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How to Conduct Valuable Marketing Research With Neurophysiological Tools

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ABSTRACT

Consumer neuroscience is gaining attention in the marketing field. The growing interest calls for a framework integrating neuroscience in marketing. This paper aims to serve as a practical guide for conducting consumer research using neurophysiological tools. The paper is organized into three main sections. The first section presents a framework for categorizing types of consumer neuroscience research based on four primary research objectives. The following section describes the use of neurophysiological tools in marketing and addresses their roots in their mother disciplines. Specifically, we address electrocardiography, galvanic skin conductance, eye-tracking, electroencephalography, functional magnetic resonance imaging, and functional near-infrared spectroscopy. Additionally, we refer to emerging measurements from hormones and genes. Likewise, this section highlights the most influential papers, equipment facilities, and software on each tool to support researchers who need to become more familiar with any of those techniques. Third, this paper introduces an integrative framework for consumer neuroscience research in marketing, covering research aims, types of stimuli, changes in organisms, and consumer response processes. In addition to core neuroscience citations, the paper incorporates specific marketing-relevant consumer neuroscience papers to guide research in the marketing field.

1 | Introduction

The utilization of neuroscience tools is witnessing a surge in marketing research (Karmarkar and Plassmann 2019), as well as in associated domains of management (Butler et al. 2016), information science (Xiong and Zuo 2020) and finance (Wu et al. 2012). Despite notable pioneering studies in marketing during the 2000s, a renewed interest has emerged over the past decade. This is evidenced by recent reviews, systematic literature analyses, and text-mining studies across various topics, including communication (Casado-Aranda, Sánchez-Fernández, Bigne, et al. 2023), decision-making (Butler et al. 2016), consumer behavior (Oliveira et al. 2022), and across methodologies such as electroencephalography (Byrne et al. 2022; Costa-Feito et al. 2023), and heart rate variability (Kakaria et al. 2023a), among others. This growing interest is driven by the increasing number of studies, as shown in the reviews, as well as by the increasing affordability and user-friendliness of neuro-tools. These advancements have made such tools more accessible to a wider range of researchers and easier to use with less technical expertise, thereby encouraging the expansion of research labs and studies.

Previous scholarly research on consumer neuroscience lacks comparability due to the different methodological approaches, contexts, stimulus types, and even software employed. Indeed, laudable reviews have focused more on delineating a future agenda based on topics-based research through consumer neuroscience tools rather than focusing on the methodological issues of consumer neuroscience from a marketing research viewpoint. The recent study by Clithero et al. (2024) offers a deeper, more critical approach by examining why consumer neuroscience has gained limited traction within the marketing field. The authors propose a layered framework—describing, explaining, and predicting consumer behavior— to improve the integration of neuroscientific methods into consumer psychology. Additionally, from a practice point of view, several professional associations have noted a need for developing methodological standards on the validity and reliability of measurement for companies, such as the 2010 NeuroStandards 2.0 projects by the Advertising Research Foundation, the NeuroMarketing Science and Business Association, and the European Society for Opinion in Marketing Research (Ramsøy 2019). Therefore, methodological reviews of consumer neuroscience are still needed (Bhardwaj et al. 2023).

Noteworthy, as Ramsøy (2019) notes, neuromarketing and consumer neuroscience are often used interchangeably, although neuromarketing focuses on the commercial application of neuroscience tools and insights, while consumer neuroscience examines the underlying research behind consumer choices. The present paper intends to provide such a review and provide methodological guidance for researchers by proposing a comprehensive framework for conducting consumer neuroscience research, including a clear overview of key tools, their applications, and implementation guidelines.

Several factors could elucidate the lack of an integrative methodological perspective on neuroscience-based marketing research. First, consumer neuroscience feeds on other disciplines, such as engineering, cognitive neuroscience, medicine-biology, and psychology. Second, as an emerging research field, consumer neuroscience grows by intermixing relevant marketing theoretical lenses with neurophysiological correlates, as evidenced by often cited papers in marketing and business journals (Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata 2023). The "invisible college" concept (see Crane 1972) fits well with the development of consumer neuroscience. The "college" starts with a small group of researchers who exchange ideas, organize workshops, and participate in special interest groups at leading conferences (e.g., Association for Consumer Research and European Marketing Academy) and specialized ones (e.g., Association for NeuroPsychoEconomics and the Society for Neuroeconomics). They also developed special issues in leading journals highlighting its relevance, such as the Journal of Consumer Psychology 2012, 22(1) and Journal of Marketing Research 2015, 52(4). The process is moving towards a corpus of knowledge adopted in larger communities' research and teaching activities.

The absence of a well-established program around consumer neuroscience triggers awareness of two main facts. First, most papers on consumer neuroscience are irregularly published in marketing journals due to lack of appropriate frameworks utilizing neuroscience principles impeding knowledge production (Clithero et al. 2024; Karmarkar and Plassmann 2019), even though the most cited ones are published in marketing or business journals (Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata 2023; Clithero et al. 2024). As a result, authors navigate insecurely when deciding on the targeted journal, necessitating a mixed publication strategy (Smidts et al. 2014). Second, editors tend to face challenges in finding proper reviewers from the marketing domain who can provide constructive improvements, and consequently, they invite reviewers with a neuroscientific background as an alternative. Those reviewers outside the marketing field may show skepticism about the methodology and interpretation of reported findings, in particular, concerning the issue of reverse inference (Poldrack 2006), or if they hold a proper neuroscience background, they may even question the validity of the findings of the studies. In explaining the relatively low volume of publications in marketing journals, Clithero et al. (2024) propose three explanations: (i) wrong equivalence between consumer psychology measures and neurometrics; (ii) excessive focus on brain imaging analysis to the neglect of other available neurophysiological methods; (iii) weak training in the fundamentals, theory and methods of neuroscience.

The above ideas motivate our paper. We aim to elaborate on research types and methodological guidelines for conducting consumer neuroscience research. For this purpose, we posit that consumer neuroscience employs neurophysiological tools to uncover, explain, and predict consumer responses and decision-making by analyzing implicit and continuous neurophysiological signals triggered by various stimuli within the marketing domain. As such, consumer neuroscience research can be divided into three parts—decisions on objectives, tools, and response types—to guide valuable marketing research with neurophysiological tools. First, we propose a framework for consumer neuroscience research types based on research objectives. The following section delineates the main neurophysiological tools. Third, we provide an integrative framework for consumer neuroscience research in marketing that also encompasses response types.

In this paper, we take a consumer-centric perspective that embraces a full suite of neurophysiological tools tied to the peripheral nervous system by measuring heart rate (ECG), galvanic skin responses (GSR), facial emotions and eye tracking, and brain-imaging responses obtained through electroencephalography (EEG), functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS). Further, we offer a brief examination of less commonly utilized tools and emerging methodologies involving biological factors such as hormones and genetic markers. We differ from He et al. (2021), who addressed only brain-imaging techniques.

We do not aim to replace in-depth knowledge of the fundamentals, theory, and methods of neuroscience, but instead guide the steps of marketing researchers new to the field. We contribute to existing research in marketing in two ways. First, we make an attempt to harmonize methodological approaches in consumer neuroscience (that overcomes Clithero et al.'s (2024) comment on equivalences between consumer psychology measures and neurometrics) and indicate the commonalities and differences between tools. Second, we offer valuable guidelines for early marketing researchers with weak training in neuroscience through two proposed frameworks: (i) a typology of research approaches in consumer neuroscience and (ii) an integrative framework for consumer neuroscience research in marketing.

2 | Research Types of Consumer Neuroscience

We propose a four-type research framework, as depicted in Figure 1,which builds on the basic, translational, and applied research framework suggested by Ramsøy (2019). By extending Ramsøy. (2019) typology, we specifically aim to structure, clarify goals, and guide research design and evaluation in consumer neuroscience. While Plassmann et al. (2015) focus on a theory-oriented approach (i.e., validating, refining, and extending marketing theories), our proposed framework focuses on the methodological approaches. Each type of research approach should adhere to Ramsøy's recommendations regarding assessing existing metrics based on sensitivity, specificity, validity, and reliability (Ramsøy 2019), as well as the challenges outlined by Plassmann et al. (2015).

The proposal includes the following four research types: (I) Direct neurometric approach, that is, capturing neurophysiological data that assimilates with a marketing variable (e.g., visual attention as measured by eye tracking); (II) Indirect neurometric association approach that identifies relationships between a neuroscientific metric and a marketing variable (e.g., linking an EEG measure to brand preference); (III) Inter-technique correlational neurometric approach between tools, that is, forming associations between metrics from each tool showing convergent and discriminant validity; (IV) Fundamental consumer neuroscience approach that investigates the underlying neurocognitive processes that contribute to a deeper understanding of consumer behavior in brain correlates.

2.1 | Type I: Direct Neurometric Approach

This study type refers to measuring the responses obtained to marketing stimuli by neuroscience tools without additional transformation. That is, established neurometrics may encompass meaningful value also in a marketing context. For example, visual attention is a meaningful marketing construct that can also be gleaned from neuroscience. Eye-tracking metrics report visual attention to different stimulus types, such as ads (Pieters and Wedel 2004), social media (Bigne et al. 2021), stores' shelves (Chen et al. 2021), or smartphones (Muñoz-Leiva et al. 2024). By applying reverse inference, the interpretation of these results is relatively straightforward since no reference to specific marketing variables is needed.

2.2 | Type II: Indirect Neurometric Association Approach

This approach informs on the association of a neurometric with topical marketing variables. This approach delineates the relationship between a particular neuroscience metric and relevant marketing variables, such as brand preference or purchase intention. For instance, EEG reports frontal alpha asymmetry (FAA), which in cognitive neuroscience has been interpreted as assessing an approach-withdrawal motivation that can be associated with preference. Type I and Type II research approaches differ in the directness of the marketing data they provide— such as whether variables like visual attention can be directly associated with specific parts of an advertisement in a way that is immediately interpretable from a marketing perspective (Type I), and in the extent to which additional analytical methods, such as surveys, are required to transform the data into usable marketing insights (Type II).

This approach usually requires additional measurements, such as questionnaires and datasets (e.g., on sales), to uncover such relationships through proxy variables. For example, visual attention has been shown to relate to preferences and choice (Bhatnagar and Orquin 2022), shopping behavior at physical stores and e-commerce sites (Chen et al. 2021; Pfeiffer et al. 2020), at virtual reality (Bigné et al. 2016), and sales (Zhang et al. 2009). In EEG studies, measures such as FAA have been shown to be correlated with consumer preference (see the systematic review by Byrne et al. 2022), and beta power at the frontal electrode F4 strongly correlated with willingness to pay (Semenova et al. 2023). In an event-related fMRI study, Knutson et al. (2007) found that product preference activated the nucleus accumbens, while excessive prices activated the insula and deactivated the mesial prefrontal cortex before the purchase decision. Plassmann et al. (2007) found that activity in the medial orbitofrontal cortex and in the dorsolateral prefrontal cortex encoded subjects' willingness to pay for snacks. In sum, this study aims to establish how specific marketing constructs can be measured with neurophysiological tools in a valid and reliable way.

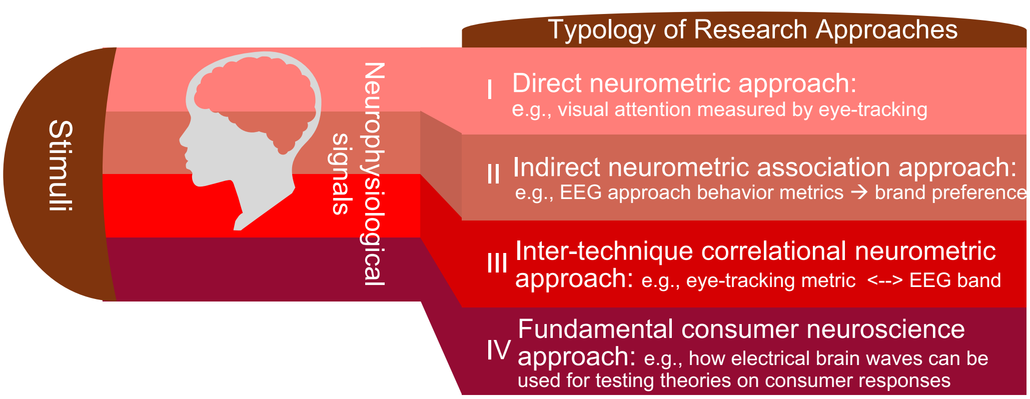

FIGURE 1 | Typology of research approaches in consumer neuroscience.Source: Own elaboration.

2.3 | Type III: Inter-Technique Correlational Neurometric Approach

This type of research seeks to identify mutual relationships between different neuroscientific metrics through correlation and covariation. By assessing the convergent and discriminant validity of the measures, insight is gained on the complementary nature of each tool. By combining metrics, a full account of the processes driving consumer behavior may be arrived at (Clithero et al. 2024). For example, whereas visual attention can be assessed best by means of eye-tracking, affective responses to the stimulus may require SCR or ECG measures. In combination, these metrics may provide a full account of the drivers of consumer responses. In this type of research, researchers identify patterns, make predictions, and decide on their simultaneous usage. The exploration of neural correlates has a well-established history within the neuroscience field (see, e.g., Dellert et al. 2021 for EEG and fMRI, and Dimigen and Ehinger 2021, for EEG and eye-tracking metrics). Currently, the consumer neuroscience field lacks proper insight into the complementary role of tools. Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata (2023) indeed call for more research on how metrics from different tools correlate in advertising and communications. Specifically, Mashrur et al. (2022) claim to conduct new research to clarify the relationship between visual attention and specific brain activity by combining eye-tracking metrics and EEG metrics. Baldo et al. (2022) studied the complementary roles of neurophysiological measures in tracking emotions, memory, and ad effectiveness. Research in this stream addresses the commonalities for predicting any variable of interest. A recent example is provided by Hartnett et al. (2025), who correlate attention measures from eye tracking, heart rate, skin conductance, facial expression, and EEG to measure attention to ads.

2.4 | Type IV: Fundamental Consumer Neuroscience Approach

Basic research refers to enhancing knowledge of the fundamental aspects of phenomena, leading to building theoretical foundations. Although its aim is not directly related to solving specific marketing problems, its contribution to explaining multiple situations seems inherent. The need and usefulness of this study type have been pointed out elsewhere (Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata 2023; Plassmann et al. 2015; Ramsøy 2019).

