteristics length:

$$L_s = \frac{L}{L_{\mathrm{rand}}}, \quad (16)$$

(ii) the small-world clustering coefficient:

$$C_s = \frac{C}{C_{\mathrm{rand}}}, \quad (17)$$

and (iii) the small-worldness of a network [55]:

$$S = \frac{C_s}{L_s}, \quad (18)$$

where C_{rand} and L_{rand} are the corresponding clustering coefficient and characteristic path length values for a random network, respectively.

(vii) Direction of flow (DoF): As motif synchronization also provides the direction of information flow in the brain network graph, a simple feature is explored here to represent the overall response of the brain network as either receiving or transmitting information, on average. DoF is defined as

$$\mathrm{DoF} = \sum_{ij} q_{ij}, \quad (19)$$

where q_{ij} is defined as the direction of information flow with 1 representing information flowing from i to j, −1 representing information flow in the opposite direction, and 0 being no preferred information flow direction.

Table 1 provides a summary of the number of features extracted for each feature group and subgroup.

2.4. Feature Selection. Previous work has shown that motif features convey complementary information to other amplitude- and rate-of-change-based features [40, 42]. As such, we explore the effects of combining the proposed motif-based features with the benchmark ones. Given the small dataset size, however, it is important to avoid issues with curse of dimensionality and overfitting; thus, feature selection is required. Here, three feature selection strategies have been explored:

(1) ANOVA-based feature ranking and selection: this selection method is based on calculating the significance of the input features with respect to the output values and returning the ranked features according to their obtained p values.

(2) Minimum redundancy maximum relevance (mRMR) feature selection: the mRMR is a mutual information-based algorithm that optimizes two criteria simultaneously: the maximum-relevance criterion (i.e., maximizes the average mutual information between each feature and the target vector) and the minimum-redundancy criterion (i.e., minimizes the average mutual information between two chosen features). The algorithm finds near-optimal features using forward selection with the chosen features maximizing the combined max-min criteria. Previous work showed mRMR paired with a support vector machine (SVM) classifier [56] achieved the best performance in EEG-based emotion recognition tasks [57].

Table 1: Summary and grouping of features extracted.

Feature name	No. of features	Group
(Weighted) graph features	20	Motif based features
(Unweighted) graph features	20	
Direction of flow	4	
Small-world features	12	
Permutation entropy	4	
Ordinal distance dissimilarity	48	
Spectral band power ratio	5	Benchmark spectrum based features
Shannon entropy	1	
Spectral power	4	
Asymmetry index	48	

(3) Recursive feature elimination (RFE): given an external estimator that assigns weights to features, the least important features are pruned from the current set of features. The procedure is recursively repeated on the pruned set until the desired number of features to select is reached. This technique considers the interaction of features with the learning algorithm to give the optimal subset of features. Since recursive training and feature elimination is required, this method takes a significant amount of runtime.

For the experiments herein, 90% of the data is set aside for feature selection and classifier training and the remaining 10% is left aside for testing. The split was performed with a random seed of 0 using the scikit-learn function in Python. The best feature selection algorithm and its corresponding optimal number of features are then selected by grid search. Classifier training and different fusion schemes are described next.

2.5. Classification. SVMs have been widely used for affective state recognition [57] and are explored herein as well. Given their widespread use, a detailed description is beyond the scope of this paper and the interested reader is referred to [58] and references therein for more details. Here, SVM classifiers are trained on two different binary classification problems, namely, discriminating between low and high valence states and low and high arousal states. For our study, a radial basis function (RBF) kernel was used and implemented with the scikit-learn library in Python [59]. As we are interested in exploring the benefits of the proposed motif features and comparing them against benchmark features, we do not perform classifer hyperparameter optimization and use default parameters instead, namely, $\lambda_{\text{SVM}} = 1$ and $\gamma_{\text{RBF}} = 0.01$.

