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ADVANCED REVIEW

A gateway to consumers' minds: Achievements, caveats, and prospects of electroencephalography-based prediction in neuromarketing

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In the last decade, the field of consumer neuroscience, or neuromarketing, has been flourishing, with numerous publications, academic programs, initiatives, and companies. The demand for objective neural measures to quantify consumers' preferences and predict responses to marketing campaigns is ever on the rise, particularly due to the limitations of traditional marketing techniques, such as questionnaires, focus groups, and interviews. However, research has yet to converge on a unified methodology or conclusive results that can be applied in the industry. In this review, we present the potential of electroencephalography (EEG)-based preference prediction. We summarize previous EEG research and propose features which have shown promise in capturing the consumers' evaluation process, including components acquired from an event-related potential design, inter-subject correlations, hemispheric asymmetry, and various spectral band powers. Next, we review the latest findings on attempts to predict preferences based on various features of the EEG signal. Finally, we conclude with several recommended guidelines for prediction. Chiefly, we stress the need to demonstrate that neural measures contribute to preference prediction beyond what traditional measures already provide. Second, prediction studies in neuromarketing should adopt the standard practices and methodology used in data science and prediction modeling that is common in other fields such as computer science and engineering.

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Economics > Interactive Decision-Making
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1 | INTRODUCTION

Consumer neuroscience, or neuromarketing as it is termed outside of academia, is a relatively new field. In the last decade it has been flourishing, with more publications appearing each year and a growing community of scientists conducting studies in the field. This has resulted in an abundance of meta-analyses and reviews (e.g., Ariely & Berns, 2010; Fortunato, Giraldi, & Oliveira, 2014; Genevsky & Knutson, 2018; Harris, Ciorciari, & Gountas, 2018; Hsu, 2017; Hsu & Yoon, 2015; Javor, Koller, Lee, Chamberlain, & Ransmayr, 2013; Karmarkar & Plassmann, 2017; Karmarkar & Yoon, 2016; Lee, Brandes, Chamberlain, & Senior, 2017; M. H. Lin, Cross, Jones, & Childers, 2018; Plassmann, Venkatraman, Huettel, & Yoon, 2015; Schneider & Woolgar, 2015; Smidts et al., 2014). In the last 5 years, top business schools (e.g., The Wharton School, Kellogg School of Management, Rotman School of Management, Fox School of Business, MIT Management, RSM at Erasmus, and more) have been hiring an increasing number of neuroscientists and have launched new programs and initiatives in an attempt to apply neuroscience to business applications and theories. Dozens of popular books have been written on the topic (see Google Search), and new companies are opening at an ever-increasing pace (see the list on the NMSBA website or in Hsu, 2017). Giant companies, like Nielsen and Ipsos, have formed special divisions dedicated to neuromarketing research (see Nielsen and Ipsos).

The field has emerged and developed due to two somewhat unrelated forces. First, within the classic marketing industry, there is a high demand for novel and superior methods that can predict the success of marketing campaigns or new products. It is well known that many campaigns do not reach their goals, either falling short of the desired impact, attaining negative return on investment or even failing entirely (Stevens & Burley, 1997). For example, there is ample evidence showing high failure rates for new products—anywhere between 40 and 80% (Castellion & Markham, 2013; Crawford, 1977). Such high failure rates may lead to very severe economic consequences, amounting to billions of dollars (Clancy, Krieg, & Wolf, 2006), as well as a loss of reputation (Heidenreich & Spieth, 2013). In fact, many reviews concerning consumer neuroscience have discussed in length the current problems in marketing research and the role that neuroscience can assume in alleviating them (Karmarkar & Plassmann, 2017; Karmarkar & Yoon, 2016; Plassmann et al., 2015; Smidts et al., 2014). This important discussion will not be the focus of this review, although we recommend these reviews for further reading.

Second, within academia, marketing experts Gerald Zaltman and Stephen Kosslyn had already developed a keen interest in employing neuroscientific methods, filing a patent in August 2000 for "neuroimaging as a means for validating whether a stimulus such as advertisement, communication, or product evokes a certain mental response such as emotion, preference, or memory, to predict the consequences of the stimulus on later behavior such as consumption or purchasing." But even prior to this, Krugman (1971) was among the first marketing scholars to utilize electroencephalography (EEG) to examine the effectiveness of advertising. Specifically, he compared between the reaction of brain activity to TV commercials and print advertisement (Krugman, 1971). His classic study included a single subject and a single electrode; recently it was reproduced and extended by modern standards (Daugherty, Hoffman, Kennedy, & Nolan, 2018). Several years after Krugman's research, a team of communication researchers studied EEG responses to TV commercials in a variety of contexts, and presented EEG features related to attention, recall, emotion, recognition, learning, and verbal versus nonverbal components of the ads (Reeves, Lang, Thorson, & Rothschild, 1989; Reeves et al., 1985; Rothschild, Hyun, Reeves, Thorson, & Goldstein, 1988; Rothschild, Thorson, Reeves, Hirsch, & Goldstein, 1986). Eventually, the growing and increasingly influential field of neuroeconomics gave rise to a promising sub-field, consumer neuroscience, which can be considered its natural extension into marketing theory and real-world applications.

2 | HARNESSING NEUROSCIENTIFIC KNOWLEDGE TO INFORM MARKETING

Consumer neuroscience is concerned with various research topics, from the decision-making process and its complementary neural mechanisms, through the neural correlates of consumer behavior, to broader consumer questions (for a review of topics, see Hsu & Yoon, 2015; Karmarkar & Plassmann, 2017; Karmarkar & Yoon, 2016). In one major avenue of research, numerous studies have attempted to harness the basic knowledge of how the brain operates to real marketing applications; this, by using the fundamental principles and laws of our cognitive systems, and most importantly, the biological constraints of the nervous system. These applications may range from understanding which marketing message will succeed the most, what packaging to use, the best location on the shelf, or the color structure or text to use on a webpage design—to name a few. There are abundant examples of how we may harness neuroscientific knowledge of nervous system functioning to help marketing campaigns, packaging, design, etc.

As a simple example, we know that eye sight deteriorates as we grow older. Therefore, marketers need to use bigger fonts in packaging, webpages and advertisement for products aimed at the elderly. Additionally, we know the minimal presentation time required to allow the visual system to detect and process information (Bachmann, 1997; De Valois & De Valois, 1980; Schall, 1995; van der Helm, 2017; VanRullen & Thorpe, 2001). Presenting stimuli faster or at a higher frequency could be a waste of effort and money. Another example of applying neuroscientific knowledge in marketing sheds light on the (still controversial) effectiveness of subliminal advertisement. In subliminal presentations, one should take into account that even if it exerts some influence over the observer, neural activation and processing is limited (compared to supraliminal presentations) and will activate fewer brain regions for shorter periods of time (King, Pescetelli, & Dehaene, 2016; Nakamura et al., 2018; Van Opstal, de Lange, & Dehaene, 2011). Even if a behavioral effect is obtained due to subliminal presentations, it is very short lived and has to be measured promptly after presentation before it dissipates (Charles, Van Opstal, Marti, & Dehaene, 2013; Dehaene, 2014; van Gaal et al., 2014). Ultimately, research has shown that the subliminal effect can only be obtained for rewards that one desires at the time of the presentation, for instance, a food or beverage stimulus when one is hungry or thirsty (Winkielman, Berridge, & Wilbarger, 2005). These studies converge to the conclusion that subliminal advertising can only induce a very limited amount of influence on consumer behavior, and that marketers might be better off looking elsewhere. Dijksterhuis, Aarts, and Smith (2005) delve into this question in a chapter titled "The power of the subliminal: On subliminal persuasion and other potential applications" (Hassin, Uleman, & Bargh, 2005). They overview the relevant literature from marketing science and conclude that the effect of subliminal advertising may be negligible, but that in larger populations it may accumulate to sizable differences that could interest advertisers.