For instance, while many EEG studies in consumer neuroscience focused on the alpha band, recent research deals with pinpointing the implications of other band waves, including theta and delta bands (Hakim et al. 2021). Dini et al. (2022) analyzed the mismatch between brand images and their logos not only by means of the N400 but also through the EEG theta band, thus adding insight into how brands that are deeply encoded in consumers' minds are less affected by fake logos. Speer et al. (2023) developed the Brain Reward Signature model to prove that affective and motivational processes are encoded in distributed systems that span multiple regions. This model can then be used to differentiate the contribution of various affective and motivational neurocognitive processes to consumer decisions. Chan et al. (2024) studied the temporal dynamics of the processes underlying advertising liking with fMRI and found that liked ads evoke an early emotional response followed by extensive mentalizing, thus providing new insights to advertising theory.

Regardless of these research types, six methodological recommendations need to be grasped in consumer neuroscience. First, caution is needed regarding reverse inference (Poldrack 2006; Jack et al. 2019), as associations between a cognitive function and a neural activation do not necessarily imply the reverse due to other causes that might affect such neural activation. Second, neurophysiological studies offer implicit insights into consumer responses that may be less reliable and generalizable than traditional marketing studies, depending on sample size and the contextual conditions of the experiments (Plassmann et al. 2015). Third, accurate calibration of each participant becomes imperative given the inherent variability among subjects in their neurophysiological signals (e.g., heart rate or visual flow). Fourth, adopting a cognitive subtraction approach using comparative or control groups properly elucidates the researched effects. Fifth, employing a multi-metric and multi-tool integration will strengthen the robustness of the results. Sixth, neural and physiological measures are often continuous, allowing dynamic effects to be tracked or trajectory studies to be conducted (Clithero et al. 2024) (e.g., monitoring emotional changes throughout a video ad), enriching the findings and their potential explanations.

3 | Neurophysiological Tools in Marketing Research

While the previous section outlined the types of research and the methodological principles, this section aims to provide a concise overview of each tool, how to use it, the contexts in which it is applicable, and the methods of its implementation. While Table 1 summarizes the distinctive features of the most used tools, the following sections offer a list of prominent studies for each tool and practical information regarding relevant software and devices. The reviewed literature reflects each neuro-tool's varying histories and application dynamics in marketing research, focusing on seminal and highly cited studies across domains to ensure a representative and influential foundation.

The tools are categorized as core, supplementary, or emerging, based on how frequently they are used in marketing research, ranging from predominant to occasional to nascent use. We focus primarily on the most widely used tools related to the peripheral nervous system (i.e., electrocardiography [ECG], galvanic skin conductance [GSR], and eye tracking [ET]) and brain tools related to the central nervous system, known as neuroimaging tools (EEG, fMRI, and fNIRS). Magnetoencephalography, positron emission tomography, electromyography, steady-state topography, and transcranial magnetic stimulation (for details, see Kansra et al. 2024) are summarized due to their limited usage in marketing. The analysis of emerging measurements based on hormones and genetics (for details, see Alsharif et al. 2024; Clithero et al. 2024; Verhulst et al. 2019) is outlined at the end of this section.

Table 1 shows the characteristics of each neuropsychological tool assessed using a three-level scale: high, medium, and low. These levels indicate the extent to which a feature is present, with "high" representing the maximum and "low" the minimum. The hardware cost is determined by comparative pricing and varies based on

TABLE 1 | Summary of distinctive features of neurotools in marketing.

Tools	Cost of hardware	Portability	Relevant Constructs	Simultaneous use with other tools	Knowledge required	Potential common artifacts	Interpretation of results	Research approaches (Section 2)
ECG	Low	Yes	Arousal, Stress, Flow	High	Low	Previous stress or physical activity	Easy	I, II, III, IV
GSR	Low	Yes	Arousal, Valence	High	Low	Sweat, Interference from electronic devices. Room temperature	Easy	I, II, III, IV
ET	Medium	Yes, with glasses	Attention, Engagement	High	Medium	Reflections on the screen or light control	Easy	I, II, III, IV
EEG	Medium	Yes	Attention, Engagement, Mental effort, Preference	High	High	Electrode position and conductance, electromagnetic interference (smart watches or phones)	Medium	II, III, IV
fMRI	High	No	Attention, Memory, Affect, Mentalizing, Preference, Decisions	Low	High	Magnetic Susceptibility Artifacts Hardware Artifacts (noise, scanner drift or spin history artifacts) Anxiety	Complex	II, III, IV
fNIRS	Medium	Yes	Affect, Preference, Decisions	Medium	High	Optode position and conductance, external light	Medium	II, III, IV

providers and the device's accuracy, electrode specifications, and portability. Portability refers to a device's ability to be used outside the laboratory, in real-world settings such as in-store environments, at home, at work, during physical activity, or at live events, thereby enabling the monitoring of more realistic decision-making processes. Knowledge refers to the specialized expertise the marketing researcher requires in the relevant disciplines associated with each tool. Simultaneous use with other neuro tools refers to the technical capability of devices to be effectively integrated in a multimodal approach, ensuring interoperability and comprehensive data collection

Potential common artifacts refer to unintended signals or distortions that can compromise data accuracy and interpretation, necessitating their control. These artifacts typically arise from factors such as movement, physiological conditions (e.g., stimulant consumption, stress, or deep breathing), environmental influences (e.g., lab temperature and light), and equipment-related issues (e.g., sensors' connections, electrical or electromagnetic interference). Controlling for these factors necessitates pre-testing the device functionality, calibrating for each subject, and measuring the signal before the experiment to establish a baseline threshold. Interpretation of results reflects the challenges of deriving meaningful insights from the data. The tools typically generate raw data, which is processed through specialized analytical software and visual outputs to support interpretation. The last column refers to the research approaches described in Section 2.

3.1 | Electrocardiogram

3.1.1 | What Is Electrocardiography?

Electrocardiography (ECG), once limited to the discipline of medical sciences, in the past decade has emerged as a novel tool in providing distinctive physiological underpinnings of consumer behavior (see for a review Kakaria et al. 2023a). It is a noninvasive and quick method to assess reliable variations in heartbeats linked to the modulation of parasympathetic and sympathetic nervous systems. Heart Rate Variability (HRV), derived from ECG, refers to the fluctuation of temporal variation in between consecutive heartbeats, whereas heart rate denotes the number of heartbeats in a specific time range (e.g., 60 s) (Shaffer and Ginsberg 2017). ECG also allows to measure respiration rate i.e., allows for the analysis of the number of breaths and their variability in a period during stimulus exposure (Potter and Bolls 2012; Bell et al. 2018). As such, it is uniquely poised to act as both (a) complementary tool vis-à-vis traditional form of marketing research such as surveys as well as nonconventional tools such as EEG and GSR; and (b) standalone tool to capture consumers' physiological variations in real-time (Zhang et al. 2023).

3.1.2 | Growing Use of ECG in Marketing Research

Recent studies (see Table 2) have utilized ECG to provide insights into marketing phenomena or domains such as attention (Huang et al. 2024), arousal (Baldo et al. 2022; Liu and Huang 2023) and flow (Herrando et al. 2022a; Liu and Huang 2023). Prior studies have rightly focused on correlating HRV metrics with emotional components of consumers (Poels and Dewitte 2006), however, its research scope can be widened to capture consumers' cognitive dimensions such as mental workload. Consumers exert mental effort during decision making involving product comparisons, information procurement and analysis, processing of cues and heuristics, which can impact their purchase decisions (Zhang et al. 2020).

In this digital era, another domain of interest could be to use ECG to measure user experience when interacting with digital and virtual interfaces. Leveraging portable ECG devices can provide real-time reactions when consumers interact with digital products or inside a virtual reality to provide better experiences. Experiential constructs such as enjoyment, delight, presence, and interactivity can be correlated with HRV metrics in digital spaces (Han et al. 2022).

3.1.3 | Using ECG for Marketing Experiments

Commonly used measures derived from ECG in marketing research are limited to the use of heart rate and the root mean square of successive differences between normal heartbeats (RMSSD) (for an exhaustive list of HRV indices used in marketing research, see Kakaria et al. 2023a). In their work, Weiß and Pfeiffer (2024) used a variety of time domain that is, metrics that cover change over a period of time, frequency domain that is, metrics derived from spectral analysis of signals, and nonlinear domain metrics. The length of ECG recordings can range from seconds to hours, depending on the kind of stimuli (static or dynamic) used by the researcher.

With technological improvements, capturing consumer psychophysiological response has become relatively feasible, prompting an increase in the use of portable ECG in marketing research as well. Table 3 provides a limited list of devices used in various studies. Due to the ease of capturing cardiac signals, there has been an increase in the use of portable ECG in marketing research as well (see Table 3)

Reliable data for ECG analysis involves considering aspects about individual's characteristics (i.e., age, gender, fatigue, physical fitness, use of alcohol and tobacco) and data collection environment (i.e., equipment, experimental procedure, temperature, visual and audible distractions) (Catai et al. 2020). Extracted ECG data requires several preprocessing steps to signal to noise ratio, for example exclude artifacts (e.g., participant's movement during data collection) and abnormal beats. As with physiological data, nonparametric testing along with bootstrapping methods is generally recommended because of its non-gaussian distribution (Massaro and Pecchia 2019). The assessment of sample size should be calculated based on the effect size and experimental manipulation. Therefore, depending on the context of the study, prior studies have used wide range of sample sizes for example, within-subject designs ($n = 2$- 1040, $X_{mean} = 107.6$, $X_{median} = 40$) and between-subjects design ($n = 21$- 290, $X_{mean} = 110$, $X_{median} = 96$) (Kakaria et al. 2023a).

In terms of analysis of ECG data, several open source (e.g., Kubios HRV [Tarvainen et al. 2014]) as well as platform-based (e.g., ARTiiFACT [Kaufmann et al. 2011]) tools with intuitive features and

TABLE 2 | Recent publications using ECG to address consumer-related constructs.

Studies (*n* =)	Phenomenon/Theoretical underpinnings	Stimuli Presented (IVs)	ECG Responses measured (DVs)
Lv et al. (2025) *(n = 63; 2 studies)*	Mind-body relationship	Tourist attraction	Heart Rate
Weiß and Pfeiffer (2024) *(n = 50)*	Cognitive Load theory	Various products in virtual environment	Linear and nonlinear metrics
Huang et al. (2024) *(n = 172)*	Attention	Live-action scenes in virtual reality	Heart rate Respiration rate
Liu and Huang (2023) *(n = 170)*	Arousal; Flow theory	Tour in virtual reality	Heart rate Respiration rate
Baldo et al. (2022) *(n = 86)*	Emotional arousal and valence	Images; Videos; Advertisements	Inter-beat interval
Luangrath et al. (2022) *(n = 144)*	Need for simulation	Retail store in virtual reality	Heart rate

TABLE 3 | Non-exhaustive list of hardware.

Device type	Device Brand	Studies
Portable	Hwawei Band 4, Shimmer Systems, Empatica E4 wristband, Bioplux Sensor System	Lv et al. (2025), Hariharan et al. (2016) Martinez-Levy et al. (2022) Sung et al. (2021)
Non-portable	Biopac MP36, PowerLab/16SP, PsychLab Peripheral Pulse Amplifier	Küster et al. (2022) Luangrath et al. (2022)

reliable accuracy are available. Likewise, device suppliers provide in-house software. Integration of ECG signals with other tools is available several platforms such as iMotions (www.imotions.com). HRV data is often extracted in correlation with neurophysiological tools, self-reports, or both (Baldo et al. 2022; Venkatraman et al. 2015). This allows researchers to combine multiple tools for triangulating consumer responses to a particular stimulus.

3.1.4 | Summarizing ECG for Marketing Research

ECGs observe fluctuations in cardiac responses that can occur due to emotional or cognitive processing of a marketing stimulus. In the last decade, the advancements in wearable health monitors and artificial intelligence have allowed researchers to capture cardiac data in a naturalistic setting of consumers through portable devices such as ECG patches, chest straps, smartwatches or bands, smart rings, and shoe-embedded sensors (Bayoumy et al. 2021). When inferring results, researchers should consider the context and individual differences for a quality insight into consumer behavior.

3.2 | Galvanic Skin Response

Galvanic Skin Response (GSR), which is also recognized as electrodermal activity (EDA), Skin Conductance Response (SCR), or Psychogalvanic Reflex (PGR), is a way of measuring electrical changes in the skin caused by sweat gland activity in the palms and finger (Benedek and Kaernbach 2010; Pozharliev et al. 2022a). GSR provides relevant information about the body's level of physiological arousal and excitement in response to stimuli. For example, studies show that higher levels of arousal are often associated with greater attention and memory retention to marketing stimuli (Ravaja 2004), which makes GSR a valuable tool for studying consumer reactions to ads and product design (Poels and Dewitte 2006). This biometric data is collected by applying a (safe and undetectable) constant voltage to the skin using GSR devices, which enables measuring the variance in skin conductance response. An increase in SCR, appearing as a rapid increase in signal value, also designated as GSR peak, is associated with heightened emotional arousal. Event-related responses, which typically occur 1–5 s after a stimulus, have been used to analyze correlations between emotional arousal, stress, and cognitive load (Boucsein et al. 2012). GSR data combined with an automated coding system such as Facial Action Coding System can effectively provide intensity (arousal) and type (valence) of an emotional response (Järvelä et al. 2023; Hamm et al. 2011) (see Table 4).

Studies employing GSR are laboratory experiments using a sample size that tends to range between 30 and 90 participants, and this technique is usually combined with others. For instance, eye-tracking, a sensor technology to capture the movement and position (point of gaze) of the eyes to determine where a person is focusing their visual attention, can provide insights about a person's cognitive processes, such as attention, perception, and decision-making (Milosavljevic et al. 2012). This technology reinforces GSR by

TABLE 4 | Recent publications using GSR to address consumer-related constructs.

Studies (*n* =)	Phenomenon/Theoretical underpinnings	Stimuli Presented (IVs)	GSR Responses measured (DVs)
Guerreiro et al. (2015) *(n = 48; final sample 41)*	S–O–R framework	Cause-related products: hedonic products (chocolate truffles), utilitarian products (laundry detergent)	Pleasure and emotional arousal driving consumer choice
Fox et al. (2018) *(n = 56)*	Emotional contagion theory + appraisal theory of emotions	Service failures Negative online consumer reviews	Consumer arousal and emotions (emotional arousal)
Johnson et al. (2018) *(n = 59)*	Cognitive evaluation theory (CET)	Videogame: three levels of video game reward (high, medium, low)	Emotional state
Hamelin et al. (2020) *Two groups (28 male + 29 female)*	Dual-process theory+ Elaboration Likelihood Model (ELM)	Persuasive storytelling (affective vs. cognitive)	Emotional state
Pozharliev et al. (2022a) *(n = 60, study 1; n = 50, study 2)*	Processing fluency	Traditional versus AR advertising	Physiological measures of arousal +WTP
Juárez-Varón et al. (2023) *(n = 30)*	—	store shopping experience	emotional arousal+ decision making (attraction toward the brand and willingness to purchase)

Note: (-) no information was available in the original paper.

giving information about the visual attention of the participants together with emotional arousal for a better understanding of the choice-decision process (e.g., Guerreiro et al. 2015; Juárez-Varón et al. 2023).