Moreover, as the DEAP database relies on 9-point scale ratings, it has typically been the case where the midpoint is considered as a threshold, where ratings greater than the threshold are considered "high," and those below are considered "low". As was recently emphasized in [4], however, subjects have their own internal biases, thus leading to varying scales for grading and, consequently, different thresholds per participant. For example, as reported in [4], by using a midpoint threshold value of 5, a 60/40 ratio of high/low levels was obtained across all participants. In turn, if an individualized threshold was used corresponding to the value in which an almost-balanced high/low ratio was achieved per participant, improved results were achieved [60]. Figure 3, for example, depicts the threshold found for each participant for arousal and valence in this latter scenario. As can be seen, on average, a threshold of 5 was most often selected, though in a few cases, much higher or much lower values were found, thus exemplifying the need for the individualized approach used herein.

2.6. Fusion Strategies. Here, we explore three different types of fusion strategies to combine motif-based and benchmark spectrum-based features, which are described below.

2.6.1. Feature Fusion. As the name suggests, this corresponds to the direct combination of motif and benchmark features prior to feature selection.

2.6.2. Score-Level Fusion. The weighted decision fusion method proposed in [61] has been used. According to this technique, the fusion classification probability p_0^x for $x \epsilon [0, 1]$ for each class $x \epsilon 1, 2$ can be denoted by

$$p_0^x = \sum_{i=1}^{N} \alpha_i p_i^x t_i, \tag{20}$$

where i is the index of a particular feature group, N is the total number of groups used, and α_i are the weights corresponding to each group ($\sum_i^N \alpha_i = 1$). The parameter t_i is the training set performance of a particular feature group such that the fusion probabilities for all classes sum up to unity and is given by

$$t_i = \frac{F_i}{\sum_i^N \alpha_i F_i}, \tag{21}$$

where, $F1$ is the $F1$-score obtained on the training set using a particular feature group. The weight space was searched for best performance as this is indicative of the contribution to the outcome made by each of the feature groups.

2.6.3. Output Associative Fusion. Psychological evidence has suggested a strong intercorrelation between the valence and arousal dimensions [62–65]. As such, the output associative fusion (OAF) method has been used to model the correlations for continuous prediction of valence and arousal scales [66]. The OAF framework has been explored here and is depicted by the block diagram in Figure 4. As can be seen, first individual classifiers make the valence and arousal predictions for each individual feature group. This is then followed by a final prediction step which considers both the valence and arousal dimensions in order to better predict each of the two outputs.

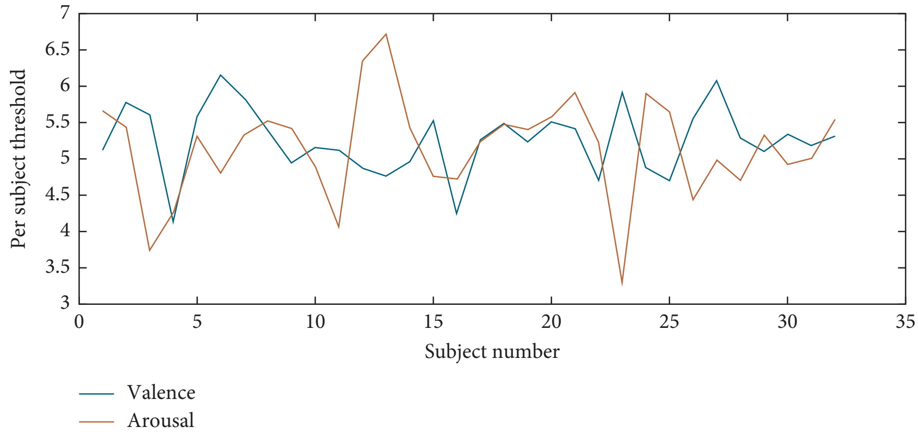

FIGURE 3: Threshold variation for each subject for valence (blue) and arousal (orange) dimensions.