Another notable example is the application of knowledge of perceptual systems, memory, attention, and language processing in the context of the principles of saliency. The term saliency is defined as "the quality of being particularly noticeable or important." Advertisers can employ what our brain considers as salient, according to neuro-cognitive research. For example, it is known that saliency is relative (Borji, Sihite, & Itti, 2013; Eckstein, 2011; Evans et al., 2011; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Veale, Hafed, & Yoshida, 2017; Yarbus, 1967), that we attend more frequently to those parts of objects that are in the upper left/right corners of our visual field (Chambers, McBeath, Schiano, & Metz, 1999), that gaze fixations are biased towards the center of natural scene stimuli ("center bias") (Mannan, Wooding, & Ruddock, 1996; Mannan, Ruddock, & Wooding, 1997; Parkhurst, Law, & Niebur, 2002; Parkhurst & Niebur, 2003; Wooding, Ruddock, & Mannan, 1995), that we are often drawn to observe faces (Becker, Anderson, Mortensen, Neufeld, & Neel, 2011; Frank, Vul, & Johnson, 2009; Langton, Law, Burton, & Schweinberger, 2008), and that clutter will usually eliminate specific saliency (Bialkova, Grunert, & van Trijp, 2013). There is accumulating evidence that value formation and choice are influenced by the amount, type, and quality of information that is perceived by the visual system (Wedel & Pieters, 2012b). It has been shown that consumers' goals interact with their eye movements while watching ads (Pieters & Wedel, 2007), and the effects that different elements of ads (text, figures, logo, exposure time) have on eye movements have also been described (Wedel & Pieters, 2012a). Advertisers should also consider the number of objects or information they present in relation to people's inherent memory capacity (Luck & Vogel, 1997). These notions can lead to ad adjustments that increase desired engagement, in addition to manipulation of color, contrast, motion, orientation, intensity, and size of objects or images. Eventually, these ideas ripened into the notion of *saliency maps* (Itti & Koch, 2001; Koch & Ullman, 1987; Treisman & Gelade, 1980), and later on to computer codes that automatically analyze the saliency of an image. Moreover, there are several commercial companies offering to use saliency-map analysis for marketing research (EyeQuant, Neurosinc). For a further discussion of this line of research, there are some reviews that demonstrate the application of knowledge from cognitive neuroscience to the improvement of marketing efforts (Ariely & Berns, 2010; Plassmann et al., 2015; Plassmann, Ramsøy, & Milosavljevic, 2012).

3 | THE POTENTIAL OF NEUROSCIENTIFIC-BASED PREDICTIONS

Another major avenue of research, and what is usually meant by the term neuromarketing, is the notion that we can employ neural and other physiological measurements to improve the prediction of future marketing success above and beyond what is obtained by standard nonphysiological measurements, such as questionnaires, interviews, focus groups, and so on. The emphasis of this effort is not to replace current measurements, which have their advantages, but rather to introduce a new layer of predictive information that has been unobtainable so far. In the current review we focus on this avenue: the use of neural measures to improve the prediction of marketing success. We aim to show that considerable progress has been made in the ability to predict using neural data, but also that there is still a long way to go to achieve industry-applicable results.

Various neural methods and signals can be used towards this aim. We briefly review the different tools available today for neuromarketing studies, but subsequently focus on a single one, EEG, due to its relative advantages for marketers. Next, we examine the literature on popular features extracted from EEG recordings and their relation to subjective values and preferences. We follow this with three important distinctions regarding prediction studies and continue with a thorough review of the latest findings in EEG-based predictions of values. We conclude with a discussion of the field's challenges and provide suggestions for the road ahead.

Another comprehensive review of the application of EEG in consumer science has been published this year (M. H. Lin et al., 2018), and we recommend reading it alongside our own. In their review, Lin et al. follow the framework outlined by Plassmann et al. (2015), which consists of five general marketing applications of neuroscience research, as follows: (a) identifying mechanisms; (b) measuring implicit processes; (c) dissociating between psychological processes; (d) understanding individual differences; and (e) improving predictions of behaviors (Plassmann et al., 2015). While the review by Lin et al. delves into each point concisely, our survey can be viewed as an in-depth analysis and expansion of point 5 alone, as we discuss various topics related specifically to EEG-based prediction and examine studies that made such attempts. Lin et al. concentrate on various ways in which EEG research can inform marketers, such as research on attention, memory, attitudes, decision-making, emotions and more, while we attempt to establish how EEG can be expressly applied to the prediction of preferences. Particularly, Lin et al. focus on a specific type of EEG analysis, event-related potentials (ERP), and include a thorough review of related research and methodological considerations, while we present multiple candidates for EEG predictors, mostly focusing on spectral analysis.

Foremost, we present the reasons that are driving consumer neuroscience researchers to try and create an unbiased and objective methodology for the prediction of market success, and why this could greatly benefit consumer marketing research. Although standard marketing measures each have their own advantages and usefulness for prediction, they contain certain fundamental flaws that in many cases lead to biased conclusions. Consumer neuroscience aims to overcome these flaws using less biased neurophysiological measurements and to add an additional layer of information that is unobtainable when using standard measures. As mentioned, we will focus specifically on EEG and emphasize its achievements, but also draw attention to the challenges that have yet to be addressed in the field.

4 | CLASSIC MARKETING TECHNIQUES AND THEIR LIMITATIONS

Questionnaires are possibly the most frequently used method to elicit individual preferences and assess the potential of marketing and commercial success of products and ads. They are easy to distribute, cost efficient, practical, speedy, scalable, and enable access to enormous cohorts of subjects, relative to neuroscientific methods (Birmingham & Wilkinson, 2003). In fact, some neuroscientific studies show that questionnaires by themselves can explain much of the variance in consumer choices (Hakim et al., 2018; Venkatraman et al., 2015). Additionally, interviews are a popular qualitative technique in marketing research that offers valuable insights, yet they fall short in obtaining quantitative and reliable measures for prediction. Furthermore, with regards to questionnaires and interviews, research has shown that different preference elicitation methods can result in different responses (Fisher, 1993; Johansson, Hall, Sikström, Tärning, & Lind, 2006; McDaniel, Verille, & Madden, 1985; Neeley & Cronley, 2004). Questionnaires can be biased or inaccurate (Cummings, Harrison, & Rutström, 1995; Nisbett & Wilson, 1977) because consumers may either decline to state their actual preferences or they cannot verbalize a justification for their preferences (Johannesson, Liljas, & Johansson, 1998; List & Gallet, 2001). Theoretically, it is possible to argue that continually refining questionnaires may eventually result in an ultimate version that overcomes these issues and unearths the precise, unbiased, and genuine preferences of individuals. However, we believe this to be true only in theory, as the "perfect" questionnaire is inherently unattainable. Thus, the door is open to contribution from objective neuroscientific measures.

Using focus groups, another classic technique, can provide valuable insights into choice processes within a social context, which at times cannot be acquired with other methods, and such groups have indeed been used to predict market success for many years. However, with regards to successful market predictions, focus groups raise some issues that are difficult to surmount. For instance, having one or several dominant individuals within a group permits only one or a few opinions to be heard, skewing the results towards the most outspoken preferences. Social relations may also interfere with results, such as when using focus groups that include both minority and majority groups: majority members may construct the minority members reported preferences. There is also some likelihood of group dynamics obscuring some of the more controversial perspectives due to the tendency for participants to produce normative discourses. Additionally, conclusions strongly rely on the researcher's subjective analysis and judgment in understanding the interactive features of the group (Smithson, 2000).

Moreover, the researcher or moderator has less control over the data produced in focus groups than in quantitative studies, insofar as focus group research is open ended and cannot be entirely predetermined or controlled. This is beneficial in a variety of contexts for gaining valuable insights, but is problematic in obtaining precise predictive information, which could be achieved in the strict and predefined settings of neuroscientific experimentation (Morgan, 1988). On a practical note, representative focus groups can be very difficult to assemble, particularly so since focus groups may discourage certain people from participating, such as those who are not very articulate or confident, and those who have communication problems or special needs. Finally, focus groups are not fully confidential or anonymous, because the material is shared with others in the group. Hence, focus group discussion may also discourage some people from trusting others with sensitive or personal information, yielding only partial and restrained responses (Gibbs, 1997).