Complementary to GSR, which primarily captures the arousal dimension of emotional response, facial measurement techniques such as automated facial expression analysis (AFE) and facial electromyography (EMG) may offer valuable insight into the valence component of emotion and are often combined with GSR. While GSR can indicate that an emotional reaction has occurred, it does not reveal its qualitative nature. Therefore, the use of facial readers using AFE or EMG techniques can fill this gap by detecting emotional expressions and enabling researchers to infer whether the elicited response is pleasant or unpleasant (Cacioppo et al. 1986).

Automated facial expression analysis. Facial readers use computer vision techniques to classify observable facial movements. These techniques offer scalable, electrode-free alternatives that can identify subtle muscle activations by analyzing interactions between extended sets of facial landmarks and centroids. Such approaches improve the classification of emotional states—particularly in the recognition of basic emotions such as happiness, anger, fear, sadness, and disgust—while also addressing limitations of traditional EMG, such as overlapping signals or discomfort caused by electrodes (Solis-Arrazola et al. 2024). While these systems offer scalability and ease of use, especially in applied or commercial settings because they can be applied without any extra equipment, they remain fundamentally limited by their reliance on visible expressions (Lewinski et al. 2014). Marketing stimuli may not evoke clear facial expressions (e.g., watching ads with a blank face) even though people may experience emotions.

EMG overcomes this limitation by directly measuring muscle activations associated with affective expression—particularly, the *zygomaticus major* for positive affect (e.g., smiling) and the *corrugator supercilii* for negative affect (e.g., frowning) (Larsen et al. 2003). This technique can register micro-expressions that may not be visible to observers (Fridlund and Cacioppo 1986). EMG is particularly useful in advertising research, where social desirability biases may distort self-report data (Hazlett and Hazlett 1999). For example, emotions such as surprise and joy have distinct impacts on how consumers engage with advertisements or other similar stimuli (e.g., persuasive storytelling) (Fox et al. 2018; Hamelin et al. 2020) and AFE is a more reliable analysis compared to questionnaires, where participants self-report their feelings using measurement scales (Teixeira et al. 2012).

Heat maps and heart-beat rates are other complements to GSR. The first represents the information with color detecting which parts of the stimuli (e.g., advertising, webpage, storytelling) engage the attention of the participants contributing to understanding the more interesting and relevant words, terms, or expressions to the reader of the text or the picture (Hamelin et al. 2020). Heart-beat rate refers to the frequency of the heartbeat per minute (Guerreiro et al. 2015; Johnson et al. 2018) and serve as a measure of pleasure that is often correlated with arousal captured using GSR and used for frameworks such as the pleasure-arousal-dominance (P-A-D) emotional state model (Mehrabian 1996) (see Table 5).

TABLE 5 | Non-exhaustive list of hardware.

Device type	Device Brand	Studies
Portable	Shimmer3 GSR device, iMotions biometric platform, Pupil Capture software v.1.23, Gazepoint Analysis UX Edition v.5.3.0ConsensysPRO software v.1.6	Fox et al. (2018), Hamelin et al. (2020), Juárez-Varón et al. (2023)
Portable	Exosomatic electrodermal activity device (a constant voltage of 0.5 V and was sampled at 500 Hz).	Johnson et al. (2018)
Non-portable	BIOPAC Skin conductance response device (captured at a 2,000 Hz rate), BIOPAC AcqKnowledge Data Acquisition	Guerreiro et al. (2015)

From the stimuli side of the studies using GSR, diverse possibilities can be found, such as advertising using immersive technology (e.g., augmented and virtual reality) (Pozharliev et al. 2022a), traditional advertising, storytelling text or image (Hamelin et al. 2020).

When measuring GSR data, both technical and procedural aspects, as well as participant-specific variables, must be taken into account. First, two flat Ag–AgCl electrodes must be placed in the fingers or palms of the nondominant hand, free of moisture, lotions, or oils, which can alter the conductivity of the skin (Boucsein 2012). The electrodes should be prepared with isotonic paste (Fowles et al. 1981). The experiments should be done in a controlled laboratory environment, and the room should have a consistent and moderate temperature due to the possible effects on skin conductance. Second, the participant's emotional state must be neutral at the start of the experiment to allow for a baseline measure to be collected, which will be used to account for individual differences. The individual skin conductance level for each participant is calculated by subtracting the minimum baseline level from the maximum level—which is often created while the subject blows a balloon to bursting (Dawson et al. 2007) using the following formula (SCL − SCLmin)/(SCLmax − SCLmin) (Lykken et al. 1966).

GSR creates a continuous measure that can be decomposed into two components. A tonic component collects the level of arousal and has a more stable response; a phasic component reflects the reactive changes to specific stimuli (Boucsein 2012). A low pass filter should be used to guarantee that high-frequency noise is smoothed and to isolate the phasic responses (Dawson et al. 2007). Due to possible electrode displacement, responses can often lead to artifacts and noise that must be corrected after the experiment. Software such as Ledalab or Matlab can be used to detect and correct unwanted noise (Benedek and Kaernbach 2010).

3.3 | Eye Tracking

3.3.1 | The Growth of Eye Tracking

People's eye movements reflect their unobserved cognitive and affective processes: the tight coupling of eye gaze with visual attention (Corbetta and Shulman 2002) makes its study relevant for the understanding of many of those unobserved processes and their behavioral outcomes. The dramatic reduction in the cost of eye tracking in the subsequent decades, software solutions, miniaturization, and other improvements in the technology have spurred academic eye tracking research (e.g., Janiszewski and Warlop 1993; Rosbergen et al. 1997). These developments fueled a rapid growth in eye-tracking applications in academic and applied marketing research.

3.3.2 | Eye Movements

In most natural tasks, such as exploration, reading, search, or decision making, eye-movement patterns are valid and accurate indicators of several cognitive and behavioral processes (Rayner 2009). Eye movements can thus be used to make inferences on underlying cognitive processes relatively unobtrusively and with a high spatiotemporal resolution. The human eye processes only about one percent of the field of view with high acuity (or about two degrees of visual angle) because photosensitive cones are concentrated in a small region in the center of the retina (the fovea). Therefore, people need to move their eyes to process their entire visual field in detail. These eye movements include saccades, which are fast (20–40 ms) jumps of the eye. In between saccades the eyes scarcely move, and during these eye fixations detailed information is acquired from a small region around the point of focus (Rayner 1998). A scan-path is a sequence of saccades and fixations. Other types of eye movements are micro-saccades (saccades with small amplitude that occur during fixations), smooth pursuits (fixations on moving objects), vergence movements (used to focus the eyes on an object that moves towards or away from the viewer), and pupil movements (that regulate incoming light, amongst others). While the analysis of patterns of fixations or gaze times is useful in many cases, alternatively analyses can consider entire sequences of fixations (scan-paths), or analyze the exact spatial coordinates of fixations.

3.3.3 | Eye-Tracking Equipment

In marketing and various other disciplines, the most common method to record eye movements uses an infrared light emitter directed at both eyes. This invisible infrared light creates reflections on the outer layer of each eye or on the pupil, which are recorded by video cameras. Based on, for example, a six or nine-point calibration during which participants are asked to follow markers on the screen, algorithms are used to infer the eyes' point focus in x-y stimulus coordinates (Duchowski 2003). The calibration task is critical for the accuracy of eye-movement recording; eye trackers provide metrics that allow one to assess the precision of the calibration. Commonly used eye trackers are built into desktop monitors, or into small stand-alone devices; head-mounted eye trackers are embedded in glasses or virtual reality devices. While desktop and stand-alone devices allow some head movements, mobile eye trackers allow entirely free head and body movements. Most commercial infrared eye trackers measure the point of focus of the eyes with a frequency of precision of 50 or 60 Hertz and have a spatial precision of about 0.5 degrees of visual angle (Holmqvist et al. 2017). Eye trackers with a higher spatiotemporal precision make use of multiple corneal reflections and have sampling frequencies of 120 up to 2000 Hertz, for which the participant's head movements may need to be minimized with a chin or forehead rest. Some head-mounted eye trackers have sampling rates in the range of 100–200 Hertz. The most frequently used eye trackers nowadays are those by such manufacturers as *Tobii*, and *ASL*[1]. For an extensive comparison of the accuracy and precision of a large number of eye trackers, see Holmqvist (2017).

In addition, eye movements can be recorded with regular front-facing (web) cameras integrated into most digital devices. These use landmarks on the face and eye, such as the center and shape of the pupil and the location of eye corners, as input to computer vision algorithms that estimate the gaze direction from images of the face (Bulling and Wedel 2019). Those eye-tracking solutions currently have lower accuracy and higher data loss than infrared eye-tracking and may not allow fixations and saccades to be distinguished. However, costs are much lower, and it is easier to collect data on large samples of participants. Some of the commercial solutions on the market are the *Gazerecorder*, and *RealEye*, while *PyGaze* and *Webgazer*[2] are free software packages. Costs of the commercial systems are charged by participants, the results are provided in graphical or tabular form, or as raw gaze data.

3.3.4 | Eye Movement Data

Infrared eye trackers collect samples of the x and y coordinates of the focus of the eyes around 50 times per second or more (along with the eye-screen distance, and pupil diameter amongst others). This typically results in several thousands of samples per respondent. Some of these samples may involve outliers or may be missing due to tracking problems. Before analyzing the eye-tracking data, the quality of the eye-tracking data needs to be assessed, and the raw gaze data are cleaned and converted to fixation-saccade data.

Algorithms are typically used to interpolate missing data, and, using the velocity or distance of the eye between samples, to calculate fixations from the raw gaze data (Salvucci and Goldberg 2000). Most of the commercial eye-tracking hardware comes with software that implements those algorithms, which require manual (or default) setting of some thresholds to calculate fixations. An example of dedicated stand-alone open-source software is the BIT algorithm (van der Lans et al. 2011), which uses robust statistics to automatically determine individual-specific thresholds to allocate the raw samples to saccades and fixations. The percentage of the raw samples that can be classified as fixations allows one to determine the quality of the eye-tracking data for each participant. A useful heuristic is that at least 80 percent of the samples should be classified into fixations for each participant (van der Lans and Wedel 2016). Individuals that do not meet that threshold should be removed, which is important to keep in mind for the purpose of sample size determination and preregistration. Once fixations and saccades are calculated, these can be graphically displayed as heatmaps or scan-path plots, or further processed to yield fixation counts and gaze durations on Regions of Interest (ROIs), selection indicators or first passage times for ROIs, or saccades between ROIs. ROIs are often manually annotated on the visual stimulus, often a static image, video, or augmented reality or virtual reality visual environment. Automated methods of ROI annotation are useful for moving stimuli. Orquin et al. (2016) provide guidelines for the annotation of ROIs in eye-tracking research.

3.3.5 | Guidelines for Eye-Tracking Studies

Conducting eye-tracking experiments is often time-consuming, especially when a limited number of eye trackers is available, because only a few participants can take part in the study at the same time and the presence of a researcher is necessary to monitor the calibration and data collection. Careful preparation and pretesting the experiment and the stimuli is critical for data quality. An eye-tracking experiment consists of at least four steps: (1) design and pretests of the sample, experimental stimuli, and procedures, (2) calibration, (3) selection of participants and collection of eye tracking data, and (4) collection of additional survey measures on attitudes, memory, and other variables.

First, the sample size needs to be determined. General guidelines may have limited use, because the sample size depends on the nature of the study (between- or within subjects, number of stimuli per participant, number of experimental conditions, etcetera), the eye-movement metrics used (gaze duration, fixation counts, or selection indicators), effect sizes, the type of eye tracker (desktop or mobile), and the available time and budget. Most published marketing studies use desktop eye tracking with sample sizes of roughly 50–150 participants. Samples at the lower end of this range may however be too small to achieve reasonable power and for findings to be replicable, especially for between-subjects designs. Power calculations for each application will provide indications of the number of participants, based on what has been used in prior research, we tentatively recommend sample sizes of at least 100 participants (e.g., Atalay et al. 2012; Janiszewski 1998; Shi et al. 2013; van der Lans et al. 2008b). A related consideration is the number of stimuli, or repeated trials, for each participant. For academic research, studies with a single stimulus (ad, shelf, website, etc.) may be ill advised because of limited generalizability of the results (see Wedel and Gal 2024). A larger number of stimuli and a within-subject design often allows for a reduction in the number of participants.

Second, the extent to which the experimental setup mimics real-life conditions is important. External validity is often easier to achieve for the study of stimuli in digital media for which exposure on desktop monitors in lab conditions closely mimics those in real-life. However, for eye tracking of mobile devices usage, head-mounted eye-trackers may be the devices of choice. On desktop monitors, the presentation of the stimuli at realistic magnitudes, the resolution of the images, websites or videos, and the commands that participants need to use to move between stimuli and to provide responses need to be carefully considered and pretested. If the resolution of a stimulus image is too low, the accuracy of the recording can be jeopardized, because the eye tracker measures the point of focus of the eyes in pixel coordinates. Lighting is important because daylight can interfere with the recording and reduce the accuracy of the tracking. Although this is much less the case for mobile eye trackers which are designed to operate under variable lighting conditions, glare can still be a problem in outdoor conditions. For desktop eye tracking, the method by which participants are instructed to respond may affect the eye-movements unintentionally. If participants are instructed to use the keyboard, their eyes may focus there, resulting in a loss of data; if participants are instructed to use the mouse, their eyes may focus on the cursor causing distortions in the eye movement record. To move from one image to the next, participants can be asked to use the space bar and keep their fingers on it throughout the experiment. Careful design and pretesting of instructions mitigate these undesirable effects.