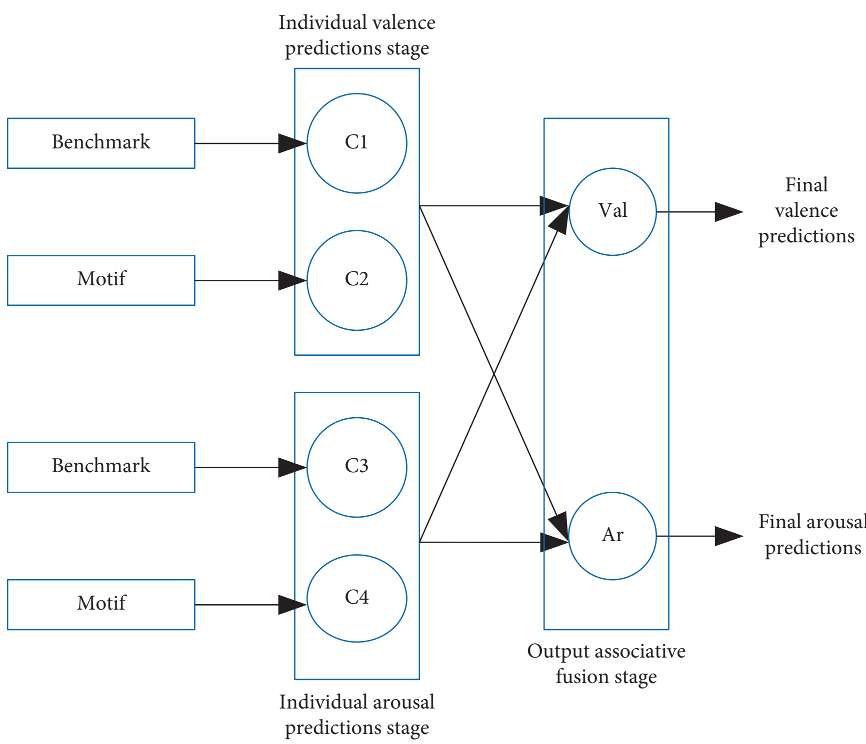

FIGURE 4: Block diagram of OAF strategy for the two feature groups.

2.7. Figure of Merit. Balanced accuracy (BACC) has been used as the performance metric as it takes into account class unbalances. Balanced accuracy corresponds to the arithmetic mean of the classifier sensitivity and specificity, i.e.,

$$\mathrm{BACC} = \frac{\mathrm{sens} + \mathrm{spec}}{2}, \tag{22}$$

where

$$\begin{aligned} \mathrm{sens} &= \frac{\mathrm{TP}}{P}, \\ \mathrm{spec} &= \frac{\mathrm{TN}}{N}, \end{aligned} \tag{23}$$

with $P = \mathrm{TP} + \mathrm{FN}$ and $N = \mathrm{FP} + \mathrm{TN}$, and TP and FP correspond to true and false positives, respectively, while TN and FN correspond to true and false negatives.

To test the significance of the attained performances against chance, an independent one-sample t-test against a random voting classifier was used ($p \leq 0.05$), as suggested in [18]. In order to have a more generalized performance of the classifier, once the feature selection step is performed, classifier training and testing are performed 100 times with different train/test partitioning. This setup provides a more generalized performance of the features and their invariance to the training set used. The BACC values reported in the tables correspond to the mean $\pm$ the standard deviation of all BACC values attained on the test set over all of the 100 iterations.

3. Results and Discussion

In this section, we show and discuss the obtained results in terms of impact of feature selection, feature group, and fusion strategy on overall performance.

3.1. Feature Selection. As mentioned previously, three different feature selection schemes were explored and tested herein. Feature selection was implemented in the benchmark features alone, proposed motif feature alone, and in the combined benchmark-motif set. The optimal BACC values obtained are shown in Tables 2–4, respectively, along with the final number of features (nofs) used in the models.