5 | A COMPARISON OF NEURAL TOOLS IN MARKETING RESEARCH

Several neural tools are being used in the attempts to predict consumer preferences (for a review, see Harris et al., 2018), such as fMRI (Berns & Moore, 2012; Couwenberg et al., 2017; Falk, Berkman, & Lieberman, 2012; Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Falk et al., 2015; Falk, Morelli, Welborn, Dambacher, & Lieberman, 2013; Falk, O'Donnell, & Lieberman, 2012; Genevsky & Knutson, 2015, 2018; Helfinstein et al., 2014; Kühn, Strelow, & Gallinat, 2016; Lebreton, Jorge, Michel, Thirion, & Pessiglione, 2009; Levy, Lazzaro, Rutledge, & Glimcher, 2011; Scholz et al., 2017; A. Smith, Douglas Bernheim, Camerer, & Rangel, 2014; Tusche, Bode, & Haynes, 2010; Venkatraman et al., 2015; A.-L. Wang et al., 2013; Levy & Glimcher, 2012 for review), MEG (Ambler, Braeutigam, Stins, Rose, & Swithenby, 2004; Braeutigam, Stins, Rose, Swithenby, & Ambler, 2001), fNIRS (Çakir, Çakar, Girisken, & Yurdakul, 2018; Krampe, Strelow, Haas, & Kenning, 2018; C. H. Lin, Tuan, & Chiu, 2010), and even eye tracking (Ramsøy, Jacobsen, Friis-Olivarius, Bagdziunaite, & Skov, 2017). Other papers have focused on physiological signals and biometrics, mainly skin conductance response/EDA, heart rate, respiration rate, pupil dilation, facial electromyography, and others (Baraybar-Fernández, Baños-González, Barquero-Pérez, Goya-Esteban, & de-la-Morena-Gómez, 2017; Gakhal & Senior, 2008; Petrescu et al., 2018). However, in this review we focus only on the attempts using EEG because it is the most prevalent tool used in the marketing industry to measure brain activities (see the list in NMSBA website). Although most relevant and peer-reviewed studies in academia use fMRI, it is less likely that the industry will employ fMRI due to its practical limitations.

An fMRI scanner has a very large, fixed-cost component and is restrictive and cumbersome in practice, severely limiting the generalizability and commercial applications of fMRI studies. It is expensive to purchase ($1M–$2M) and maintain ($100K–$150K yearly), it requires a costly dedicated facility, and it is immobile. Moreover, the cost verges in the order of $500–$1,000 per subject. Lastly, there are also technical limitations to fMRI, primarily a relatively low temporal resolution in the order of 2 s (Huettel, Song, & McCarthy, 2004). This resolution makes it difficult to examine the rapid dynamics of neural signals that are relevant for the neural mechanisms underlying value representation. In contrast, the most advanced EEG devices cost roughly $50K, require little support and maintenance, and have a very low marginal cost for running experiments. Importantly, EEG also has a very high sampling rate, in the order of 1–2 ms (Luck, 2014). This enables identification of very fast changes in the neural signal over short time scales, in the order of 50 ms (Luck, 2014), which may have strong predictive information about consumer preferences and choice behavior.

Although EEG holds considerable advantages for commercial use, it also includes several significant drawbacks. Most renowned of these is the poor spatial resolution. Due to the high resistance of the skull, any voltage change generated within the brain is broadly distributed across the scalp (for more details, see chapter 2 in Luck, 2014). Therefore, and due to additional issues with electrical conductance, the spatial resolution of EEG is fundamentally undefined, since boundless combinations of signal origins may produce the same recorded pattern. This drawback is particularly problematic when trying to understand the neural mechanism of choices, since it is difficult to relate outcomes to specific brain regions. Secondly, the EEG signal is infamous for the high levels of noise it contains. The noise can stem from multiple sources, including eye movements (saccades and micro-saccades), speech, perspiration, blinks, head adjustments, shifts in posture, and nearby electrical activity. Furthermore, the subjects' emotional states, educational level of development, age, and neurological and cognitive conditions can also affect the quality of EEG data recordings (Wood et al., 2012). Various techniques have been proposed to reduce the contamination of the signal, such as using accelerometers to correct head movements, independent component analysis to remove blinks, electro-oculogram for removing eye movements, and specially constructed isolated rooms to shield from disruptive adjacent electrical activity. However, although many techniques to improve the signal have been suggested, EEG is still considered as having a low signal-to-noise ratio, and therefore limited in its application and interpretation. Lastly, EEG devices measure activity only from the scalp, and therefore cannot directly measure activity from deep brain structures (Luck, 2014) that may contain valuable information, such as the ventral striatum (Glimcher & Fehr, 2014). Some of the cortical activity recorded could be reflecting processes in deeper structures, but it would be impossible to discern them and therefore impractical to address. This introduces an obvious detriment to EEG-based market predictions, as some of the information originating in deeper structures certainly eludes the device. However, as we will demonstrate in the following passages, there is still much information the device may capture. Importantly, the aforementioned disadvantages accentuate the value of using multiple methods conjointly for neuromarketing research. For example, the high spatial resolution of the fMRI can complement the high temporal resolution of EEG devices (Reimann, Schilke, Weber, Neuhaus, & Zaichkowsky, 2011). Also, biometric recordings can provide access to responses of the autonomous system that are unattainable via EEG recordings (Ohme, Reykowska, Wiener, & Choromanska, 2009; Vecchiato, Astolfi, Fallani, et al., 2010).

6 | INTRODUCTION TO ELECTROENCEPHALOGRAPHY

EEG is an electrophysiological method to record the electrical activity of the brain by attaching several electrodes (electrical conductors) along the scalp (Haas, 2003). When neurotransmitters bind to post-synaptic receptors, a change occurs in the flow of ions into the neurons, causing fluctuations in post-synaptic potentials (PSPs). These PSPs can occur in multiple neurons, possibly linked to the same functionality or located in close proximity (for more details, see Buzsáki, Anastassiou, & Koch, 2012). Thereupon, the PSPs are summed and speedily conducted through the brain, skull and scalp, where they can be measured by the electrodes placed on the scalp. Thus, EEG recordings provide an approximation of neurotransmitter-mediated neural activity, with high temporal resolution (milliseconds) but poor spatial resolution. That is, the recordings are precise in their timing, but it is difficult to pinpoint their exact origin within the brain, even when multiple electrodes are placed throughout the scalp.

Analyses of EEG recordings are usually split into two general types. The first is termed "ERP," which refers to the recorded voltage time-series resulting from a particular event, such as a stimulus onset or a button press. This form of analysis is popular in psychological and cognitive experiments, where multiple cortical responses to the same event are averaged to obtain a cleaner voltage time-series that may contain components relevant to a research question, such as positive or negative peaks in the time-series. The second analysis technique is termed "spectral analysis" and involves investigating the spectrum of frequencies that comprise the electrical signal. The "power spectrum" indicates the power of each frequency component present in the time-series signal. Many studies report their findings in terms of changes in powers of particular frequencies or frequency bands (a range of frequencies). We provide further detail of each analysis technique and the predictive features that they supply in the next section.

Before we describe the attempts at EEG-based predictions, we present a brief and inexhaustive review of previous EEG studies, in order to identify candidate neural signals that may be used for measurements and predictions of values. The aim of this section is to try and consolidate a large body of literature to find the candidates that may best represent neural valuations and hence become the focus of prediction studies.

7 | PROMINENT CANDIDATE EEG FEATURES

Several features of the EEG signal have been suggested as representing some aspects of the valuation process across many years of research and various teams and fields. Before we detail the most prominent features, it is important to be aware of a known misinterpretation of this body of work termed "reverse inference" (Plassmann et al., 2015; Poldrack, 2006). All candidate EEG features mentioned in this review were found to correlate with different aspects of valuation, but they have necessarily not been proven to be explicit signals of the valuation process. In other words, it is a legitimate claim that eliciting various evaluation or decision behaviors brings about certain responses in the EEG signal. However, it is incorrect to state that these neural responses, viewed in another context, mean that valuation behavior has been elicited. Nonetheless, this issue does not disqualify the contribution that these features may have for understanding the neural mechanisms of decision-making and preference prediction.

7.1 | Event-related potentials

The leading candidates related to valuation are the following components of ERP study design (for additional components, see M. H. Lin et al., 2018): event-related negativity (ERN, sometimes termed "feedback-related negativity", FRN), P300, and N200.