Third, the criteria for including participants in an eye-tracking study need to be specified. Most academic eye-tracking studies use samples of college students, these samples are useful for theory testing and investigating mechanisms; oftentimes working with secondary data provided by companies allows one to use samples from the general population, which provides better generalizability. Participants with glasses with very thick rims, bifocal glasses and sunglasses, long eyelashes, droopy eyelids, and corneal (laser) surgery, may need to be excluded from a study because these features can obstruct or distort the recording of eye movements. Eye tracking participants with glasses is not possible with head-mounted eye trackers. For stationary eye tracking, the researcher needs to ensure that the participant is seated comfortably (using chairs without wheels), and that the height of the screen and the seating is calibrated to enable an optimal distance of the eyes from the screen throughout the experiment (usually 50–100 cm). During calibration, participants focus on two or more (often two, six, nine or 13) markers that move across the screen. The higher the number of calibration markers (which can be set in the eye-tracking software) the higher the accuracy of the recording. If after calibration the data quality is insufficient, the position of the eye-tracker and/or seating of the participant should be adjusted, the participant should be instructed to reduce head movements, limit touching their face, or to avoid looking at the keyboard. Recalibration may be necessary; recalibration can also be necessary half-way through long studies with many stimuli. Modern eye trackers fortunately have a high recapture rate of the eyes after interruptions and allow calibration results to be saved, which is useful for studies that have built-in interruptions or require participants to come back later. Finally, the data collection process needs to be monitored as well, to minimize the loss of data due to failures to track the eyes (van der Lans and Wedel 2016). While mobile eye trackers are less sensitive to some of these influences on the accuracy of eye movement recording, the connection with the recorder that is often placed in a participant's pocket requires attention. For head-mounted eye trackers, the free movement of participants and the ability to track their eye movements in natural conditions can be a major advantage for some studies, but at the same time creates more challenges for data summarization and analysis.

3.3.6 | Relation to Theoretical Constructs

In the marketing literature, eye movement research has been used to make inferences on a wide range of behavioral and cognitive constructs and processes. Compared to some other neuroscience tools, eye tracking offers the advantages of a high spatiotemporal precision and relatively unobtrusive measurement thus often providing greater ecological validity. Table 6 provides a sample of the constructs that have been studied, a key reference to each of them in the psychology/vision literature, references to marketing studies, and the main measures that have been used. To briefly summarize (see Wedel 2015; Wedel et al. 2023 for extensive reviews), taking an indirect approach (Type II in Figure 1), research has shown that attention plays an important role in many real-life tasks, such as *memorization*, *exploration*, *search*, and *choice*. Various studies have investigated these *behavioral effects* of eye movements, as recently reviewed by Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata (2023). Other research, taking a direct approach (Type I in Figure 1), has focused on the *cognitive processes* underlying eye movements. During various tasks, people switch between attention strategies that determine "where" objects are located and "what" these objects are; these *what/where* strategies are reflected in the observed eye movements: "what" strategies tend to produce short and "where" strategies long saccades. Bottom-up factors residing in the stimulus, such as the size of the stimulus and its elements, affect both the *capture and retention* of attention. Especially during search, *targets and distractors compete for attention*. The *salience map* captures the conspicuousness of locations in the visual field based on basic features such as luminance, colors and edges, and directs eye movements. This produces a *scan-path* of the eyes across the stimulus. During various tasks, the scan-path often starts with a *fixation in the center* of the stimulus, which helps direct subsequent eye movements to other salient or informative locations. During choice and search processes the scan-path often ends with a *gaze cascade*, where gaze quickly accumulates on the chosen alternative just before a decision is reached. *Top-down factors*, residing in the person and the task, such as goals, affect eye movements in an interplay with these bottom-up processes.

3.4 | Electroencephalography

3.4.1 | What is EEG?

Electroencephalography (EEG) captures electrical activity originating from the brain by positioning electrodes on the scalp. These signals can then be decoded into the mental processes evoked in consumers' minds towards products, brands, or services. Measures from the ongoing EEG and Event-Related Potentials (ERPs; see below) in response to marketing stimuli can provide valuable insights into consumer behavior, deepening our understanding of the emotional and cognitive processes relevant for advertising, thereby potentially facilitating the development of more effective marketing strategies.

EEG has been pivotal in investigations into the human brain. First developed by Hans Berger in 1929 it has a history spanning over 100 years. EEG measures the amplitude of electrical

TABLE 6 | Publications using eye movements to address cognitive constructs and processes.

Constructs	Theory	Marketing Applications	Eye-tracking metrics
Behavioral			
Attention and memory	Zelinsky and Sheinberg (1997).	Wedel and Pieters (2000).	Fixation counts on ad elements, implicit memory
Attention and exploration	Rayner and Pollatsek (1992).	Janiszewski (1998).	Gaze on ROIs
		Liechty et al. (2003).	Fixation sequences and durations on ads
Attention and search	Wolfe and Horowitz (2004).	van der Lans et al. (2008a).	Fixation sequences on shelves, search performance
Attention and choice	Russo and Rosen (1975).	Russo and Leclerc (1994).	Fixation subsequences, pair comparisons
		Stüttgen et al. (2012).	Fixation counts, decision outcomes
		Martinovici et al. (2023).	Fixation counts, decision outcomes
Cognitive			
What and where states	Ungerleider and Mishkin (1982).	Liechty et al. (2003).	Fixation sequences and durations on ads
Attention capture and engagement	Loftus (1983).	van der Lans et al. (2008a).	Fixation sequences on digital shelf
Competition for attention by targets and distracters	Duncan and Humphreys (1992).	Janiszewski (1998).	Gaze on ROIs
		Pieters et al. (2007).	Gaze on feature ads
Salience map	Itti and Koch (2001).	van der Lans et al. (2008a).	Image features, spatial fixations
Scan-path	Noton and Stark (1971).	Pieters et al. (1999).	Fixation sequences on ROIs
Central fixation tendency	Tatler (2007).	Chandon et al. (2009).	Gaze on ROIs on shelves
		Atalay et al. (2012).	Gaze duration and fixation counts on ROIs
Gaze cascade	Shimojo et al. (2003).	Shi et al. (2013).	Fixation sequences on ROIs over time
		Atalay et al. (2012).	Gaze duration and fixation counts on ROIs
Top-down influence	Yarbus (1967).	van der Lans et al. (2008b).	Image features, spatial fixations

currents and voltage changes over time, which are then amplified and processed for statistical analysis (Ohme et al. 2011). EEG analyses can be broadly classified into two categories: analyzing continuous EEG frequency oscillations and ERPs.

Oscillations in the electrical signal can be classified into different frequency bands—delta (δ, 0.5–4 Hz), theta (θ, 4–8 Hz), alpha (α, 8–12 Hz), beta (β, 12–30 Hz), and gamma (γ, > 30 Hz)—which have been associated with different cognitive and affective states of individuals. For example, Venkatraman et al. (2015) associated occipital alpha activity with increased allocation of attention to advertising stimuli, while Barnett and Cerf (2017) demonstrated that alpha oscillations during movie trailers were associated with later recall and Kislov et al. (2022) suggested that the beta/alpha ratio that they found to be particularly predictive of advertising efficiency at the population level reflected cognitive engagement. (in line with Research Type III in Figure 1).

Analyzing ERPs, on the other hand, is a neurophysiological technique that investigates the brain's immediate response to specific stimuli, offering insights into cognitive processes by isolating and analyzing components of the EEG signal time-locked to events or stimuli (Pei and Li 2021). Sensory stimuli cause characteristic sequences of waves on the EEG, varying by sensory modality and stimulus intensity. The target stimulus evokes a specific waveform, which, when averaged across multiple presentations, produces an average wave called an ERP. ERPs are characterized by their latency, amplitude and topography (Khondakar et al. 2024). Commonly used ERP components in marketing research include the N200 (associated with attention selection mechanisms and stimuli identification), P300/LLP (increased attentional resource allocation to relevant information), and the N270 (brand-product discrepancy, with greater amplitude indicating greater incongruity between stimuli). Similarly, the early sensory ERP component, P100, typically recorded at occipital electrodes, likely reflects visual attention (Woodman 2010; Lin et al. 2018).

3.4.2 | Why Use EEG?

One of EEG's main advantages, relative to other brain-related measurement tools such as fMRI and MEG, is its affordability and portability. The comfortable and quiet environment of EEG makes it an ideal tool for neuromarketing studies, enhancing the external validity of respondents' choices and cognitive processes in ecological paradigms, making EEG a popular choice in commercial settings for evaluating marketing stimuli (Leeuwis et al. 2021; Boksem and Smidts 2015). EEG's portable headset and non-claustrophobic environment enable more unobtrusive measurements, reducing the potential influence on behavior compared to fMRI (Ozkara and Bagozzi 2021). EEG offers high temporal resolution, capturing cognitive processes in real time (Cohen 2011). Furthermore, EEG directly records neural activity and tracks affective-cognitive processing without relying on behavioral responses. Research utilizing EEG spans various applications, from identifying specific mental processes (Astolfi et al. 2008; Kawasaki and Yamaguchi 2012) to analyzing marketing or investigated phenomena (Kong et al. 2012). EEG methodologies, combined with measurements of autonomous variables, offer marketers access to insights otherwise unobservable. For instance, Vecchiato et al. (2014) proposed leveraging these tools to assess television ad perception and tailor production based on consumer gender, such as how the Prada ad scored higher than the Cartier ad in memory and interest metrics.

EEG measures provide real-time data on cognitive processes, attention levels, emotional responses, engagement with stimuli, cognitive load, and memory encoding. Emotional valence is obtained through the “frontal alpha asymmetry” (FAA) index, which gauges the likelihood of engaging in approach versus withdrawal behaviors (Coan and Allen 2004). Higher activity in the left frontal region (indicated by lower alpha power) correlates with a greater inclination to approach positive stimuli, while increased right frontal activity corresponds with withdrawal from negative stimuli. EEG, particularly through the FAA Theory, can measure user engagement by analyzing approach-withdrawal behavior, a key characteristic of positive affect (Berkman and Lieberman 2010).

Attention is measured through changes in amplitude in the alpha, beta, and theta frequency bands. Cognitive load, related to the mental resources necessary for task completion, indicates the mental effort required for the task (Gevins and Smith 2003). For instance, the EEG cognitive load index measures the complexity of visual metaphors by reflecting the cognitive resources needed for their processing (García-Madariaga et al. 2019); or deepens the understanding of the neural mechanisms distinguishing between planned and unplanned buying, providing valuable insights into consumer decision-making processes (Kakaria et al. 2023b). Memory metrics are obtained using EEG, which quantifies global brain activity in the prefrontal channels, filtered in the theta band. Encoding is analyzed through the Theta band in the frontal channels. Deitz et al. (2016) demonstrated the potential of these implicit measures in analyzing online social engagement and the dissemination of paid brand content.

3.4.3 | EEG in Marketing

These mental processes as derived from EEG provide insights into consumer processing and reactions to marketing messages, aiding marketers in optimizing their strategies for greater effectiveness. By combining neurophysiological data with self-reports and other measures, researchers achieve a comprehensive view of consumer responses, optimizing marketing efforts. One of the first studies highlighting the use of EEG in marketing research was conducted by Ohme et al. (2010). This study utilized EEG to identify the activation of the frontal cortex in response to different creative proposals for a TV brand advertisement. The researchers found that EEG was suitable for pre-testing advertisements to assess their alignment with the brand's objectives (Robaina-Calderín and Martín-Santana 2021). This study demonstrates EEG's application in understanding consumer responses to marketing stimuli and evaluating the effectiveness of advertising campaigns.

Boksem and Smidts (2015) and Boksem et al. (2025) aimed to enhance the predictive power of models determining individual preferences and the box office success of movies. They compared EEG measures with self-report measures, such as the willingness to pay for a DVD, and found that EEG data added significant predictive value beyond behavioral measures. As another example, Pozharliev et al. (2022c) correlated neurophysiological data, such as EEG signals indicating attention or emotional arousal, with self-reported measures of attitudes or purchase intentions towards influencer advertising on social media platforms like Instagram. By measuring neurophysiological responses, researchers can access implicit, subconscious reactions that participants may not be able to articulate through self-reports alone. Leeuwis et al. (2021) demonstrated that neural synchrony is a significant predictor for public appreciation on Spotify for 3 weeks and 10 months after the release of the albums, especially when combined with the release of a single. Their results indicate that brain activity measures have greater predictive value than stated preferences. Combining several types of EEG measures can enhance the predictive capability of the EEG signal, as each measure captures distinct cognitive facets of the valuation process (Shestyuk et al. 2019; Hakim et al. 2021).

ERPs are also used to evaluate brain electrical activity associated with cognitive functions such as attention and memory in response to specific stimuli (Handy et al. 2010; Jin et al. 2015), attitudes and preferences (Telpaz et al. 2015), information-based decision making by a variety of product forms when users chose between them (Guo, Ding, et al. 2016; Schaefer et al. 2016) and affect and emotions (Pozharliev et al. 2015). For example, Guo, Zhang, et al. (2016) discovered a relationship between P300 latency, which is related to mental performance and the difficulty of detection and judgment, and response time. Their research showed that the N200 component was more pronounced with unfamiliar recommendation sources, whereas the P300 component was most significant during familiar recommendations. The study concluded that the N200 component reflects information processing in decision-making tasks, while the P300 component predicts the likelihood of purchase, suggesting that familiarity is linked to trust.

3.4.4 | Combining EEG With Other Methods

EEG measurements, combined with other tools, enhance understanding of consumer behavior by validating findings and providing a holistic view of responses. For example, combining EEG with eye-tracking, fNIRS, and other neurophysiological measures can provide a more comprehensive analysis of consumer responses to marketing stimuli (Robaina-Calderín and Martín-Santana 2021). EEG may provide an objective measure of cognitive processes that may not always align with self-reported data. While self-reports rely on participants' subjective perceptions, EEG recordings offer direct insights into neural activity, uncovering implicit or unconscious aspects of decision-making (Ozkara and Bagozzi 2021). By correlating EEG data with self-reported measures of brand preferences or purchase intentions, researchers can validate and complement findings, offering a comprehensive understanding of consumer behavior (in line with Type II in Figure 1). Combining EEG-based ERPs with eye-tracking data (Type III in Figure 1) allows for examining how visual stimuli influence cognitive processing and decision outcomes, linking neural activity with gaze patterns and behavioral responses for a holistic perspective (König et al. 2012; Steinemann et al. 2016; Lin and Li 2023). For instance, Nolte et al. (2024) integrated the classified eye-tracking data with EEG data, producing fixation-onset ERPs confirming the accuracy of the eye movement classification and the timing of event onset (Nolte et al. 2024). The combined EEG and eye-tracking method enable researchers to break down the processing speed task into manageable cognitive and perceptual components, such as working memory, distractibility, uncertainty, and sustained attention (Langer et al. 2017).

3.4.5 | Using EEG

Notwithstanding all the benefits that EEG measures may provide, marketing scholars have been hesitant to embrace EEG methods, preferring relatively newer, yet more expensive and complex techniques like fMRI. Nevertheless, Table 7 summarizes seven prominent marketing studies using EEG as the main approach, including information about stimulus types, independent variables, dependent variables, sample size, theory used, and hardware/software information.