As can be seen, for ANOVA-based feature selection, fewer than 10 features were used in the models for both valence and arousal dimensions with the benchmark features, thus representing roughly one-sixth of the total amount of available features. For the motif group, in turn, roughly 40 were shown to be useful, thus amounting to roughly one-third of the available feature pool. When combining both feature sets, the optimal model also relied on roughly 40 features, thus one quarter of the available feature pool.

The mRMR algorithm, in turn, generally resulted in fewer top features but with similar overall BACC, thus corroborating the results in [56, 57]. For the benchmark feature set, for example, BACC ≈ 0.54 was achieved with just three features for valence, thus in line with the ≈ 0.55 achieved with ANOVA-selected features. For arousal and motif features, similar BACC was achieved, but relying on roughly half the number of features relative to ANOVA-based selection. With the combined feature set, in fact, improved BACC was achieved for the arousal dimension but with fewer than half the number of features chosen by ANOVA.

Lastly, RFE selection typically resulted in the highest accuracy with the best BACC vs. nof tradeoff. This is expected as RFE considers the interaction of features among themselves and the final outcome. Overall, the best accuracy was achieved with the combined set, followed closely by the models trained on the proposed motif features. These findings corroborate the complementarity of the two different feature types and show the importance of motif features for affective state recognition.

A one-way ANOVA was computed between the different pairs of feature selection algorithms (ANOVA vs. mRMR, ANOVA vs. RFE, and RFE vs. mRMR) for the benchmark, motif, and combined feature sets to assess the algorithm performance. For the benchmark feature set, in the arousal dimension, the three algorithms perform similarly with no statistical differences observable. However, for the valence dimension, the RFE performs significantly better than the mRMR algorithm ($p_{\mathrm{val}} < 0.05$), while there are no significant differences observed between RFE and ANOVA performances, the RFE obtains a similar performance with fewer features. For the motif feature set, in the arousal dimension, we observe the RFE performs significantly better than both ANOVA ($p_{\mathrm{val}} < 0.01$) and mRMR ($p_{\mathrm{val}} \approx 0.01$). In the valence dimension, we observe a significant difference in algorithm performance between RFE and mRMR; however, the performance of ANOVA is not significant compared to both the algorithms. However, we again observe that RFE gives similar performance to ANOVA with half the number of features, thus being more efficient. Finally, for the combined feature set, in the arousal dimension, both mRMR and RFE perform significantly better than ANOVA ($p_{\mathrm{val}} < 0.01$) while there are no differences between mRMR and RFE performances with mRMR reaching equivalent performance with fewer features than RFE. In the valence dimension, we observe ANOVA ($p_{\mathrm{val}} \approx 0.05$) and RFE ($p_{\mathrm{val}} < 0.01$) perform significantly better than mRMR, while there is no performance difference between ANOVA and RFE in this case. It is interesting to note that the number of features for both ANOVA and RFE is almost the same. In general, we find the RFE gives significant or equal performance compared to ANOVA and mRMR with fewer number of features. For feature fusion, the algorithm giving the highest average performance has been considered the algorithm of choice.

Tables 5 and 6, in turn, report the top 20 features used in the models that achieved the best BACC for valence and arousal, respectively. As can be seen for valence (Table 5), the γ/β and β/θ power ratios showed to be important, along with alpha-band spectral power. This corroborates previous work

Table 2: Comparison of different feature selection algorithms and number of features (nof) for benchmark feature set.

Feature groups	Valence		Arousal	
	BACC	nof	BACC	nof
ANOVA	0.5490	9	0.5316	8
mRMR	0.5404	3	0.5281	4
RFE	0.5531	3	0.5318	15

Table 3: Comparison of different feature selection algorithms and number of features (nof) for motif-based feature set.

Feature groups	Valence		Arousal	
	BACC	nof	BACC	nof
ANOVA	0.5818	40	0.5362	42
mRMR	0.5757	44	0.5385	20
RFE	0.5872	20	0.5500	16

Table 4: Comparison of different feature selection algorithms and number of features (nof) for combined benchmark-motif feature set.