First, previous researchers have proposed the existence of a generic, high-level error-processing system in humans based on ERN, which is a negative deflection in an ongoing EEG and is seen when human participants commit errors in a wide variety of psychological tasks with many types of stimuli and contexts (Holroyd & Coles, 2002). It has been shown that the size of the ERN is sensitive to the size of the error (Bernstein, Scheffers, & Coles, 1995) and to rewards (Gehring, Goss, Coles, Meyer, & Donchin, 1993; Gehring, Gratton, Coles, & Donchin, 1992), and signals monetary losses (Gehring & Willoughby, 2002). Finally, ERN is considered to reflect a signal similar to the reward prediction error (Holroyd, Coles, & Nieuwenhuis, 2002), which refers to the discrepancy between an expected and received reward, famously shown to be coded by dopaminergic neurons (Schultz, Dayan, & Montague, 1997; Schultz, 2016). This feature should not be viewed as a direct estimate of subjective value, but rather a preliminary contributor to the valuation system, which measures negative feedback associated with unfavorable outcomes or the reward prediction error. This can supply partial information for value predictions, but not the entire picture. That is, the reward prediction error signal may be used as a proxy for the consumer's expectations regarding stimuli or rewards. In a marketing context, for example, one could present a subject with an ad intended to solicit high expectations towards a product and measure the ERN with respect to receiving the actual product. Through "reverse inferencing" (with caution), a stronger ERN signal could testify to the discrepancy between the ad-solicited expectations and the product itself. Marketers could interpret higher reward expectations as effective advertising or as underwhelming products, depending on their context. Under the assumption that higher expectations indicate higher chances of purchase or product consumption, the signal could serve to predict product valuation or purchase intent.

Next, there is also a positive ERP component, termed P300 (appearing approximately 300 ms after stimulus onset), which is elicited by positive feedback informing of a reward (Holroyd, Krigolson, & Lee, 2011; Mushtaq, Wilkie, Mon-Williams, & Schaefer, 2016; Proudfit, 2015). It is regarded by some as a signal for positive reward prediction error (Holroyd et al., 2011), meaning that it is stronger when the reward received was higher than expected. It has also been shown that it is stronger for gains than for losses (Kardos et al., 2016). Moreover, P300 has been found to be influenced by the value of the obtained outcome, the value of an alternative option, and the relative value of the alternative outcome in comparison with the chosen outcome (Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Miltner, Braun, & Coles, 1997; Yeung & Sanfey, 2004). One study has shown that the P300 is sensitive to the motivational significance of the stimulus and to the amount of expended/invested attention (Nieuwenhuis, Aston-Jones, & Cohen, 2005). Another study found a higher P300 when there was a similarity overlap between a product and the expectation towards it (J. Wang & Han, 2014). Finally, it has been shown that the P300 is affected in various decision-making tasks (Hajcak, Holroyd, Moser, & Simons, 2005; Hajcak, Moser, Holroyd, & Simons, 2007; Luu, Shane, Pratt, & Tucker, 2009; Sato et al., 2005; Toyomaki & Murohashi, 2005; Yeung, Holroyd, & Cohen, 2005; Yeung & Sanfey, 2004).

As described above, ample evidence supports the conclusion that P300 is related to valuation. However, it has also been one of the most studied components since it was first reported in the 1960s (Desmedt, 1962; S. Sutton, Braren, Zubin, & John, 1965). It is implicated in a large number of cognitive and affective processes and is traditionally associated with allocation of mental resources and attention (Duncan-Johnson & Donchin, 1977; Polich, 2007; Polich & Kok, 1995; Squires, Squires, & Hillyard, 1975). Therefore, controversy remains concerning the aspects of the valuation process to which the P300 is sensitive, and whether it can be disentangled from other cognitive processes and subsequently utilized in preference prediction.

There is another event-related component that has been investigated in recent years in connection to valuation. Telpaz, Webb, & Levy (2015) found that the N200 component, a negative wave peaking between 200 and 350 ms after stimulus onset, can differentiate between high- and low-preferred goods. This finding was later replicated by an independent research team (Goto et al., 2017). Moreover, Gajewski, Drizinsky, Zulch, & Falkenstein (2016) reported an enhanced fronto-central N200 during purchase decisions regarding overpriced and underpriced items. However, most research on this component has focused on cognitive mechanisms related to but different than valuation, such as cognitive control, attention, novelty or sequential matching (Folstein & Van Petten, 2008). There is much evidence that the N200 component belongs to the family of attention-related components, which would explain its relative success in predicting preferences, but invalidate it as a direct measure of subjective value.

Lastly, another ERP-based methodology worth mentioning is "steady-state topography" (SST), developed by Silberstein, Ciorciari, & Pipingas (1995). This unique method involves a key addition to the experimenter's paradigm: a dim, ongoing, oscillating visual stimulus that is presented in the peripheral visual field throughout the task. This elicits a small rhythmic sinusoidal brain response at the same frequency, termed the "steady-state visually evoked potential" (SSVEP). After the EEG signal is recorded, a Fourier-transform is performed on the signal to extract smoothed coefficients of the 13 Hz frequency. These coefficients are transformed to represent the phase and magnitude of the frequency. Changes in the phase difference are said to reflect variations in latency between the SSVEP signal and the task itself, which in turn have been connected to excitatory or inhibitory changes in synaptic transmission time. A latency reduction is considered to reflect an increase in synaptic excitation or simply "SST activity" and vice versa. SST has been investigated in relation to a large variety of cognitive functions, such as visual attention, working memory (Ellis, Silberstein, & Nathan, 2006; Perlstein et al., 2003; Silberstein, Nunez, Pipingas, Harris, & Danieli, 2001) and visual imagery (Silberstein, Danieli, & Nunez, 2003). In the context of marketing and decision-making, SST activity has been studied as an indicator of long-term memory encoding of brand information presented during television advertising, and therefore of ad effectiveness (Pynta et al., 2014; Rossiter & Silberstein, 2001; Silberstein & Nield, 2008; Silberstein, Harris, Nield, & Pipingas, 2000). Silberstein later took this methodology to the marketplace, founding a neuromarketing company of his own based on these ideas (Neuro-Insight). Moreover, his technique has become popularized in brain–computer interface research as a method for motor control (Amiri, Fazel-Rezai, & Asadpour, 2013; Zhu, Bieger, Garcia Molina, & Aarts, 2010). We are uncertain as to the exact validity of this measure, yet it seems that most of the evidence, even in recent years, suggests a fairly strong connection to working memory (Camfield et al., 2012; Macpherson et al., 2014; Peterson et al., 2014).

In conclusion, for event-related designs, marketers could use the N200 and P300 components to measure the extent of viewers' attention to an ad, but not their effectiveness in directly eliciting purchase intent or product favorability. Viewers might be wholly attentive to an ad due to its striking content (even though it might be negative), which in turn could be captured by the mentioned neural components, but their preferences may still remain unchanged. The ERN signal may be applied to examine differences in expectations elicited by advertisements towards the product itself, and higher expectations may reflect purchase intent. Lastly, evidence regarding SST shows that it is most likely a measure of memory and can inform marketers as to the retention of advertisements.

7.2 | Spectral powers

The abovementioned components are only available in an ERP design, which requires static stimuli repeatedly presented in a fixed time frame. They are difficult to employ in experimental designs that involve continuous stimuli, such as videos, songs or speeches with durations longer than 1–2 s (Luck, 2014). This is particularly inconvenient for marketing research, which mostly examines long-duration dynamic stimuli such as TV or radio commercials, trailers, slogans, etc. Hence, EEG studies that incorporate long-duration stimuli often use markers and features from the signal's frequency domain (which can also be used in an ERP-type design). The most common analysis of the EEG's frequency spectrum is to divide the signal into the following frequency bands: delta (1–3.5 Hz), theta (4–7.5 Hz), alpha (8–12 Hz), beta (13–25 Hz), and gamma (26–40 Hz).