One reason for this relatively slow take-up within the marketing research community is the relative complexity of EEG analyses and the expertise required. The extensive list of preprocessing steps from raw signals to results can be daunting. EEG systems typically provide hardware or software-based quality indicators, visually representing electrode impedance (Khondakar et al. 2024). Low impedance ensures that recorded signals accurately reflect internal brain processes rather than external interference. Data cleaning and preprocessing are crucial steps in EEG analysis, involving artifact, baseline correction, and normalization to ensure the data's integrity and comparability. Once the signals are digitized and amplified, they are recorded and then need to be cleaned (Leach et al. 2023). There are two types of artifacts that "contaminate" the signal and must be removed: (a) Physiological artifacts—derived from muscle activity, eye movements, and blinking, and (b) External artifacts—originated from the environment or caused by the movement of an electrode or abrupt movements of the subject. Once the signals are digitized and amplified, they are recorded and then need to be cleaned. After cleaning the data, one can proceed with its analysis. According to the metrics that are intended to be obtained, calculation algorithms will need to be applied to the obtained data. Crafting effective EEG paradigms demands artistic skill, while analyzing EEG data requires technical expertise. Proficiency in signal processing, artifact detection, attenuation, and feature extraction are essential. Each of these steps necessitates informed decisions to accentuate desired EEG processes or metrics. In addition, appropriate sample sizes are required to ensure reliable measures (van Diepen et al. 2025). For TV commercials, it was shown that, in addition to repeated viewing of the ad (at least twice), for most EEG metrics, sample sizes between 30 and 40 are required for reliable measurement of the overall performance of an ad. For reliably tracking the temporal pattern of an ad, sample size needs to increase further.

To record and post-process the data free software available on the internet can be used or the software provided by the device manufacturer, which usually has an additional cost. However, when choosing the software, we must consider two aspects: (a) If we will use other devices besides EEG, such as ET, GSR, or FC, as is common, we will need software that allows for temporal synchronization of the signals from the devices we will use simultaneously. This software is called integrators, and there are several providers in the market (e.g., Ussens from Bitbrain, iMotions). However, it is essential to verify which devices it can integrate (which ones and what brand) and what type of data it provides (raw or processed); (b) If we do not have knowledge about signal post-processing and metric calculation it would the best to look for software that, in addition to data recording, also handles post-processing and metric calculation.

Typical software for EEG data processing includes tools like EEGLAB, a MATLAB toolbox designed for advanced EEG analysis, and MNE-Python, which is a comprehensive open-source package for processing and visualizing EEG and MEG data. These tools provide robust functionalities for preprocessing, analyzing, and visualizing EEG data, facilitating in-depth neurophysiological research.

3.4.6 | Summary of EEG in Marketing

EEG plays a pivotal role in marketing by capturing brain electrical activity through scalp electrodes, allowing marketers to decode mental processes related to consumer reactions toward products, brands, or services. By analyzing both ongoing EEG and ERPs, EEG provides insights into consumer behavior, revealing emotional and cognitive processes crucial for marketing effectiveness. EEG, developed over a century ago, measures electrical current amplitudes and voltage changes, classified into frequency bands like delta, theta, alpha, beta, and gamma. These bands correlate with cognitive and affective states, enhancing our understanding of consumer attention and memory. For example, alpha oscillations have been linked to attention allocation and recall prediction, while the beta/alpha ratio predicts advertising efficiency. ERPs, on the other hand, offer insights into immediate cognitive responses to stimuli, aiding in the understanding of attention, memory, and brand perception.

The application of EEG and ERP in marketing is transformative. EEG's affordability and portability make it ideal for neuromarketing, enabling unobtrusive and real-time measurement of

TABLE 7 | Prominent marketing studies using EEG.

Study Title	Stimulus Type	Independent Variables	Dependent Variables	Sample Size	Theory Used	Hardware/Software Information
Khushaba et al. (2013)	Crackers described by shape, flavor, and topping	Label of preferences	EEG signals (Delta, Theta, Alpha, Beta, Gamma)	18 participants aged 25–65 years	Probability Theory, Information Theory	Emotiv EPOC wireless EEG headset with 14 channels, Tobii-Studio eye tracker system
Boksem and Smidts (2015)	Movie trailers viewed in random order	EEG measures and Individual liking of the movie	Commercial success	32 participants	Fully data driven selection of EEG metrics predictive of commercial success	Brain Vision Analyzer, EEG recorded from 64 active Ag–AgCl electrodes (Biosemi ActiveTwo)
Hakim et al. (2021)	Video commercials of six food products	EEG measures (frontal powers in the alpha band, hemispheric asymmetry in the beta band, and inter-subject correlation in delta and alpha bands)	Binary choices over the food products, consumer preferences, marketing success	31 participants aged 19–41	Neural distance, Machine learning	StartStim8 EEG, band width of 0–125 Hz, resolution of 24 bits
Ozkara and Bagozzi (2021)	Experienced, review-based, unknown brands	Purchase intentions, brand experience, brand familiarity	Awareness or unconsciousness of decisions to purchase, ERP components	35 participants aged 20–27	Purchase intentions (Schlosser et al. 2006), ERP components	G.Tec headset, 32 active dry electrodes, EEG data analysis using EEGLAB under MATLAB
Kislov et al. (2022)	Banner Ads	EEG, Eye-Tracking, Behavioral Data (likeability)	Session Duration Index (SD-index)	Study 1: 25 participants; Study 2: 48 participants	Neuroforecasting	EEG: NVX36 amplifier, 500 Hz sampling rate, 28 electrodes; Eye-Tracking: SMI RED-m, 60 Hz sampling frequency
Pozharliev et al. (2022b)	Instagram posts	Influencer type (micro vs. meso), argument quality (weak vs. strong)	Neurophysiological responses, consumer responses to influencer advertising	109 participants	Dual Coding Theory, Influencer Marketing	Custom-made 10-electrodes frontal band, BEmicro portable 24-channel device, Tobii Pro X2-30 eye tracker
Kakaria et al. (2023b)	Planned versus Unplanned shopping behavior	Impulsivity, Cognitive load	Shopping behavior, EEG measurements Satisfaction levels	32 participants	Stimulus-Organism-Response (SOR) framework	EEG cap, HMD (Head-Mounted Display) VR technology, Self-report measures

cognitive processes in naturalistic settings. High temporal resolution allows EEG to capture neural activity with millisecond precision, providing real-time data on attention, emotional responses, cognitive load, and memory encoding. Studies like those by Ohme et al. (2010) and Boksem and Smidts (2015) have demonstrated the utility of EEG in pre-testing advertisements and enhancing predictive models of consumer behavior. By combining EEG with other methods (i.e., Research Type III in Figure 1), such as eye-tracking and fNIRS, marketers gain a comprehensive view of consumer responses, validating findings and optimizing marketing strategies. Despite its complexity, EEG remains a valuable tool for understanding consumer decision-making processes, offering unparalleled insights into the neural mechanisms underlying consumer behavior and allowing for more effective and targeted marketing efforts.

3.5 | Functional Magnetic Resonance Imaging

3.5.1 | fMRI: Definition and Relevance in Marketing Research

Functional Magnetic Resonance Imaging (fMRI) constitutes one of the most commonly used brain imaging techniques in academic consumer neuroscience research. It is a noninvasive tool that measures metabolic changes in the brain's blood flow triggered by underlying neural activity—a phenomenon known as blood oxygenation-dependent level or BOLD signal (Huettel et al. 2009). The technique can be seen as the major work horse of cognitive neuroscience. The growing interest in fMRI to better understand processes related to consumer behavior is fourfold. First, it enables a direct moment-by-moment measurement of physiological processes as they occur in the brain. Second, fMRI allows the ability to localize activation to deep brain structures that cannot be accessed with other physiological techniques but play a crucial role in many marketing relevant affective and cognitive processes such as mentalizing, self-relevance, moral cognition, credibility, and reward (Knutson et al. 2007). Third, fMRI allows to distinguish consumer-related constructs that, although subjectively perceived as a part of a single continuum, are in fact processed differently, such as trust and distrust (Dimoka 2010). Fourth, fMRI has a high spatial resolution, making it possible to detect changes in specific brain regions and thus establish in detail, for example, the distinct role of the posterior, middle and anterior dorsomedial prefrontal cortex in resolving response, decision, and strategic control, respectively (Venkatraman et al. 2009). In comparison to EEG, the temporal resolution of fMRI is much lower in that brain response is averaged across 1–2 s. The core advantage of fMRI is its high spatial resolution. As such, fMRI is uniquely positioned as a tool to inform about the neuroanatomical framework underlying consumer processing and decision making in product, branding, pricing, and communication contexts.

3.5.2 | Growing Use of fMRI in Marketing Research

fMRI experiments require participants to lie on a horizontal bed within the MRI-scanner while they passively view marketing stimuli such as commercials or movie trailers or engage in marketing-related tasks by indicating their preferences and choices by pressing buttons on a response box. The application of fMRI in consumer behavior research experienced an exponential growth at the beginning of the 21st century. A first category of fMRI studies (in fact, the largest) adopted a direct approach and showed interest in measuring the neural correlates (i.e., the neurobiological bases) of marketing-associated constructs. Along this line, scholars have unveiled the neural correlates of experienced taste pleasantness (Schmidt et al. 2017), package aesthetics (Reimann et al. 2010), ad persuasion (Falk et al. 2010) and loved brands (Schaefer and Rotte 2007). For example, the study by Yoon et al. (2006) revealed greater neural activity in object processing-related brain regions during the assessment of brand products, as opposed to persons.

Building upon this study stream, more advanced fMRI studies have explored the neural correlates of marketing-related constructs to build and improve knowledge on traditional phenomena and theories (i.e., basic research). For example, a study by Klucharev et al. (2008) tested the effects of source expertise on memory of and attitude towards the product. They found that an expert endorsing a product evokes stronger hippocampal and semantic memory network activity improving memory encoding of the product thus boosting recognition of the product 24 h later. An expert also evoked more activity in the caudate which was predictive of a higher purchase intention of the endorsed product. Whereas source effects are commonly denoted as "peripheral cue" effects in the Elaboration Likelihood Model (ELM), this study detailed the fast and largely unconscious underlying persuasion process of source expertise. Studies by Chua et al. (2009) and Casado-Aranda et al. (2022a) give empirical support to the ELM by highlighting the mediating role of neural activity associated with self-relevance in making (healthy) behavior change more likely. Additional fMRI research makes use of the neural correlates of message framing to refute or reveal the underlying mechanisms of traditional theories such as the Regulatory Focus Theory (Minich et al. 2023).

More recent fMRI studies apply an indirect approach and explore causal relationships between neural correlates and marketing variables. For example, the seminal work by Knutson et al. (2007) reported that brain activity in the nucleus accumbens during product exposure, as well as activity in the medial prefrontal cortex when learning about the price of the product, predicted subsequent purchases beyond self-reports. In the context of communication, mounting fMRI studies have found that brain areas associated with reward, self-reference and mentalizing during persuasive messages predict behavior change within the sample (Falk et al. 2010) or even viral marketing success out-of-sample (Motoki et al. 2020). Predicting market-level outcomes by measuring a relatively small sample of brains is also denoted as neuroforecasting (Knutson and Genevsky 2018). In this latter context, a study by Tong et al. (2020) found that brain activity in regions linked to anticipatory emotions—specifically, increased activation in the nucleus accumbens and decreased activity in the anterior insula—could predict the overall frequency and duration of video views on YouTube. Along the same line, Chan et al. (2019) observed that neural patterns in the temporal lobe and cerebellum—areas typically involved in sensory integration and emotional processing—were strong predictors of out-of-sample preference and recall for TV commercials above and beyond in-sample preference. Brain activity's ability to predict aggregate behavior has also been demonstrated in outcomes such as crowdfunding (Genevsky et al. 2017), cultural popularity of pop songs (Berns and Moore 2012), and the success of a nationwide smoking cessation campaign (Schmälzle et al. 2020).

Some scholars have explored correlations between fMRI metrics and other physiological tools such as EDA, ECG and eye-tracking (in line with research type III as depicted in Figure 1). Most notably, Venkatraman et al. (2015) investigated the links between traditional measures of advertising success (i.e., ad liking and ad recognition), eye-tracking metrics (number of fixations or percentage of fixation on the ad), biometric responses (heart rate deceleration), EEG metrics (e.g., frontal alpha asymmetry) as well as fMRI metrics of cognitive (dorsolateral prefrontal cortex) and affective (nucleus accumbens, amygdala) neural activations in response to ad exposure. They found that whereas traditional metrics (e.g., ad recognition) were strongly predictive of advertising success, only the fMRI metrics were additionally predictive.

More recently, novel fMRI metrics and more sophisticated data analysis approaches have emerged, most notably neural synchronization and multi-voxel pattern analysis. Neural synchronization (i.e., the level of similarity across participants viewing the same marketing-related stimulus) is assumed to measure engagement with the stimulus (Chan et al. 2019). In multi-voxel pattern analysis, the information contained in distributed patterns of neural activity is explored to infer the functional role of brain areas. In a marketing context, Chan et al. (2018) applied these techniques to decode brand image, showing, for example, that strong brands activate more similar patterns of neural activity across consumers than weak brands.

Table 8 provides examples of early fMRI studies applied in product, brand, price and communication contexts.

3.5.3 | Conducting fMRI Experiments in Marketing

Conducting an fMRI study involves four main phases: (1) formulating proper research questions which are based on social science, marketing and cognitive neuroscience theories, providing a step forward in revealing the neuropsychological origin of constructs whose dimensionality has not been corroborated, or in identifying the underlying neural antecedents or consequences of constructs of interest for marketing scholars; (2) designing the fMRI procedure, consisting of: developing a pretest study to provide behavioral support to the fMRI session, recruiting appropriate participants (considering exclusion criteria such as neurological diseases, claustrophobia, pregnancy, body metals, or vision issues), calculating power analysis to establish sample size, selecting image acquisition parameters (e.g., voxel size, slice order, time repetition or time echo), obtaining approval of the ethics committee, and fMRI data collection; (3) analyzing fMRI data which involves three main steps: data preprocessing (to minimize the impact of variables unrelated to the imaging protocol on the data: realignment, slice timing, coregistration, segmentation, normalization and smoothing), first and second level statistical analyses following a General Linear Model procedure for a whole brain analysis with appropriate thresholding, or conducting a Region of Interest (ROI) approach, which entails the extraction of signal from theoretically selected regions of interest, based on prior meta-analyses or similar studies. There are several open source tools and software available for preprocessing (e.g., fMRIprep), statistical (e.g., SPM or FSL) and ROI analyses (e.g., Marsbar) of neuroimaging data; (4) finally, an interdisciplinary team with specific neuroscience and marketing expertise is required to properly interpret fMRI data and draw theoretical and managerial implications.