Feature groups	Valence		Arousal	
	BACC	nof	BACC	nof
ANOVA	0.5930	40	0.5446	39
mRMR	0.5816	29	0.5645	17
RFE	0.6010	38	0.5598	20

Table 5: Top 20 features used in the best valence models for the different feature groups.

Benchmark (nof = 3, FS = RFE)	Motif (nof = 20, FS = RFE)	Combined (nof = 38, FS = RFE)
γ/β	Tr (α)	C (α)
β/θ	PE (γ)	γ/β
Spectral power (α)	G^w (θ)	$(\gamma+\beta)/\theta$
	k^w (θ)	α/θ
	C^w (θ)	G^w (θ)
	C (θ)	PE (γ)
	PE (β)	$D_m(P3, P4)$ (β)
	S (β)	$D_m(\mathrm{O}1, \mathrm{O}2)$ (θ)
	S (γ)	k^w (θ)
	L_s (γ)	Tr^w (θ)
	$D_m(T7, T8)$ (γ)	C (θ)
	$D_m(Fc5, Fc6)$ (β)	Spectral power (α)
	DoF (θ)	C (β)
	$D_m(P3, P4)$ (β)	k_w (β)
	$D_m(\mathrm{O}1, \mathrm{O}2)$ (β)	DoF (θ)
	$D_m(F3, F4)$ (θ)	C^w (θ)
	Tr^w (θ)	$\mathrm{AI}(C3, C4)$ (β)
	L_s (θ)	$\mathrm{AI}(P3, P4)$ (γ)
	$D_m(\mathrm{O}1, \mathrm{O}2)$ (θ)	$D_m(F3, F4)$ (θ)
	$D_m(F3, F4)$ (β)	$D_m(T7, T8)$ (γ)

Table 6: Top 20 features used in the best arousal models for the different feature groups.

Benchmark (nof = 15, FS = RFE)	Motif (nof = 16, FS = RFE)	Combined (nof = 17, FS = mRMR)
$(\alpha+\beta)/\gamma$	PE (β)	$D_m(\mathrm{O}1, \mathrm{O}2)$ (θ)
$(\gamma+\beta)/\theta$	Tr (β)	DoF (γ)
AI(O1, O2) (β)	C_s (β)	k^w (θ)
γ/β	$D_m(T7, T8)$ (α)	DoF (α)
AI(P7, P8) (γ)	L^w (α)	$D_m(T7, T8)$ (β)
AI(F3, F4) (β)	$D_m(FC1, FC2)$ (α)	$D_m(P3, P4)$ (β)
β/θ	PE (θ)	$D_m(T7, T8)$ (α)
Spectral power (β)	$D_m(P7, P8)$ (γ)	PE (θ)
AI(Cp5, Cp6) (θ)	L^w (γ)	$D_m(F3, F4)$ (θ)
AI(FC1, FC2) (α)	C^w (β)	$D_m(C3, C4)$ (γ)
AI(P3, P4) (θ)	$D_m(C3, C4)$ (β)	C^w (θ)
AI(P3, P4) (β)	C (α)	DoF (θ)
AI(C3, C4) (θ)	$D_m(Cp1, Cp2)$ (β)	L_s (α)
AI(Cp1, Cp2) (α)	$D_m(P3, P4)$ (α)	$D_m(Fc5, Fc6)$ (θ)
AI(T7, T8) (γ)	$D_m(F7, F8)$ (α)	C^w (α)
	k (α)	$D_m(Fc5, Fc6)$ (α)
		$D_m(Fc5, Fc6)$ (γ)

which has linked γ/β and β/θ to audio comprehension [67, 68] and, consequently, to perceived valence in low-quality text-to-speech systems [5]. For the motif-based features, in turn, small-worldness (γ and β band) and weighted graph features (θ band) showed to be important, alongside PE for γ and β bands. Previous studies have indicated to a time-locked theta-band synchronization occurring during affective picture processing [69] related to the valence dimension. This synchronization seems to be captured by motif-based graph-theoretic and ordinal similarity features, as eight of the top 20 features come from the θ band.