Many researchers have studied the relationship of these bands to choice behavior and subjective preferences. For instance, both gamma and alpha band oscillations have been correlated with subjects' choices of consumer goods in specific time epochs and brain locations (Braeutigam, Rose, Swithenby, & Ambler, 2004). In a more recent study, Ravaja, Somervuori, & Salminen (2013) found that greater left frontal activation in the alpha band, measured just a few seconds before choice, predicted the affirmative decision to purchase a consumer good. Higher perceived need for a product and higher perceived product quality have also been associated with greater relative left frontal activation in the alpha band. M. E. Smith & Gevins (2004) found that a frontal component in the lower frequency portion of the alpha band was attenuated during commercials that elicited high subjective interest. Additionally, Khushaba et al. (Khushaba, Greenacre, et al., 2012; Khushaba, Kodagoda, et al., 2012; Khushaba et al., 2013) demonstrated that several frequency bands were related to participants' preferences, and Astolfi et al. (2008) found that activity in four of the bands, elicited by the viewing of TV commercials, was significantly different for commercials that were remembered than for those forgotten.

7.3 | Hemispheric asymmetry

Since the late 1970s, hemispheric asymmetry in the EEG signal has been shown to be related to approach/withdrawal behaviors, and later also to emotion and depression (Davidson, 1998) or motivation and affect (Harmon-Jones, Gable, & Peterson, 2010). This, in accordance with the early hypothesis that the right hemisphere is more inclined to emotional and abstract thinking, while the left hemisphere is more analytical. On this basis, when asymmetric activation is recorded between the hemispheres, particularly in anterior regions, the involvement of two possible systems can be suggested, each represented in separate neural circuits. Davidson proposed that higher activation in the left hemisphere means activation of an "approach system" that facilitates appetitive behavior and positive affect. In contrast, higher activation in the right hemisphere may indicate more emotional alertness, leading to what he termed the "withdrawal system," which facilitates avoidance of aversive stimulation and negative affect (Davidson, 1998).

Furthermore, several studies have shown that frontal asymmetry is also related to value modulation. For example, subjects with greater alpha resting activity in left-frontal electrodes selected more pleasant stimuli in a subsequent behavioral task (S. K. Sutton & Davidson, 2000). Pizzagalli, Sherwood, Henriques, & Davidson (2005) found additional supporting evidence for the connection between approach behavior and valuation. A related study also demonstrated the relationship between hemispheric asymmetry and risk aversion (Gianotti et al., 2009). Ohme et al. (2009) showed that there are significant differences in frontal alpha asymmetry between two versions of a commercial with one altered scene. Thereafter, the same team tested left hemispheric dominance in three TV commercials and found that dominant reactions were present only in response to one of the tested ads. According to their research, respondents reacted to the emotional part of the ad, as well as to its informational part, leading them to conclude that the frontal asymmetry measure may be considered a diagnostic tool in examining the potential of advertisements to generate approach-related tendencies (Ohme, Reykowska, Wiener, & Choromanska, 2010). Another research team found that the relationship between asymmetry and approach to TV advertisements is modulated by age and gender (Cartocci et al., 2016), demonstrating that this measure is complex and sensitive.

While asymmetry is most commonly found in the alpha band, it has been shown that asymmetry in the theta and gamma bands are related to retention between commercials, which is an element affecting preferences. Vecchiato et al. found that cortical activity elicited during the observation of TV commercials that were remembered was higher and localized in the left frontal brain areas, compared to the cortical activity elicited during the presentation of TV commercials that were later forgotten (Vecchiato, Astolfi, Cincotti, et al., 2010; Vecchiato, Astolfi, Fallani, et al., 2010). In a later study, the group found an asymmetrical increase of theta and alpha activity in the left (right) hemisphere related to the observation of pleasant (and unpleasant) video advertisements (Vecchiato et al., 2011). Moreover, another study by this group found a significant increase of cortical power spectral density across left frontal areas in the alpha band during the observation of TV commercials that had been judged as pleasant (Vecchiato et al., 2014). In conclusion, there is evidence linking this measure to emotion, motivation, value modulation and possibly retention. Although these do not confirm a direct association between value and hemispheric asymmetry, they are conceptually highly related to subjective value and may be considered an aspect of the valuation process. Hence, we believe the measure has merit in terms of preference prediction.

7.4 | Inter-subject correlation

Lastly, EEG inter-subject correlation (ISC, or synchronization, or coherence) is a relatively newer measurement that is most suitable for study designs that include long-duration stimuli. Findings suggest that synchronization between subjects in EEG activity can be used as a measure of overall engagement levels with a video stimulus. The original idea was first demonstrated in neuroscience studies of vision. Hasson, Nir, Levy, Fuhrmann, and Malach (2004) placed five subjects in an fMRI scanner to freely view half-an-hour of a popular movie. By using spatiotemporal activity patterns in one brain to "model" activity in another brain, they found high synchronization between subjects in primary, secondary, and association areas in the visual and auditory systems. They concluded that during natural vision, subjects' activity patterns tend to synchronize during emotionally engaging scenes (Hasson et al., 2004). Dmochowski, Sajda, Dias, and Parra (2012) took this concept to EEG and examined activity evoked by multiple presentations of short film clips, in order to locate events with high correlation across subjects. They found that the occurrence of peak correlations of neural activity across viewings corresponded with arousing moments in a film. Moreover, viewing the film a second time or with scenes out of sequence-reduced ISCs (Dmochowski et al., 2012). As this measure becomes more frequently used, evidence is converging on its connection to arousing video stimuli, making it a promising candidate to measure engagement. It is important to note that many marketing researchers use the term "engagement" in various ways. We find that for our purposes, the following definition encompasses it best: the occupation of attention or efforts of a person by attracting or pleasing stimuli, sometimes leading to an explicit interaction or implicit response.

8 | THREE ASPECTS OF NEURO-PREDICTION

Now that we have surveyed various candidate signals, we will continue with a review of studies that have applied some of these EEG measurements, and some novel ones, in order to perform predictions. We summarize our literature review on prediction using EEG signals in the Table 1. But before we describe the various studies, it is essential to make three distinctions regarding predictions when aggregating the findings of different studies.

8.1 | Within-sample versus out-of-sample

First, some studies attempt to predict within-sample only, meaning they record and extract measures of their subject pool and use them to predict the same subjects' future choices, preferences or ratings. Other studies attempt to predict out-of-sample, meaning they use measures from their subject pool to predict the general success of marketing stimuli at the population level, measured by YouTube metrics (views, likes, etc.), ad meters, tweets, actual sales, or otherwise. It is important to distinguish between these two types of predictions, as they suggest different applications and implications. Predicting within-sample can teach us more about the determinants and neural underpinnings of subjective valuation, and therefore answers questions from a more basic science perspective. However, out-of-sample predictions, while being less informative in regard to valuation mechanisms, are much more applicable to the marketing industry and offer prediction measures and techniques that may enhance marketing effectiveness, lower marketplace uncertainties, increase profit gain, improve brand image and add value to shareholders as well as consumers. Out-of-sample predictions can inform us regarding the relationship between a subject pool and the aggregate success of a product or ad. A model that was effective in out-of-sample predictions could be shown data from subjects that viewed new products and ads and could estimate their overall market success based on a generalization of the model from previous data.

8.2 | Fitting versus testing

The second critical distinction to make is whether predictions are made by fitting a prediction model to all the sampled data and reporting the explained variance (as is usual in regression analyses), or by training a model on one subset of the data (training set) and performing predictions on the complementary subset of the data (test set). Fitting a model to the entire dataset and reporting on coefficients and explained variance is not as generalizable as predicting based on data the model has not seen, and it might be prone to overfitting. A model of the entire dataset may provide insights into the relationship between the features and the predicted variable (explanation) but prove useless when attempting to use the model to evaluate new data that it has not seen before (prediction)—which is often the requirement in marketing research. Studies which hold out some of their data as a separate test set and report their prediction results on that test set are more practical and useful for application in the real world. Their results reflect the extent to which their model will be able to make inferences with new data, that is, estimate the value or market success of a new product or advertisement.