To reduce reverse inference issues (Poldrack 2011), large-scale meta-analytic databases such as Neurosynth (Yarkoni et al. 2011) can help in interpreting whole-brain patterns of neural activity. This publicly available meta-analytic database is built upon automatic text mining and data extraction of the extant neuroscientific literature. A recent example of the use of Neurosynth in a marketing context is the study by Chan et al. (2024) who decoded the psychological processes underlying advertisement liking.

Whereas fMRI is currently the main neuroimaging tool applied in academic consumer neuroscience research, given the complexity of conducting proper fMRI research, this method is less popular than EEG in neuromarketing practice.

3.6 | Functional Near-Infrared Spectroscopy

3.6.1 | Purpose and Function

Functional near-infrared spectroscopy (fNIRS) is an optical brain imaging tool used to indirectly measure brain activity. The technique was discovered in 1977, when Jöbsis made use of NIRS to noninvasively assess changes in human brain oxygenation caused by hyperventilation (Jöbsis 1977). This groundbreaking discovery opened new avenues for understanding brain function with first applications in 1992/1993 for NIRS to explore functional activation of the human cerebral cortex through oxygenation and hemodynamic changes (Ferrari and Quaresima 2012). Since then, fNIRS has steadily gained attention in a wide spectrum of topics in the field of cognitive and social sciences, functional neuroimaging research, and medicine (Quaresima and Ferrari 2019b), and in the last decade also in the field of marketing research and consumer neuroscience (Casado-Aranda and Sanchez-Fernandez 2022).

fNIRS is a noninvasive, lightweight, and cost-effective neuroimaging technique that employs near-infrared light to measure hemoglobin concentrations in cerebral blood flow (Hoshi 2016). The near-infrared light can penetrate skin, tissue, and bone with minimal interference (Pinti et al. 2020), making it suitable for monitoring cortical brain areas specifically. Within the optical window, specific wavelengths are absorbed by oxygenated and deoxygenated blood: oxygenated hemoglobin (HbO) absorption is higher for wavelengths greater than 800 nm, while deoxygenated hemoglobin (HbR) absorption is higher for wavelengths less than 800 nm (Pinti et al. 2020). By measuring reflected wavelengths with photodiode-active sensors, hemoglobin concentrations can be quantified, allowing determination of neural activity (Ferrari et al. 2004).

fNIRS can be used to explore the neural processes underlying consumer behavior through task-based functional experiments such

TABLE 8 | Examples of early fMRI studies.

Studies (*n* =)	Phenomenon/Theoretical underpinnings	Stimuli Presented (IVs)	Responses measured (DVs)
Knutson et al. (2007) *(n = 26)*	Effects of product and price in driving purchase	A shop trial: product followed by a price and a yes/no purchase choice	BOLD signal in nucleus accumbens, insula and mesial prefrontal cortex. Predicting: Purchases
Venkatraman et al. (2015) *(n = 277 main study; n = 33 for fMRI)*	Ad attention, affect, memory, and desirability	30-s television ads	Traditional (liking, familiarity, recognition…), IAT (valence and memory), eye-tracking (fixation count, pupil size), biometrics (heart rate deceleration/ acceleration and skin conductance), EEG (occipital alpha and frontal asymmetry) and BOLD signal (dlPFC, vmPFC, amygdala, hippocampus, ventral striatum). Predicting: advertising elasticity
Falk et al. (2012) *(n = 31)*	Neural prediction of population- media effects	3 real television campaigns promoting the National Cancer Institute's telephone hotline to help smokers quit	BOLD signal in medial prefrontal cortex (MPFC), self-reported ad effectiveness. Predicting: Ad population level success (call volume from the month before and the month after each ad aired)
Klucharev et al. (2008) *(n = 34)*	Brain mechanisms underlying persuasion of 'expert power'	Celebrities followed by a congruent object relevant to the celebrity expertise (*high expertise condition*) and celebrities followed by an incongruent object (a product with no obvious link to the celebrity expertise: *low expertise condition*)	BOLD signal in areas associated with memory formation (medial temporal lobe and diverse prefrontal cortical areas) and reward/trustful behavior (caudate nucleus). Predicting: Recognition memory and Purchase intention of endorsed products, one day later
Plassmann et al. (2008) *(n = 20)*	Experienced product pleasantness during price information	Tasting three different Cabernet Sauvignon wines and an affectively neutral tasteless control solution	BOLD signal in medial orbitofrontal cortex and self-reported wine liking
Reimann et al. (2012) *(n = 17)*	Neurophysiological responses to novel and familiar brand choice	20 novel logos and 20 familiar logos participants neither liked nor disliked	BOLD signal in executive, reward and value-related brain areas

as event-related experiments or blocked design experiments, as well as resting-state functional connectivity or hyperscanning approaches (Ferrari and Quaresima 2012; Quaresima and Ferrari 2019b). Due to the portability of certain fNIRS systems, researchers are able to examine human behavior in naturalistic settings such as real-world scenarios, high-workload environments, and face-to-face interactions (Doherty et al. 2023; Quaresima and Ferrari 2019b).

3.6.2 | fNIRS in Marketing Research

There is a growing interest and application of fNIRS in marketing research and in practice (Alsharif et al. 2023; Casado-Aranda and Sanchez-Fernandez 2022), as it enables cost-effective and portable measurement of consumer behavior in real-world environments. Since fNIRS and fMRI rely on the same underlying neural mechanisms, fNIRS allows researchers to apply well-established neural markers outside the lab, offering comparable insights—limited to cortical regions—at a significantly lower cost. Since its introduction of fNIRS in consumer neuroscience and marketing in 2014 (Kopton and Kenning 2014), a growing number of studies have applied this method within the marketing domain. To provide a structured overview of the current state of research, a literature review was conducted using the Web of Science database with the keywords "fNIRS" and "marketing," yielding 61 results. Narrowing the focus to peer-reviewed journal articles (n = 43), and further filtering for potentially the most influential studies—those with more than 10 citations ($n = 15$) and a clear marketing focus based on abstract screening ($n = 9$)—the final selection offers a concise overview of the development and application of fNIRS in marketing research. Initial studies validated the applicability of fNIRS in marketing research by replicating established effects, such as the first-choice brand effect (Krampe, Strelow, et al. 2018), and by investigating well-studied processes like subjective preferences and brand or label influences (Kim et al. 2016; Meyerding and Mehlhose 2020). Simultaneously, research has begun to investigate the practical applicability of fNIRS in marketing contexts, with a particular focus on its deployment in real-world retail environments. Within these settings, studies have examined consumer purchase behavior (Çakir et al. 2018) and merchandising effects (Krampe, Strelow, et al. 2018; Liu et al. 2018), highlighting the potential of fNIRS to inform point-of-sale strategies relevant to marketing practice.

In addition, another body of research has employed fNIRS to investigate and predict the effectiveness of marketing communication strategies—both at the point of sale (Gier et al. 2020) and within digital environments, focusing on factors such as popularity and persuasiveness (Cha et al. 2020; Burns et al. 2019). Table 9 provides an overview of these fNIRS studies in the marketing context.

3.6.3 | Brief Application Overview

As the applicability and analysis of fNIRS are explained in more detail elsewhere (Ferrari et al. 2004; Pinti et al. 2019; Tak and Ye 2014) and guidelines are available (Almajidy et al. 2020; Krampe 2022; Yücel et al. 2021), only a brief overview will be given here. As mentioned above, fNIRS can be used to measure two types of hemoglobin concentrations (HbO and HbR; Hoshi 2016), which are useful for various analyses such as linear, correlative or connectivity approaches. Increased HbO and decreased HbR values indicate increased neural activation, while decreased HbO and increased HbR values indicate decreased neural activation (Hoshi 2016). These signals can be interpreted separately, with HbO showing a stronger correlation with cerebral blood flow (Hoshi et al. 2001) compared to HbR, which seems to correlate more strongly with the BOLD signal in fMRI (Steinbrink et al. 2006). Alternatively, they can be used together to provide robustness of the neuronal signals and to check the consistency of activation. In this case, a channel is considered robust if both HbO and HbR values indicate the same neuronal activation, i.e., HbO increases while HbR decreases and vice versa (Tachtsidis and Scholkmann 2016). In addition, various derivatives can be calculated from these measurements (Hoshi 2016), including total blood volume/total blood flow/hemoglobin (HbT = HbO + HbR), oxygenation

TABLE 9 | Potentially most influential publications based on literature review using fNIRS in marketing.

Studies (n =)	Phenomenon	Stimuli Presented (IVs)	fNIRS Responses measured (DVs)
Gier et al. (2020) ($n = 34$)	Merchandising success, cortical relief effect	Merchandising elements	Sum of HbO signals in the dlPFC
Kim, JY; Kim, KI; Han, CH; Lim, JH; Im, CH (2016) ($n = 10$)	Subjective preference	Packaged food and drinks	HbO concentration
Cha, KC; Suh, M; Kwon, G; Yang, S; Lee, EJ (2020) ($n = 56$)	Online music popularity, neural attunement effect	Audio sounds of pop songs	Total blood flow and hemodynamic randomness
Liu, XL; Kim, CS; Hong, KS (2018) ($n = 20$)	Merchandising instore design aesthetics	Fashion store displays	Linear discriminant analysis with mean, variance, peak, skewness, kurtosis, t-value, and slope of the HR signals
Burns, SM; Barnes, LN; Dagher, MM; Storey, JD; McCulloh, IA; Falk, EB; Lieberman, MD (2019) ($n = 41$)	Persuasion	Health and safety videos	Average percent change in HbO concentration
Krampe, Gier, et al. (2018) ($n = 32$)	Product preference, first-choice-brand effect	Coffee brands	HbO signal
Krampe, Strelow, et al. (2018) ($n = 21$; $n = 15$)	Perception of merchandising communication strategies	Shopping scenario videos	HbO signal
Çakir et al. (2018) ($n = 33$)	Purchase behavior, functional roles of PFC regions[a]	Grocery items with prices	Oxygenation signal (HbO minus HbR)
Meyerding and Mehlhose (2020) ($n = 31$)	Brand and Label effects	Fresh food products and drinks	HbO signal

[a]According to the model of Passingham and Wise (2012).

signal (O = HbO - HbR), relative concentration measures (HbO/(HbO + HbR) or HbR/(HbO + HbR)) and conversions to effect size measures (Balconi et al. 2022) or hemodynamic randomness (Cha et al. 2020).

With its wide range of signal options, fNIRS provides multiple options for experimental application (Quaresima and Ferrari 2019a). These are not just about practical aspects like being silent, portable, tolerant to movement artifacts, allowing long-time continuous measurements, and being cost-effective (Doherty et al. 2023); it also extends to analytical approaches (Tak and Ye 2014). However, coupled with its relative novelty, the variety of experimental and analytical possibilities brings a challenge: the lack of standardized pipelines and reporting (Yücel et al. 2021). This hampers replicability and comparisons between fNIRS studies (Yücel et al. 2021).

In general, fNIRS has a low temporal resolution compared to direct measures like EEG (Li et al. 2022) and more similar to fMRI (Steinbrink et al. 2006), as both rely on the hemodynamic response. Spatially, fNIRS has a penetration depth of 2–3 cm, limiting measurements to outer cortical grey matter and brain regions (Strangman et al. 2013). Despite this limitation, fNIRS offers good spatial resolution compared to EEG, as brain activity can be clearly localized due to the signal characteristics and comparability with fMRI results (Li et al. 2022; Steinbrink et al. 2006).

Various types of fNIRS devices are available, some stationary and others portable (often referred to as mobile fNIRS), typically utilizing continuous wave NIRS technology (for a comprehensive overview, see Scholkmann et al. 2014). Generally, light sources are positioned on the head surface, emitting near-infrared light into the tissue (Pinti et al. 2020). Long-range light detectors, approximately 3 cm apart, measure scattered, non-absorbed lightwaves from which hemoglobin concentrations can be calculated afterwards (Pinti et al. 2020). In addition to these long-range detectors, short-channel detectors can be placed directly around the light sources (ca. 1 cm; Brigadoi and Cooper 2015) to measure local extracerebral hemoglobin signals in human tissues, such as blood pressure waves, Mayer waves, changes in respiration, and the cardiac cycle (Zhang et al. 2007), serving to reduce noise in the long-channel signal in the data afterwards (Brigadoi and Cooper 2015). The number and localization of fNIRS channels vary from single to whole-cortex measurements, emphasizing the importance of precise reporting (Yücel et al. 2021).

For data acquisition, various software tools are available, often provided with the fNIRS device, such as NIRStar, Aurora (NIRx Medical Technologies LLC), or OxySoft (Artinis Medical Systems BV). Unlike acquisition modalities, analysis configurations and software tools vary (an overview of software tools is provided at (an overview of software tools is provided at The Society for functional Near Infrared Spectroscopy 2024). However, preprocessing of raw data remains essential in fNIRS analysis. Initially, data might be cleaned (e.g., removing missing values, oversaturated channels, files lacking stimulus information, and renaming stimulus conditions), followed by resampling to address the high autocorrelation in the fNIRS signal (Huppert 2016). Subsequently, after potential further data cleaning (e.g., removing excessive baseline at the beginning and end of each scan), raw data is converted to optical density and finally, using mainly the modified Beer–Lambert law (Kocsis et al. 2006), into hemoglobin values. These values can then be further analyzed according to the chosen analytical approach (e.g., using general linear models).

3.7 | Other Neurophysiological Tools

Other neuroscientific tools that are less used in consumer research include magnetoencephalography (MEG), transcranial direct current stimulation (tDCS), transcranial magnetic stimulation (TMS), and positron emission tomography (PET). Our aim here is to showcase its potential future usage. We briefly describe each tool and show recent research based on them (for further details, we refer to the specific literature and review papers such as Shaw and Bagozzi 2018; Zhang et al. 2023).

The aforementioned tools are seldom utilized in consumer research due to their relatively high costs, technical complexity and specialized infrastructure, or limited availability (see Alvino et al. 2024, for details). Additionally, some advantages they offer are often overshadowed by EEG, fMRI, and fNIRS.