Lastly, for the combined feature set, it can be seen that a mix of benchmark and motif features are selected, thus exemplifying the complementarity of the two feature sets. Over the entire nof = 38 features used in the model, 11 are benchmark features and 27 are motif-based features. In particular, 17 of the top motif features showed importance across the motif and combined sets, as well as all of the top benchmark features across benchmark and combined sets. Additionally, for the combined set, 6 asymmetry features are also in the top selected features; of these, 3 are from the same electrode pairs as the top ordinal dissimilarity measures, thus showing a complementary nature of the two feature sets. The power ratios α/θ and $(\gamma+\beta)/\theta$ also appear in the combined feature sets. From the motif feature sets, apart from the overlapping features, additional D_m and clustering coefficient features appear in the combined feature set along with two DoF features from the θ and γ bands.

For arousal (Table 6) and benchmark feature set, almost all power ratios showed to be important alongside several asymmetry index features, particularly those in the frontal and parietal regions. Such findings corroborate previous literature showing the relationship between (i) arousal and frontal asymmetry [29] in alpha band (e.g., [70]) and other bands (e.g., [71]), (ii) an inherent asymmetry in the right parietal-temporal regions, responsible for modulating autonomic and behavioural arousal, and (iii) arousal and EEG band power ratios [72].

For motif-based features, in turn, roughly half the top features corresponded to ordinal distance dissimilarity measures, thus corroborating the literature on EEG asymmetry and arousal [71, 73]. Moreover, the majority of the top features are from the beta and alpha bands (13 of the top 16), which have been linked to attention-based arousal changes [74] and to changes in visual selective attention [75, 76], which is very closely linked to arousal [77].

Interestingly, for the combined sets, none of the top features were from the benchmark feature set, thus suggesting that the proposed motif features conveyed improved arousal information relative to benchmark features. The majority of the features corresponded to ordinal distance dissimilarity across all EEG bands. Moreover, the best achieving model for motif only and combined feature sets were attained using different feature selection algorithms (RFE and mRMR, respectively). Notwithstanding, two features coincided as being important, namely, PE(θ), $D_m(T7, T8)(\alpha)$, and a third showed similar behaviour ($C(\alpha)$ and $C^w(\alpha)$), thus suggesting their importance for arousal prediction. In the combined set, θ showed up in seven of the nof = 17, thus also corroborating previous findings [71, 73]. Lastly, most of ordinal dissimilarity features come from frontal, parietal, or temporal regions, thus in line with previous research connecting parietal-temporal regions with autonomic and behavioural arousal, as well as frontal regions with arousal [78].

3.2. Individual Feature Groups. So far, we have explored the performance achieved with benchmark, motif, and combined feature sets. It is interesting, however, to gauge how each individual feature subgroup contributes toward affective state recognition. Table 7 reports the balanced

Table 7: Performance comparison of different individual feature groups and subgroups.

Feature (sub) group	Valence		Arousal	
	BACC	nof	BACC	nof
Weighted graph	0.5662*	2	0.5066	6
Unweighted graph	0.5581*	8	0.5006	6
Small world	0.5533	6	0.5208	2
Other motif	0.5578*	9	0.5632*	12
Spectral power, AI	0.5400	15	0.5344	11
Power ratio	0.5467	3	0.5000	1

*Cases where the results are significantly greater than a random voting classifier.

accuracy for each individual feature subgroup for the best achieving model found after RFE feature selection.