8.3 | Standalone versus beyond

Third and last, as neuro-prediction aspires to benefit marketers and managers, it is not enough to demonstrate an ability to predict preferences from neural signals alone. Although there are many studies that do so and that have contributed greatly to our understanding of neural-based predictions, there are only a few which have examined whether neural signals contribute to prediction above and beyond the traditional marketing prediction techniques detailed earlier in this review. For the industry to accept neural-prediction as a practical tool, studies on neural-based predictions should also investigate whether their results improve upon what can already be achieved with questionnaires or focus groups. Studies should inquire whether the neural signals they researched contain new information on values or preferences that was not explained by traditional techniques. We will outline these three distinctions as we review the following studies.

9 | CURRENT FINDINGS IN EEG-BASED PREFERENCE PREDICTION

9.1 | Fitting without standard measures

The papers in this section, although highly influential, did not conduct a hold-out testing nor did they attempt to predict beyond standard marketing measures. One of the important EEG studies in the field of neuromarketing was conducted by Dmochowski et al. (2014). They employed an ISC-type measurement, which they termed *neural temporal reliability*, building on their previous work mentioned earlier in this review (Dmochowski et al., 2012). First, they computed the ISC from EEG signals recorded from a small group of subjects watching an episode of *The Walking Dead.* Next, via regression, they showed a significant correlation between the ISC measurements and (a) the number of related tweets during the episode in the general population and (b) the actual viewership of the episode in the general population (as estimated by Nielsen). Thereafter, they showed that the ISC measurements from a different, small group of subjects watching Super Bowl commercials significantly correlated with the within-sample ratings and the population ratings of the same Super Bowl commercials. Their paper provides strong evidence that the EEG-based ISC measure can serve as a proxy for overall engagement with a continuous stimulus. Moreover, their study shows that scalp measurements may be able to predict naturally occurring audience behaviors on a large scale.

One of the first successful examples of this type of study was conducted by Vecchiato et al. (2011), who attempted to base their predictions on a different measure: cortical hemispheric asymmetry. They showed that alpha and theta asymmetries measured while subjects watched 18 TV commercials were significantly correlated with subjects' pleasantness ratings reported 2 hr after watching the commercials. In contrast to the research of Dmochowski et al. (2014), they did not relate their findings to the population level but only predicted within-sample, as their goal was to predict measures that are similar to standard marketing measurements (pleasantness ratings) but not to predict beyond them. However, this was one of the first studies that demonstrated the ability to use EEG signals to predict future consumer-related behavior. Another study by Ravaja et al. (2013) used an alpha asymmetry measure extracted while participants watched 14 products. In each trial, participants had to choose whether they would purchase the product or not, while prices varied between trials. Their results showed that relatively greater left frontal activation (i.e., higher approach motivation, as detailed earlier) during a pre-decision period in each trial predicted an affirmative purchase decision for the same trial. This measure was also associated with higher perceived need for a product and higher perceived product quality, as obtained from participants answering a survey after the experiment. Notably, they predicted affirmative purchase decisions based on EEG data that was very close in temporal proximity to the choice itself. In other words, it might be that some of the signals that they used for prediction were not a value signal per se but preparatory motor signals that were confounded in the design. Nevertheless, this study demonstrated the ability to use cortical asymmetry as a valid predictor of choice.

Yet another study, published as a white paper by Laurence & Gerhold (2016) from HeadSpace Neuromarketing, was able to shed more light on alpha asymmetry as a temporally sensitive predictor. Their massive study included 42 TV commercials watched by 20–30 subjects each, for a total of 520 participants (some participants watched two or more of the advertisements), whose cortical activity was recorded. Subjects also answered a questionnaire afterwards to obtain their purchase intent of each product advertised. Their best regression model, out of the five models attempted, found that higher self-rated purchase intent was significantly associated with a higher combination of left frontal activation (approach) during the last 10 s of the commercial and higher right frontal activation (withdrawal) during the first 10 s of the commercial, explaining 35.7% of the variance. Note, however, that neither of these studies used a hold-out test set, nor did they attempt to predict out-of-sample (at the population level) or beyond standard marketing measures.

9.2 | Fitting beyond standard measures

Several studies did try to demonstrate that using various neural measures improves prediction above and beyond traditional measures, but did so without a hold-out test set. Venkatraman et al. (2015) collected EEG data (along with many other data) from 29 subjects while they watched 30 commercials. They extracted two measures from the EEG activity, occipital alpha and alpha asymmetry, and attempted to predict commercial elasticity, a measure for market-level response to the commercials.

When predicting with EEG data alone they reached an adjusted-R^2 of 0.338; when adding the traditional measures, the estimators for the EEG features were no longer significant (although using fMRI activity did yield a small increase in explained variance). It is possible that by furthering the analysis and extracting additional features from the EEG, a larger contribution could be made, thereby generating a prediction beyond standard measures. Another analysis they performed examined the relationship between modeled variables, which can be thought of as a within-sample prediction from their EEG variables to traditional features. However, this analysis did not yield significant coefficients.

Barnett & Cerf (2017) further strengthened the notion that EEG features can contribute beyond standard measures. They recorded the cortical activity of 58 movie-goers while they watched movie trailers in an actual theater, and also collected their willingness-to-pay (WTP) and subjective ratings for the movies. Their research showed that cross-brain correlation (CBC), a measure extracted from the EEG recordings similar to ISC, was highly correlated with the subjects' ability to recall the movies later ($r = 0.66$, $p = 0.01$) and with the movies' actual sales in the general population ($r = 0.68$, $p = 0.01$). Moreover, the correlation between WTP or subjective ratings and recall or sales was lower than the CBC metric and not significant. This demonstrates their neural measure's robustness against the standard measures, although they did not provide any measure of explained variance. To our knowledge, this is one of the few attempts ever made at such an ecological design, recording EEG at a real business venue in an authentic setting. However, we must treat these findings with caution. Although high ecological validity was gained, subjects' motor movements are harder to monitor and control, and the abundant surrounding electrical activity is likely to disturb the sensitive recording of cortical activity, decreasing the signal-to-noise ratio substantially. Further analysis of this data, such as multivariate regression to determine the CBC's explained variance beyond standard measures, or a held-out test set to perform prediction on, could have further informed us of this measure's robustness and generalizability.

Another influential study, by Boksem & Smidts (2015), presented 29 subjects with various movie trailers while recording their EEG activity, and collected their *Liking* and *WTP* scores for each movie trailer. After extracting spectral powers, they used these measures to predict subjects' ordered preference, rankings of the movies they saw, and also box office income, as a metric of population preferences. Importantly, their results showed significant prediction success for the beta and gamma bands, even beyond the prediction of the WTP measure. Although impressive, their analysis technique provided only a pseudo-R^2 measure (and not an out-of-sample prediction accuracy) for their model's success, which was between 1 and 2%.

9.3 | Testing without standard measures

Some studies did perform some sort of hold-out testing but did not attempt prediction beyond standard marketing measures. One such study was performed in our lab (Telpaz et al., 2015). We had 15 subjects view images of 10 consumer products while their cortical activity was recorded. Later, subjects performed a binary choice task, where they had to choose their favorite product from all possible pairs. From this task, individual subjects' ratings of products were determined and used as responses. Using the N200 component and the theta power band from the EEG recordings of product viewing, we were able to predict subjects' subsequent choices to varying degrees with a neural random utility model. However, we did not attempt to predict population metrics, and all our predictions were conducted within the subject pool, although without a held-out test set.

Another study worth mentioning within this category performed EEG-based prediction of a value-related concept. The study by Koelstra et al. (2012) investigated the response to 40 music videos, while recording EEG activity, peripheral physiological signals, and facial expressions. The researchers posed three different binary classification problems: predicting low/high arousal, low/high valence, and low/high liking, as obtained from the same subjects' ratings. Their results varied between chance level and 62% accuracy when testing their EEG features, but they were able to improve upon this when they combined these features with those from other modalities, particularly basic auditory and visually based features, which they termed *multimedia content analysis*. However, they did not perform testing on population metrics nor did they attempt to predict above and beyond traditional measures.