MEG detects magnetic cerebral signals generated by activities in the cortical structures using a helmet placed on the respondents' scalp (Zhang et al. 2023). It is similar to EEG but provides sub-millisecond temporal resolution and good spatial resolution, albeit at a higher cost than EEG or fMRI (Baillet 2017). Unlike fMRI which can cause a sense of uneasiness to the participant due to its claustrophobic closed tunnel-like view, MEG has an open view due to its helmet (Ahlfors and Mody 2019). Ishida et al. (2022) demonstrated links between emotional eating and cognitive restraint in eating behavior.

tDCS uses electrical current to deactivate specific brain areas temporarily. It has a low spatial resolution. Silva-Filho et al. (2025) found that TikTok videos provided minimal helpful information to the audience. With a similar aim, TMS uses electromagnetic impulses to (de)activate a specific brain region and focus on others. It can thus provide causal evidence on the role of a particular brain area in driving a specific response. Klichowski and Kroliczak (2020) used it to investigate whether a price after a discount is a real bargain. Klucharev et al. (2011) used TMS to reduce social conformity to peer opinions.

PET records gamma rays emitted by active biological tracer molecules that are invasively introduced into participants' bodies before they are exposed to a stimulus and focused on metabolic processes and blood flow. It is invasive due to radioactive substances and shows high spatial but low temporal resolution. Its high cost determines its usage only in clinical research (e.g., oncology, neurobiology, and psychiatry) to assess serious diseases. In consumer research, fMRI is used in most studies to measure metabolic issues and offers better spatial and temporal resolution than PET (Kable 2011).

3.8 | New Directions: Hormones and Genetics

Recent research on neuroscience claims to adopt a holistic understanding of consumer neuroscience by adding levels of analysis that address internal body signals (Smidts et al. 2014; Bagozzi and Verbeke 2014; Clithero et al. 2024) and integrative approaches to neuroscience (Shaw and Bagozzi 2018). These signals involve hormones and genetics.

Hormones and neurotransmitters influence behavior (Sarmiento Rivera and Gouveia 2021). Their application broadens the scope of neuroscience into social neuroscience, as "social neuroscience seeks to specify the neural, hormonal, cellular, and genetic mechanisms underlying social behavior" (Cacioppo and Decety 2011, p. 163). While hormones are chemical messengers produced by the endocrine glands and carried through the bloodstream, neurotransmitters are chemical messengers that convey signals between neurons in the nervous system, facilitating communication within the brain and body.

The adoption of endocrinology and hormones in consumer research is scarce and recent. A pioneering contribution by Bagozzi and Verbeke (2014) shows that neurobiological processes can also help to test marketing phenomena by linking neuroscience, endocrinology, and genetics. This approach requires a deeper understanding of such disciplines, specific lab equipment, analytical methods, and caution regarding inverse inference. Its adoption is rooted in the Stimulus-Organism-Response (S-O-R) paradigm, which emphasizes the organism's internal changes in response to stimuli. This approach contrasts with the traditional behavioral Stimulus-Response (S-R) paradigm, which neglects internal human processes. In the S-O-R framework, the organism becomes central to investigating how responses to stimuli are mediated.

Glands, organs, and tissues synthesize and secrete over 50 hormones. The primary hormones in consumer neuroscience include two key types: steroid hormones, such as cortisol and testosterone, and peptide hormones, such as oxytocin and vasopressin (Bagozzi and Verbeke 2014). Important neurotransmitters, including dopamine, serotonin, and endorphins, are also significant due to their roles in cognitive and emotional processes.

Briefly (see further details in Alsharif and Pilelienė 2023; Bagozzi and Verbeke 2014; Sarmiento Rivera and Gouveia 2021; Reuter and Montag 2016), cortisol is associated with stress responses and is a valuable biomarker for evaluating reactions to marketing stimuli. Testosterone and estrogen influence risk-taking behavior, responses to fear and anxiety, empathy, and trust, making them relevant for studying risk-related purchasing decisions (see Durante et al. 2011). Oxytocin is critical for trust and social bonding, offering potential applications for assessing brand emotional attachment, reward processing, and social interactions. Conversely, vasopressin is linked to anxiety and may contribute to gender-specific behavioral outcomes, eliciting aggressive responses in males and affiliative behaviors in females. Regarding neurotransmitters, dopamine is crucial for regulating euphoria and is closely associated with pleasure, reward, and motivation. Serotonin modulates mood, emotions, and anxiety, contributing to emotional regulation. Lastly, endorphins reduce pain and induce pleasure.

Hormone analysis encompasses four critical stages: collection, preservation, analysis, and interpretation. Collection involves extracting biological samples from various sources, including blood, urine, saliva, or scalp hair. Among these, saliva is often preferred due to its ease of collection, non-invasiveness, and rapid processing. Samples should be obtained by comparing baseline measurements with postexposure hormone levels at different time intervals. Preservation is crucial to prevent sample degradation before analysis. The analysis phase requires specialized expertise and advanced analytical techniques, such as Enzyme-Linked Immunosorbent Assay (ELISA) or Liquid Chromatography-Mass Spectrometry (LC-MS), which differ in sensitivity and cost (for an introduction, see Wild 2013). Lastly, interpretation involves comparing the collected samples; however, detecting short-term hormonal changes is challenging and may be influenced by external factors such as ambient conditions or hair treatments.

Genes are fundamental in shaping phenotypes, which refer to observable traits or conditions that influence behavior. Genotypes exert their effects by modulating hormone levels, production, and reception, affecting brain function, behavior, emotions, and cognition. While neuroeconomics research has acknowledged the influence of genetics (Reuter and Montag 2016), Bagozzi et al. (2012, 2014) pioneered a novel neurobiological framework in marketing research. This paradigm elucidates the intricate relationship between hormones and genetics, recognizing that genes influence neurological processes. Simonson and Sela's (2011) paper was among the first to draw attention to the potential influence of heritability and genetic factors on consumer decision-making. The study of the biological basis of consumer choice behavior was underscored by Smidts et al. (2014).

Daviet et al. (2022) propose several applications of genetic measures in marketing research, including using genetic measures as instrumental variables via genetic risk scores to estimate causal relationships, employing a genetic risk score as a control variable to isolate genetic predisposition toward specific behaviors, identifying which stimuli will not influence certain consumer types based on their genetic scores, and finally, aligning genetic scores with neuroscience metrics, that fits with Research Type IV as outlined in Table 1.

Genes exhibit more excellent stability than hormones, which may explain some consumers' slow responses, such as long-term stress, recovery processes, risk-taking behavior in adopting new products, and salespeople's traits (Bagozzi et al. 2012). Consumer research utilizing genetics can significantly benefit from advancements in medical research. In gene-nutrient interactions research, it is well-established that genetics plays a crucial role in determining food intake, intolerances, allergies, and eating disorders (Rankinen and Bouchard 2006). This genetic knowledge can influence marketing research by shaping sample profile selections, determining product development and advertising content, and enhancing the understanding of how consumers process non-desirable cues or preferences. Daviet and Nave (2024) demonstrated how genetic data can predict consumer preferences. Bagozzi and Verbeke (2020) investigated the effects of three genes, dopamine *DRD4*, *COMT*, and *OXTR* on influencing salespeople's motivation and satisfaction. Likewise, Winter et al. (2024) showed that genetic variation and traits predict prospecting in salespeople. Future research on hard biomarkers, including DNA and others, will build customer profiles (De Keyser et al. 2021).

Genetic tests are delivered through saliva, blood, and hair samples or invasive methods such as skin or tissue biopsy. Since their prices are becoming cheaper, a large genome-wide association study data set that brings multiple subjects is advancing. However, theory-driven research is still in its infancy.

The Human Genome Project was officially declared complete in April 2003. The human genome sequence brings appealing research for biology and medicine by revealing the DNA (https://www.genome.gov/about-genomics), which might result in a fascinating new window for its potential extension to the decision-making process and willingness to act in consumer research. Genetic data requires special attention to privacy, storage and ethical use.

4 | An Integrative Framework for Consumer Neuroscience Research

While the previous section provided an overview of the application of neurophysiological tools in marketing research, this section presents a four-stage framework to guide specific consumer neuroscience studies involving aims, stimuli, changes in organisms, and consumer processes, coined as ASOP, as shown in Figure 2. It is inspired by the valuable S-O-R framework (Mehrabian and Russel 1974; Jacoby 2002). The process should begin with defining the study's aims by focusing on the focal construct (s) to be investigated and the type of research approach as described in Section 2 and Figure 1. The study then needs to address the stimuli and, accordingly, the methodological design. This is followed by the choice of brain, physical, or biological measures to be used to elucidate the changes in the organism. The final stage consists of analyzing and interpreting the types of consumer response processes that differ from just the pure response of the S-O-R framework. The following paragraphs outline the stages of the ASOP framework.

This proposal introduces two distinct elements from previous approaches. First, it utilizes a theoretically grounded framework based on marketing principles as a foundational starting point. Second, rather than centering exclusively on consumer responses, it emphasizes the underlying processes that give rise to various response types. Certainly, neurophysiology and neurobiology are well-established fields in the literature. We argue for integrating the two fields to address consumer neuroscience research. The motivation is rooted in three main ideas. First, with a strong focus on organisms, it conveys a holistic view of internal changes in organisms. Second, it is a refinement of the well-known S-O-R framework to refer to types of neural changes in the organism rather than to other responses derived from self-reported data. Third, it is a unifying concept for interdisciplinary research, bridging neurophysiology and neurobiology to broaden the scope of research. Indeed, some research has combined genetics with neurophysiological data (e.g., Bagozzi and Verbeke 2014). This proposal aims to delineate the dynamic interplay of cognitive, affective, and behavioral consumer responses by focusing on the processes.

4.1 | Aims

We propose a theory-driven approach to examining focal constructs instead of a data-driven search without theoretical grounding. This view is particularly important where different disciplines—marketing and neuroscience—intersect. Research aims involve discovering, explaining, and predicting knowledge based on consumer neuroscience processes. Discovering entails disentangling how a signal reveals consumer behavior. For example, whereas previous research has demonstrated that visual attention is related to consumer preference, yet emerging research may yield new insights, such as finding that brain responses provide additional drivers of consumer preference beyond visual attention.

Regarding explaining, it refers to the mechanisms underlying decision-making and related processes (Plassmann et al. 2015), through neurometrics, which provides new insights for a deeper or alternative comprehension of phenomena. The aim of predicting consumer responses (Venkatraman et al. 2015)—termed neuroforecasting by Knutson and Genevsky (2018)—relies on using neurometrics; however, the emerging use of synthetic data in neuroscience is challenging established research practices (see emerging methods in Gopinath et al. 2024). Recent advancements in artificial intelligence have fueled this latter aim, contributing significantly to this endeavor (Lobo-Marques et al. 2025; Marques dos Santos and Marques dos Santos 2024).

The research objective should refine the scope of the time frame of the process to be analyzed by capturing short- or long-term processes (e.g., immediate response to television vs. long-term

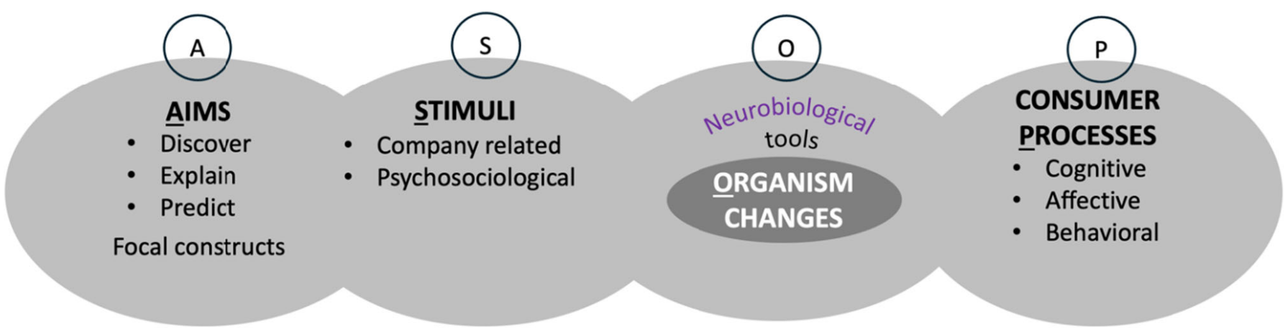

FIGURE 2 | Integrative framework for consumer neuroscience research.Source: own elaboration.

effects of hormones). Further, the portability of some devices (e.g., HR watches, eye-tracking glasses) enables an extension of the analytical timeframe beyond the duration of the stimulus itself (e.g., coincident with a video ad) to more extended periods (e.g., 12 h or even longer for hormones). This extended observation allows for tracking stimulus-driven response processes, including decay effects and carry-over phenomena.

Two key elements should be considered when establishing research objectives in consumer neuroscience. First, objectives can be addressed with an ex-ante approach by establishing a baseline threshold line (typically before exposure to the stimulus) and subsequently measuring the impact of a given stimulus relative to this baseline. Second, research objectives can be examined dynamically, capturing processes such as responses to television advertisements or consumer purchase journeys. Some portable devices (e.g., ECG watches, eye-tracking glasses) allow the extension of the timeframe of analysis from the stimulus duration (e.g., coinciding with the ad duration) to extended periods (e.g., 12 h) to trace a stimulus's decay or carry-over effects.

4.2 | Stimuli

The stimuli influencing consumer responses and decision-making can be categorized into two primary types: company-related factors, which encompass the well-established "four Ps" (product, price, place, and promotion), and psychosociological factors, such as social presence, self-identity and perceptions of risk. We outline the key factors, accompanied by recent marketing research examples, to inspire further research. See also Panteli et al. (2024) who reviewed EEG and consumer behavior and identified 118 papers whose key components resemble those of our paper: marketing stimuli, social factors, and internal characteristics.

4.2.1 | Company-Related Stimuli

Based on the four Ps framework, the elements that warrant applying neurophysiobiological measures are outlined below. These factors fit well with the S-O-R approach (Mehrabian and Russel 1974) and our proposed ASOP. The effect of these company-related factors on consumers can be assessed using neurophysiobiological measurements, including visual attention, memory, arousal, engagement, emotional responses, stress levels, approach-avoidance behavior, pleasantness, and reward. A non-exhaustive list of studies on these company-related factors is shown hereafter. Tools-focused reviews have addressed advances in consumer neuroscience on marketing mix elements, consumer decision-making, and purchases (e.g., brain imaging, He et al. 2021). Here, we showcase specific studies by variable type of interest.

4.2.1.1 | Products, Brands and Services. Neurophysiobiological studies concerning a product or service involve the evaluation of various attributes, such as benefits (e.g., core and potential), branding (e.g., logo, brand name, and positioning), product design (e.g., size, formats, colors, and customization), packaging, service experience (e.g., delivery and failures), and perceived value (e.g., price-value), among others.