As can be seen, for valence, the weighted and unweighted graph features achieve similar performances though the model based on the former feature subgroup relies on nof = 2, as opposed to nof = 8. In fact, all motif-based features achieved similar performance, with small-worldness features being the only ones not significantly better than the benchmark (i.e., $p < 0.01$ and indicated by an asterisk in the table). For arousal, in turn, it is observed that graph and small-world feature subgroups do not significantly improve over the benchmark, whereas other motif features, such as permutation entropy and ordinal distance dissimilarity, do. Overall, models relying on these two feature subgroups showed to provide the most discriminatory information for valence and arousal models.

Additionally, among the EEG features, we observe that SE, θ, and γ spectral power never appear as top selected features. This could be due to the fact that power and entropy measures are averaged over all electrodes, thus removing any spatial information relevant for the features. Notwithstanding, averaging ensures that the proposed features are invariant and robust to the electrode set considered, as seen with the global graph-theoretic features using motif synchronization. For valence, in turn, we observe that none of the AI features show up among the top in the EEG feature set alone scenario. When using only motif features, on the other hand, seven D_m features (out of nof = 20) are selected, thus suggesting that motif features may carry more relevant asymmetry signatures for the task at hand. With the combined feature set, it can be seen that proposed features from all groups appear in the top list for both valence and arousal.

3.3. Fusion Strategies. As mentioned previously, three fusion schemes were explored: feature, score, and output associative fusion. Tables 2–4 show the effects of feature fusion and the gains attained with the combined set relative to using only a feature group individually. For the valence dimension, for example, gains of 8.6% and 2.4% were achieved with feature fusion relative to using benchmark and motif feature alone, respectively. As shown in Table 5, the model based on the combined set relied on features from both feature groups, thus emphasizing their complementarity for valence prediction.

For arousal, feature fusion resulted in more modest gains relative to the benchmark (i.e., 6.1%) and to motif features (2.6%). Interestingly, the best model relied on mRMR selected features which did not include benchmark ones. The second best model, on the other hand, was achieved with RFE feature selection and the top 20 features included seven benchmark ones (i.e., $(\alpha+\beta)/\gamma$, β/θ, AI(01, 02) (β), AI(Fc1, Fc2) (β), AI(C3, C4) (γ), AI(F3, F4) (β), and AI(Fc1, Fc2) (γ)), three of which overlap with the top features selected from the benchmark alone set. The remaining 13 features were from the motif group, nine of which showed to be top features selected in the motif alone set, namely, PE(β), PE(θ), $L^w(\alpha)$, $L^w(\gamma)$, $C_s(\beta)$, $D_m(P7, P8)(\gamma)$, $D_m(Fc1, Fc2)(\alpha)$, $D_m(T7, T8)(\alpha)$, and $D_m(C3, C4)(\beta)$. By comparing the feature sets selected by mRMR and RFE, it seems the former is capable of removing redundancies that may exist between D_m and AI asymmetry features but favouring the motif ones as they provide maximum relevance. Four features overlap between the two feature selection algorithms, namely, PE(θ), $D_m(Fc1, Fc2)(\alpha)$, $D_m(T7, T8)(\alpha)$, and $D_m(C3, C4)(\beta)$, thus further suggesting their importance for the task at hand.

For decision fusion, in turn, the weight space was searched in steps of 0.1, and it was found that for valence, the benchmark feature set resulted in a weight of 0.2 (i.e., 0.8 for motif features), whereas a weight of 0.3 was found for arousal (i.e., 0.7 weight for motifs). Such findings highlight the importance of motif features over the benchmark ones for both valence and arousal prediction. The BACC results shown in Table 8 show the effect of score-level fusion over feature fusion. As can be seen, gains are attained only for the arousal dimension, thus further suggesting the complementarity of the two feature groups. For comparison purposes, a random voting classifier is also shown for comparison, and all attained BACCs are shown to be significantly better than chance ($p \leq 0.01$).