There are also two studies in this category that employed innovative machine-learning models to perform predictions. For example, Yadava, Kumar, Saini, Roy, & Prosad Dogra (2017) applied a hidden Markov model on EEG signals of 40 participants while they were watching images of 14 different products, to predict their like/dislike of the products. They also tested various other models, such as support vector machine, random forest, and nearest neighbor, with varying results. Using their proposed methodology, they were able to reach 63.5–70.3% prediction accuracy on a leave-one-out testing. Machine learning models are in ever-growing use throughout the market and academia, and their utilization represents a very promising strategy, although it is still in its early stages. A somewhat related study was conducted by Murugappan, Murugappan, Balaganapathy, & Gerard (2014), who applied a probabilistic neural network and k-nearest neighbor's prediction models in their experiment. They had participants view four commercials per four different vehicle brands, and extracted spectral energy (SE), power spectrum density (PSD), and spectral centroid (SC) of the alpha band as predictors, and participants' self-assessments as a response. Using a 10-fold cross-validation technique they were able to reach a 96.62% accuracy rate at their highest (which is extremely high compared to all other studies, and hence susceptible to overfitting). However, importantly, interpreting these high prediction accuracies is problematic and very limited since it was achieved when predicting only one vehicle brand (Toyota) with a single feature (PSD) and not the entire dataset. The Toyota brand was the overall most-liked brand in their experiment, hence it is quite possible they were able to predict the general response to its commercials rather than its favorability or likeability. Moreover, in these two studies the authors did not examine prediction on any population metric, nor did they try to predict above and beyond traditional measures.

9.4 | Testing beyond standard measures

There are only a few studies that both predict using a hold-out test set and attempt to predict beyond traditional measures. A recent study, by Guixeres et al. (2017), attempted to predict the effectiveness of Super Bowl commercials based on EEG signals, using a measure termed the global field power (GFP) to quantify the cerebral activity in each band (Wackermann et al., 1993). In addition to the *z*-score of GFP for each EEG band, they also extracted two measures: a pleasantness index, which is based on hemispheric asymmetry, and an interest index, which considers the relative number of peaks in beta and theta bands during a particular commercial (Colomer Granero et al., 2016). Together with data from eye tracking and heart rate, they used a neural network model and achieved an average accuracy of 82.9% in predicting the number of YouTube viewings for each commercial. Their model also included questionnaire responses, which were shown to make a small contribution to prediction, relative to their EEG measures. Among the EEG measures, the theta pleasantness index showed the highest contribution. However, they did not examine their accuracy with and without their traditional measures, and therefore, the contribution of their neural measures beyond traditional measures was not available and could not be examined.

A study that was conducted in our lab employed a multitude of EEG measures for preference prediction: ISC, hemispheric asymmetry, and spectral power bands (Hakim et al., 2018). Subjects watched six different product commercials while their EEG was recorded. Afterwards, they completed a binary choice task among the products they watched, as a measure of their individual preference, and completed a marketing questionnaire, as a traditional marketing measure. YouTube metrics and a questionnaire answered by an online cohort were collected as a measure of the commercials' success in the general population. We utilized various machine learning models, such as Support Vector Machines, Decision Trees, Kernel Discriminant Analysis, and more. Thus, we were able to achieve 68.5% accuracy in predicting the most- and least-preferred products in our subject pool when using both EEG and questionnaire measures. This, while the questionnaire reached 64.2% at best, thereby demonstrating the contribution of EEG measures in predicting individual preferences, above and beyond the traditional measures. When predicting metrics of population success, our best model predicted product population preferences with a root mean square error of 1.78, based on both EEG and traditional measures alone, reflecting the same conclusion.

Some research teams attempted to make predictions based on in-house indices extracted from EEG data. However, it is hard to determine the validity of these in-house measures, as they had not been tested or validated in previous literature, nor was the robustness of the results reported. For example, Baldo, Parikh, Piu, & Müller (2015), a team from Neuromarketing Labs, reported that they were able to predict, using EEG signals, successful and unsuccessful sales of shoes, using their custom-made "preference index computed through an internally developed algorithm loosely associated with parameters from basic emotional neuroscience". They reached 80% accuracy with their testing procedure, using a one-dimensional linear classifier, which was higher than their prediction accuracy from a questionnaire, which reached only 60% accuracy. Furthermore, Sands Research produced another example of such a study, although without test results, when they extracted their propriety neuro-engagement index from the EEG activity of subjects watching Super Bowl commercials, in order to predict various YouTube metrics of these commercials (Deitz, Royne, Peasley, Huang, & Coleman, 2016). We cannot attest to the validity of such reports, as the actual prediction models are not provided and the data could not be examined in the published papers. Markedly, these three studies did not include predictions based on their own sample pool.

10 | PROSPECTS AND CHALLENGES FOR THE FUTURE

Based on the current literature review, we would like to highlight several important points, with the hope that they inform the neuromarketing community and help advance applicability and success of the field:

10.1 | Predicting value beyond specific stimuli characteristics

The first point concerns predicting metrics of the population from a small sample of subjects, which is usually considered one of the main goals of neuromarketing. The problem is that if we have a good representative sample group of the population for the purpose of recording neural signals, and the overall rankings of commercials or products are highly correlated within the sample group, then prediction of population success becomes a triviality. In other words, if most or all subjects from the sample group like a particular product the most, and that same product is also the most preferred in the population, then the EEG-based prediction might not predict based on real preference or value-related neural signals, but rather based on a general signal specific to that commercial/product, which could simply be attributed to any number of the commercial's/product's characteristics. For example, Telpaz et al. (2015) attempted a form of out-of-sample prediction: they used half of the data from each participant to predict their remaining choices. However, their results show that only one product out of the 10 they tested was chosen a total of 605 times in their binary choice task, while another was chosen 225 times, across all subjects. The other eight products ranged in between. This gives rise to the possibility that their model identified some response to the most- and least-preferred products—a response that could be entirely unrelated to a value signal—and attained a reportable positive result simply by predicting these products as most- and least-preferred per subject. Nevertheless, they also conducted an additional analysis in which they successfully predicted choices on a trial-by-trial basis for each subject.

This issue emphasizes the contribution of conducting trial-by-trial predictions, attempting to predict each subject's future preferences from their neural signal, rather than only population or out-of-sample metrics. Thus, we urge researchers to combine their efforts to predict population preferences from a subject pool with the predictions modeled on the subject pool itself. This practice will better inform on the validity of features and the reported results. Additionally, in order to increase the robustness and generalizability of a prediction model based on previously recorded EEG features taken from a sample group, it is important to have high variability in personal preferences between products in the sample group, so that on average all products are similarly preferred. This will increase the chances that the prediction model captures a measure of valuation, rather than any other characteristic of the most- or least-liked products in general.

10.2 | Prediction is better for distinctly preferred stimuli

It has been previously shown that prediction accuracy is far better for products that are distant in their preferences, while prediction accuracy is at chance level for products which subjects are indifferent to (Hakim et al., 2018; Levy et al., 2011; Telpaz et al., 2015). Another study has shown that it is harder to discriminate between the neural activation of similar brands (Chen, Nelson, & Hsu, 2015). These findings can be explained by the notion of neural distance (Levy et al., 2011), which states that disparate preferences are also represented in more divergent neural activity, enabling the models to separate them more easily. Therefore, we should take into account that it is much harder to make successful predictions based on highly similar stimuli. Almost all studies that we reviewed used very different stimuli for demonstrating successful predictions. This presents a major issue for real-world applications in any methodology. For example, in many cases marketers need to choose between advertisements that are very similar and contain only slight variations. The challenge of future studies is to develop methods based on neural and other physiological signals that demonstrate successful predictions for very similar stimuli.

10.3 | Prominent EEG features are still inconclusive

One impression that stands out in the review is a lack of convergence on predictive EEG features. As can be inferred from Table 1, the summary of prediction papers does not conclusively yield features which researchers should focus on. Several studies rely on ERP measures, but they are difficult to extract in long-duration real-world experimental designs. A more popular measure for prediction is alpha frontal asymmetry, which seems to center on the idea of approach/withdrawal, rather than on a pure value signal. Although it is a decent approximation of value, as the studies reviewed demonstrate, it is not the holy grail to which neuromarketers aspire. Nonetheless, the various studies using ISC measures show relatively greater promise. The supposition that cortical activity converges to similar patterns when minds are engaged with the same stimuli seems to be well-established in neurological principles and could serve as a valuable piece of the puzzle in determining valuation (mainly engagement), under relevant experimental designs. Lastly, the most predictive spectral bands are yet to be determined, as mixed results have emerged from the reviewed papers. It is likely that an automated procedure for feature extraction, which would determine the predictive features by algorithmic learning, could inform us better as to which frequency bands hold value information. Hence, further systematic research is needed in order better identify the most prominent features of the EEG signal that could be used for predicting future preferences and marketing success at the population level. It might be the case that a combination of features from several signal types (ERP, frequency bands, ISC, asymmetry) will prove to be the most fruitful.