A review of consumer neuroscience on branding and packaging by Rodríguez et al. (2023) identified 258 targeted publications clustered in five thematic areas. They reported that attractive packaging generates brain cortical activity in areas related to visual attention, memory, and reward.

Rita et al. (2021) found that EDA arousal was similar for national and private-label brands. The visual attention paid to a brand correlates with the subject's preference, termed "gaze bias" (Pieters and Warlop 1999). Logos have been approached via EEG through N400 peak and relative theta power, demonstrating the necessity of encoding a logo with its authentic brand (Dini et al. 2022). Lastly, the service domain has attracted multiple studies examining servicescapes (Verhulst et al. 2019).

4.2.1.2 | Marketing Communication. Consumer neuropsychological research on communication and promotion examines various elements, including the message content, slogans and claims (e.g., fear of missing out), execution factors, such as characters, endorsers and influencers, music, colors, images, layout or composition (e.g., autonomous sensory meridian response). It also examines the impact of different media types, including websites, social media platforms, advertising formats, and email campaigns. The most relevant studies relate to visual attention, reward, approach-avoidance behavior, arousal, and emotions. A good starting point is the review conducted by Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata (2023). Pieters and Wedel (2004) wrote the most influential paper, which investigated 1363 print advertisements with ET on more than 3600 consumers, resulting in the Attention Capture and Transfer to Elements of Advertisements, AC-TEA, model. Venkatraman et al. (2015) also contributed to predicting success of advertising using neurophysiological measures.

Some examples at the advert message level include the following. Sandoval and García-Madariaga (2024), using EEG and ET, found that advertisements using positive appeals more effectively elicit favorable attitudes and emotional valence toward the ad. The attention paid to pictures is significantly greater in product-focused cause-related posts. In contrast, text attracted greater attention in cause-focused posts (Badenes-Rocha et al. 2022). Using EEG, EDA, and a questionnaire, Simonetti et al. (2024) investigated narrative advertising, finding higher positive perceptions toward advertisements with a high (vs. low) narrativity level in self-reported data. However, the neurophysiological metrics revealed no differences in arousal levels, cognitive load, and approach-avoidance behavior.

Banners have also drawn attention. Simonetti and Bigne (2024) investigated the effectiveness of banner ads via ET and found higher levels of visual attention when consumers browsed a website than when they engaged in the focused task of reading news. Furthermore, via an fMRI study, Casado-Aranda et al. (2022b) found that banners based on hedonic layouts engage brain areas associated with reward, self-relevance, and emotion. In contrast, utilitarian banner ads trigger brain networks related to object identification and recognition, reasoning, executive function, and cognitive control.

At the advert execution level, Ausin et al. (2021a) found that noncongruent ad music generates higher levels of visual attention, cognitive mental workload, and advertisement recall. However, frontal asymmetry was higher with congruent music. Ausin et al. (2021b) used ET, EEG, EDA, and facial coding to examine the effects of 360-degree advertisements for durable goods. Their findings indicated that such ads enhanced positive emotions but carried the risk of non-exposure to some ad content. For social media content types, Bigne et al. (2024a) showed that specific online reviews are more diagnostic than general reviews, and the positive effect of specific versus general reviews on credibility is more substantial for familiar tourism destinations than for unfamiliar ones. Using fuzzy-set qualitative comparative analysis, Bigne et al. (2020) found that the order of positive and negative online comments significantly affects respondents' perceptions of the overall meaning of a series of online reviews, thereby supporting the primacy-recency effect. In a subsequent study, Bigné et al. (2021) addressed the issue of online advertisements and online reviews competing for visual attention.

4.2.1.3 | Price. The neurophysiobiological investigates the influence of price on consumer behavior, focusing on aspects such as willingness to pay, perceptions of excessive pricing, freemium services, rewards, signaling effects, and price-value relationships. These issues are examined with metrics such as visual attention, processing-based evaluations, arousal, gain and loss studies, emotional responses, and brain activity. Two influential studies from 2007 notably advanced fMRI research on pricing. Plassmann et al. (2007) discovered that the medial orbitofrontal cortex and the dorsolateral prefrontal cortex encode individuals' willingness to pay for everyday products. Meanwhile, Knutson et al. (2007) found that excessive prices activated the insula and deactivated the mesial prefrontal cortex before the purchase decision.

In the next decade, an EEG study found that prefrontal asymmetry in the gamma frequency band was strongly related to willingness to pay (Ramsøy et al. 2018). Karmarkar et al. (2015) used fMRI to find that primacy exposure to the price instead of the product alters the medial prefrontal cortex activity, challenging its worth. However, when the value of a bargain-priced product is easily recognized, the purchase likelihood increases. Casado-Aranda et al. (2018b) demonstrated that perceived risky e-payments activate brain regions associated with negative emotional processing, whereas secure e-payments predominantly engage areas involved in reward prediction. The brain reward signature significantly predicts the magnitude of rewards and losses.

Also, ET has been used to explore the impact of pricing. Laurent and Vanhuele (2023) proposed a six-step model for price reading and verbal encoding, emphasizing the importance of multiple visual fixations in this process.

4.2.1.4 | Place. Neuroscientific research concerning place involves spatial or digital disposition (e.g., restaurants, stores, homes, and e-commerce sites), storefronts and displays (e.g., point of sale signage and e-banners), product assortment size, picking up and setting down products, product examinations, time to brand choice, layout, and section disposal. Gier et al. (2020) suggest that neural signals in the dorsolateral prefrontal cortex (dlPFC), as measured by mobile functional near-infrared spectroscopy (fNIRS), can predict actual sales linked to point-of-sale merchandising elements. Casado-Aranda et al. (2018a) used fMRI to investigate perceptions of online risk during an e-shopping task. Bigne et al. (2024c) found that visual inspection of shelves and products was greater than physical inspection through virtual handling, particularly for durable and fast-moving consumer goods. Bigne et al. (2024b) used clickstream data, ET, and EDA to investigate the impact of voice assistant avatars in retail settings. Their findings indicate that these avatars prompted consumers to focus more visual attention on products and elicited higher arousal levels during 2D online shopping compared to experiences in virtual reality stores.

4.2.2 | Psychosociological Factors

These factors involve pure individual factors as well as sociological ones. Individual factors refer to demographics, motivation, personal identity, trust, social media behavior, self-representation, impulsivity, status, and prestige, among others. For example, recent research has explored the connections between the Big Five personality traits and brand personality using EEG and EDA (Xu et al. 2023). While sociological factors involve research on how the self leads to or is influenced by social interactions in the presence of others (e.g., through avatars), social norms and group influences, testimonials and influencers, social media networks, and brand communities on neurophysiological responses.

For instance, Kakaria et al. (2023b) found that impulsivity and unplanned versus planned shopping affect cognitive load (captured via EEG) and time spent in virtual supermarkets. Boksem et al. (2005) investigated mental fatigue regarding attention via EEG. An excellent example of integrating multiple measures is found in Chan et al. (2024), who used neuro measures of psychological processes, cognitive functions, and social-affective response to predict subsequent self-report and ad liking. Emotional contagion has also garnered significant scholarly attention (Verhulst et al. 2019; Herrando et al. 2022b). Wedel et al. (2023) reviewed psychometric and econometric modeling of eye movements during decision-making and provided a framework for its analysis.

4.3 | Methodological Challenges

Research on neuropsychological tools faces at least two methodological challenges. First, as referenced earlier, several of these tools are applied with the purpose of reverse inference, that is, inferring underlying cognitive processes from the data. Such reverse inference can be accomplished by formulating concise hypotheses derived from theory and testing them using carefully designed experiments. Depending on the theoretical framework and the goal of the analyses, neurophysiobiological measures can be used as endpoints or mediators explaining the effects of marketing instruments on downstream behaviors. Examples of this approach are Zhang et al. (2024). Alternatively, for observational data reverse inference can be accomplished through statistical modeling, using statistical models that provide an abstract formalization of theories. Examples of this approach are Liechty et al. (2003), Shi et al. (2013), and van der Lans et al. (2008a, 2008b). Furthermore, large-scale, automated meta-analysis platforms including Neurosynth (Yarkoni et al. 2011) help overcome the problem of reverse inference in fMRI research: by analyzing thousands of studies, it allows researchers to assess whether brain activity in a region is selectively associated with a particular cognitive function, rather than assuming it based on prior beliefs. Through reverse inference maps and statistical base rate corrections, Neurosynth supports more objective and empirically grounded interpretations of brain-behavior relationships.

A second challenge in the analysis of consumer neuroscience measures is sample heterogeneity: oftentimes, the measures exhibit extensive individual differences that need to be accounted for in the analyses, which can be accomplished by including demographic or psychographic variables in models to capture those individual differences. Latent class (mixture) models have been proven to be effective at identifying consumer segments in the data (Rosbergen et al. 1997). Other research has captured individual differences via (Normal) distributions of model parameters, where Bayesian approaches have proven to be useful (van der Lans et al. 2008a, 2008b).

4.4 | Consumer Response Processes

The cornerstone of consumer neuroscience is elucidating the process behind consumer decision-making. In consumer neuroscience, organism responses are dynamically intertwined, and as such, research must focus on the interactions between different response types. Consumer responses can be sorted into three levels with close interrelationships: cognitive, affective, and behavioral. Cognitive response encompasses visual search, attention, and memory components elicited by any stimulus. Affective responses involve emotions, attitudes, and preferences. Behavioral responses comprise consumer decision-making regarding purchase decisions, adoption, and subscriptions. A highly relevant outcome type refers to sales prediction. Gier et al. (2020) demonstrated that neural signals in the dorsolateral prefrontal cortex, measured with mobile functional near-infrared spectroscopy (fNIRS), can predict sales outcomes associated with point-of-sale merchandising elements.

4.5 | Simultaneity of Consumer Neuroscience Tools

A holistic approach that combines several consumer neuroscience tools enriches consumer insights. Despite their complementarity, the simultaneous use of diverse consumer neuroscience tools poses significant challenges. The complementarity of these tools should consider two critical aspects: the potential introduction of artifacts, and the necessity for specialized software capable of synchronizing signals across modalities to enable accurate and simultaneous recording.

Figure 3 illustrates the feasibility of using various neuroscience tools simultaneously, categorized into three groups: physiological changes, brain activation, and biochemical changes. Arrows indicate tool compatibility, either within physiological tools (e.g., ECG and eye-tracking), within biochemical tools (e.g., genes and hormones), or across different types (e.g., EEG and eye-tracking). This simultaneous and combined use of multiple tools fits well with research approaches II, III, and IV.

Notably, temporal synchronization needs further attention for effective triangulation of responses and warrants attention. For instance, genetic data do not demand high temporal synchronization, as they represent the most stable of the measured parameters. Overall, neurophysiological tools exhibit high compatibility both among themselves and with the other two measure types. Biochemical metrics are also compatible with the other two types. However, conducting studies involving the simultaneous use of multiple brain imaging tools remains challenging. It would be beneficial to have more studies that apply brain imaging tools to the same stimuli, as such an approach, even if not simultaneous, provides valuable insights and enhances the understanding of neural processes.

5 | Conclusion and Future Insights

This paper seeks to help in conducting consumer neuroscience studies. We outline that consumer neuroscience employs neurophysiological tools to discover, explain, and predict consumer responses and decision-making by analyzing implicit and continuous signals triggered by various stimuli. Accordingly, this paper delineates research types, tools, and response types.

Our attempt goes beyond descriptive approaches. Specifically, we propose a typology of research approaches in consumer neuroscience (see Figure 1) and present an integrative framework for conducting consumer neuroscience research, coined ASOP (see Figure 2). Additionally, we provide a succinct

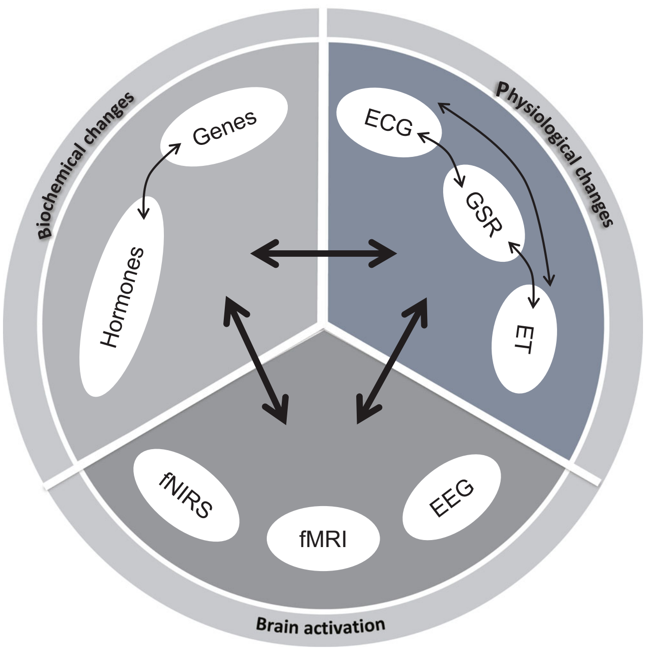

FIGURE 3 | Simultaneous and combined use of consumer neuroscience tools. Bold arrows indicate combined use, whereas the regular arrow indicates simultaneous use.Source: Own elaboration.

overview of each tool, detailing its application contexts, appropriate usage, and implementation methods.

As practical implications for marketing researchers, we propose a forward-looking process comprising four key recommendations. First, given the interdisciplinary and technically complex nature of consumer neuroscience research, adopt a collaborative, team approach, whether across disciplines or with established marketing groups experienced in neurophysiology. Second, clearly define a specific research aim (as highlighted in Section 4.1) that aligns the appropriate neurophysiological tool with the research approach types, as described in Figure 1. Third, when seeking publication, target marketing journals that have previously published work on the topic by maintaining a strict balance of neuroscientific standards and relevant contributions to consumer research findings by exploring consumer subconscious decisions vis-à-vis marketing stimuli. Fourth, strengthen your research through two holistic strategies: integrating relevant neuroscience tools and adopting a mixed methods approach that includes consumer qualitative and quantitative feedback via surveying and voice recording.

Despite its length, the paper's scope faces two main limitations. First, advanced consumer neuroscience researchers could further complement the tools discussed in this paper with specialized content on neuroscience to gain deeper insights. Second, the practicalities of each tool's software and software for synchronizing tools (e.g., iMotions 2014); have not been thoroughly explored. Future research could provide valuable practical insights in this area.

Endnotes

[1] www.Tobii.com, iMotions.com/, www.asleyetracking.com

[2] https://gazerecorder.com/, https://www.realeye.io/, https://webgazer.cs.brown.edu/, https://www.pygaze.org/

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