Lastly, the output associative fusion method was outperformed by all other fusion methods, despite showing to be significantly better than chance. Notwithstanding, for the valence dimension, it achieved results similar to score-level fusion without the need for an exhaustive search of weights. Here, only two feature groups were explored, thus such advantage may become more critical in more complex scenarios involving additional feature groups (e.g., amplitude modulation [4]). Overall, feature-level fusion showed to be the best strategy for valence and was observed to be significantly better than score-level ($p_{\text{val}} \approx 0.01$) and output associative fusion ($p_{\text{val}} \approx 0.01$), whereas score-level fusion for arousal was significantly better than both feature ($p_{\text{val}} < 0.01$) and output associative fusion ($p_{\text{val}} < 0.01$). In both cases, the proposed motif features showed to provide important discriminatory information and to be complementary to existing benchmark features.

3.4. Comparison with Previous Work. There is increased interest in affective state recognition from EEG, and different methods have been recently proposed in the literature, many of which have also relied on the DEAP database. The work in [20], for example, explored graph-theoretic features computed from magnitude square coherence values. Such

Table 8: Performance comparison of different fusion methods and a random voting classifier with chance levels.

Fusion methods	Valence BACC	Arousal BACC
Feature	0.6010	0.5645
Score	0.5875	0.5807
OAF	0.5873	0.5568
Random voting	0.5018	0.5028

features were shown to outperform several other spectral-based and wavelet-based methods, and on the DEAP dataset, they achieved an $F1$ score of 0.63 for valence and 0.60 for arousal using an SVM classifier. For direct comparisons, the best models proposed herein achieved an $F1$ score of 0.5883 for valence and 0.6960 for arousal, thus representing a 16% increase in arousal, but a drop of 6.6% for valence. It is important to emphasize, however, that the results in [20] relied on leave-one-sample-out (LOSO) cross validation; thus, the reported results are likely higher than what are achieved with the method described herein.

More recently, in turn, the work in [4] proposed new amplitude modulation coupling features to gauge connectivity patterns as a function of valence and arousal. BACC values of 0.594 and 0.598 were reported for valence and arousal, respectively, using SVM classifiers and feature fusion, whereas somewhat lower values were attained with score-level fusion for arousal (no changes seen for valence). The values reported in [4] were obtained using a LOSO cross-validation scheme. Under the same testing setup, our proposed schemes achieve a BACC of 0.614 and 0.581 for valence and arousal, thus representing a 3.3% increase and a 2.85% decrease in performance, respectively. It is important to point out that motif-based methods did not rely on amplitude or rate of change information; therefore, fusing them with amplitude modulation features might further improve performance.

3.5. Study Limitations. This work has taken the first steps at gauging the advantages of motif-based features over exiting spectrum-based benchmarks. To this end, no optimization was done on the classifiers per se in order to directly compare performances achieved with the same classifier setup but with varying feature inputs. As such, it is expected that further gains may be observed not only with classifier hyperparameter optimization but also with more complex classification methods or alternate fusion schemes. The work in [20], for example, showed that relevance vector machines (RVMs) and fusion of RVMs outperformed SVMs, especially for the arousal dimension. Recent work using deep neural networks has also shown to be a promising route [79]. Future work should explore these more complex machine learning principles combined with motif-based features.

4. Conclusion

In this work, we propose the use of motif series and graph theoretic features for improved valence and arousal level predictions. Experiments on the widely used DEAP database show the proposed motif features outperforming several spectrum-based benchmark features. Feature-level fusion showed to provide important accuracy gains for both emotional dimensions, thus highlighting the complementarity of the two feature groups for affective state recognition. Score-level fusion, in turn, provided further improvements for arousal prediction. Overall, gains of 8.6% for valence and 9.2% for arousal could be achieved with the proposed system relative to the benchmark, and gains up to 16% could be achieved relative to prior art.

Data Availability

The DEAP database used to support the findings of this study were supplied by I. Patras under license and so cannot be made freely available. Requests for access to these data should be made to I. Patras (i.patras@qmul.ac.uk) by filling in and sending the end user license agreement at http://www.eecs.qmul.ac.uk/mmv/datasets/deap/download.html.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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