TABLE 1 Summation of current findings in EEG-based preference prediction

Authors	Year	EEG predictors	Standard predictors	Prediction model	Stimuli	Response (within/population)	Subjects	Success (fit/test)
Vecchiato et al.	2011	Alpha and theta asymmetry	None	Correlation	18 TV commercials	Within: pleasantness ratings	11	Fit: significant coefficients
Koelstra et al.	2012	Theta, slow alpha, alpha, beta, and gamma spectral powers and asymmetry	None	Gaussian naive Bayes classifier	40 music videos	Within: arousal, valence, liking	32	Test: 50–62% accuracy
Ravaja et al.	2013	Alpha asymmetry	None	Generalized estimating equations	14 grocery products	Within: purchase decision; product need; product quality	33	Fit: significant coefficients
Dmochowski et al.	2014	Neural reliability (ISC)	None	Regression	Episode of "the walking dead"	Pop: tweet rate|pop: viewership| within: rating	16	Fit: 16% variance explained| 36% explained variance| 26% variance explained
Dmochowski et al.	2014	Neural reliability (ISC)	None	Regression	Super Bowl commercials	Pop: Facebook-USA today ad meter	12	Fit: 66% explained variance
Murugappan et al.	2014	Alpha band SE, PSD and SC	None	K-NN, PNN	16 vehicle commercials	Within: self-assessment	12	Test: 96.62% highest accuracy
Telpaz et al.	2015	N200, theta band power	None	Neural random utility model	10 products	Within: binary choice rankings	15	Test: 59–60% accuracy
Boksem and Smidts	2015	Beta and gamma band powers	WTP, liking	Mixed-models regression	56 movie trailers	Within: ordered preference|pop: US box office	29	Fit: significant results
Baldo et al.	2015	Preference index	Questionnaire	1D linear classifier	30 shoe products	Pop: successful/unsuccessful sales	40	Test: 80% accuracy
Venkatraman et al.	2015	Alpha asymmetry, occipital alpha	IAT, questionnaire	Regression	30 TV commercials	Pop: advertising elasticity within: questionnaire	29	Fit: adjusted-R^2 = 0.338|no significance
Deitz et al.	2016	Neuro-engagement score	USA today ad meter	Regression	Super Bowl commercials from 2008 to 2013	Pop: YouTube metrics	30–35	Fit: R^2 = 0.28–0.46
Laurence and Gerhold *white paper	2016	Alpha asymmetry	None	Linear mixed-effects regression	42 TV commercials	Within: purchase intent	20–30	Fit: R^2 = 0.357
Yadava et al.	2017	DB4 wavelet coefficients (power bands)	None	HMM (SVM, RF, NN)	14 products * 3 image variations each	Within: likes/dislikes	40	Test: 63.5–70.3% accuracy
Guixeres et al.	2017	GFP per band	Liking, recall	Neural network	8 TV Super Bowl commercials	Pop: online views on YouTube	35	Test: 82.9% average accuracy
Barnett and Cerf	2017	Cross-brain correlation (ISC)	WTP, rating	Correlation	13 movie trailers	Within: free recall pop: movie sales	58	Fit: r = 0.66|fit: r = 0.68
Hakim et al.	2018	ISC, power bands, hemispheric asymmetry	Questionnaire	SVM, regression, decision trees, KNN, KDL	6 product commercials	Within: binary choice rankings| pop: YouTube metrics/online questionnaire	31	Test: 68.5% accuracy|test: 1.78 RMSE

Note. fMRI: functional magnetic resonance imaging; fNIRS: functional near-infrared spectroscopy; EEG: electroencephalography; GFP: global field power; HMM: hidden markov model; IAT: implicit-association test; ISC: inter-subject correlation; KDL: kernel discriminant learning; K-NN: k-nearest neighbours; KNN: k nearest neighbours; MEG: magnetoencephalography; NN: neural network; PNN: probabilistic neural network; PSD: power spectrum density; SC: spectral centroid; SE: spectral energy; SVM: support vector machine; RF: random forest; RMSE: root mean square error; WTP: willingness-to-pay.

10.4 | Align with data science methodology

As this review demonstrates, there are now several studies that have attempted, with various degrees of success, to use EEG signals for prediction. However, many of them lack a unified methodological approach or clear guidance on good research practices, while some appear in lower-ranked journals, so that new researchers in the field may receive a biased view on the acceptable research standards in the field, as mentioned in a previous review on the field (Lee, Chamberlain, & Brandes, 2018). We propose that if one of the main aims in neuromarketing is to use EEG (or any other signal) for prediction, the field should adopt methodologies widely used in data and prediction science, which deal with very similar problems in other domains (Jordan & Mitchell, 2015). That is, in striving for enhanced and precise prediction we should extract a multitude of EEG features, perform variable selection, and predict on a held-out test dataset. Regardless of the aforementioned approach that discards the need for feature extraction, if extraction is already attempted, we propose extracting an abundance of features from the EEG signals. Nearly every paper we reviewed extracted a single feature only. Since the most predictive neural features are still unknown, it is hard to know in advance which measures to focus on, and which of their combinations would increase prediction accuracy through their interactions.

Therefore, after multiple EEG features have been extracted, they should be reduced to the most predictive ones to avoid unnecessarily high dimensionality. This may be accomplished through various variable-selection and dimensionality-reduction techniques, such as principal component analysis, stepwise (backward or forward) procedures, subset validations, lasso regression, and more. These techniques usually involve peeking into the response variable to evaluate the feature's contribution to prediction, and therefore, require that final testing of the model be performed on a held-out dataset that has not been used in the variable selection procedure, in order to avoid inflated accuracies. Out of many possible report metrics for prediction, reporting on a held-out test set is by far the most robust and attests to generalizability more than any other metric of model fitness or cross-validated results.

Lastly, many successful advances in prediction modeling applications, such as machine vision, natural language processing, and more, rely on vast benchmark datasets accessible to all researchers. These datasets contribute substantially to their respective research fields, since they allow the gathering of an enormous number of samples that are usually unattainable by a single lab. This provides researchers with higher power and robustness in their own attempts at modeling and feature extraction approaches. Additionally, constructing a benchmark dataset enables research teams to compare their modeling results sensibly, so that it becomes possible to confidently determine which features or approaches yield better prediction rates on the same dataset. Hence, we believe that neuromarketing prediction modeling will benefit tremendously from a large benchmark dataset of EEG signals acquired when viewing commercials or products and corresponding responses, which could translate to a measure of preference.

10.5 | Benefit beyond traditional measures

Only several of the studies reviewed here examined the contribution of EEG signals to prediction above and beyond standard marketing measures, such as questionnaires, focus groups or interviews. It is possible that a continuous and gradual effort to improve and refine the predictive power of questionnaires would make neural measures redundant. However, devising the perfect questionnaire could take an immaterial amount of trials and errors, while collecting EEG measures is relatively inexpensive, and their attendant experimental designs are mostly economical in cost and time. Neural measures still hold the highest likelihood of producing unbiased and concrete predictors, free from the limitations of traditional subjective measures.

In summary, the field of neuromarketing is relatively new, and the first wave of prediction attempts has shown some promising results and opened new avenues for future studies. However, there are still not enough studies that demonstrate an ability to predict what marketers actually desire: which of two or three versions of a marketing message with very similar variations of a stimulus would be most successful. Moreover, even when we do achieve successful predictions, we are still far from deconstructing the advertising message into its various components and understanding why some succeed while others fail. It is of paramount importance to learn more about this, both in order to construct rules or guidelines that could help marketers build their future campaigns, and to assist researchers in their quest to understand the basic principles that affect subject choice and valuation.

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

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