International Journal of Consumer Studies

Neuroscience Research in Consumer Behavior: A Review and Future Research Agenda

Pedro Oliveira[1], João Guerreiro[1], Paulo Rita[2]

[1] Instituto Universitario de Lisboa (ISCTE-IUL), Cidade Universitária, Av. das Forças Armadas, 1649-026 Lisboa, Portugal

[2] NOVA Information Management School (NOVA IMS), Universidade NOVA de Lisboa, Campus de Campolide, 1072-312 Lisboa, Portugal

This is the peer reviewed version of the following article:

Oliveira, P. M., Guerreiro, J., & Rita, P. (2022). Neuroscience Research in Consumer Behavior: A Review and Future Research Agenda. International Journal of Consumer Studies. [Advanced online publication on 11 March 2022]. https://doi.org/10.1111/ijcs.12800

Neuroscience Research in Consumer Behavior: A Review and Future Research Agenda

Pedro Oliveira[1], João Guerreiro[1], Paulo Rita[2]

[1] Instituto Universitário de Lisboa (ISCTE-IUL), Cidade Universitária, Av. das Forças Armadas, 1649-026 Lisboa, Portugal

[2] NOVA Information Management School (NOVA IMS), Universidade NOVA de Lisboa, Campus de Campolide, 1072-312 Lisboa, Portugal

Consumer neuroscience is a growing field in both marketing and consumer behavior research. The number of articles published on the topic has increased exponentially in the last 15 years. However, there is still no compreenshive analysis of the literature highlighting the main constructs, trends and research gaps found in such a large collection of papers. Therefore, this paper provides a text mining (TM) analysis that clusters and systematizes the complex and dispersed information of 469 articles, using the correlated topic model algorithm (CTM). Results show that "consumer neuroscience", "brand memory", and "willingness to buy" are the most relevant topics in the field. This study also reveals that the literature has been focusing on ethical concerns as well as on controversial concerns in the use of consumer neuroscience techniques. We include a final section on future research questions and opportunities that emerged from the conducted research.

Keywords: Consumer Research; Consumer Behavior; Neuroscience; Text Mining; Correlated Topic Models

1. Introduction

The study of the human brain is no longer a matter of interest just to neurologists and health professionals (Camerer & Yoon, 2015). The last 15 years have seen significant advances in neurosciences, and multiple neurophysiological methods have been used to generate insights in marketing, consumer behavior and advertising (Stipp, 2015). Samples collected through computational methods can now provide more accurate predictions than self-reported measures (Ariely & Berns, 2010). In fact, the human brain hides useful information regarding consumer attitudes that cannot be easily uncovered just by assessing self-expressed individual preferences. The widely used questionnaires to register individual preferences and attitudes can lead to biased and inaccurate conclusions (Fisher, 1993).

Shiv et al. (2005) published one of the pioneering articles discussing the relevance of neuroscience and how it could significantly improve future studies on decision making. In fact, "neuroscience has become both a useful tool and a source of theory development and testing in decision-making research" (Yoon et al., 2012, p. 474). The advances in technology provide new computerized neurophysiological recording systems that allow a non-invasive collection of behavioral data, building rich databases for theoretical analysis (National Research Council, 2008).

In the course of time, scholars have reviewed the existing knowledge in consumer neuroscience and neuromarketing research. However, most previous literature reviews on the topic have used systematic approaches based on a limited number of articles, period range and research fields. For example, Smidts et al. (2014), Solnais et al., (2013), Jordão et al. (2017) and Lee et al. (2018) are limited to studies done more than 5 years ago. More recently, Rawnaque et al., (2020) studied only papers from 2015 to 2019, and focused on a technological scope, while our time frame and scope is much wider. Our paper is also the first to use a text mining approach to uncover latent topics in the text, removing some potential bias in the interpretation of the articles. Despite the important contributions of past literature reviews, Lin et al. (2018) relied only on studies using EEG, while Lim (2018a) focused exclusively on studies around business-to-business (B2B) marketing without a systematic procedure. The review by Alsharif et al. (2021) was based on advertising research, Vences et al. (2020) limited themselves to studies on social networks and Mandolfo and Lamberti (2021) on impulsive buying. Finally, Alvino et al. (2020) conducted an overview of consumer neuroscience tools, based on a traditional review of a 15-year period, and restricted to non-invasive tools. Past studies have also looked at a limited number of articles. For example, the systematic review conducted by Cruz et al. (2016) was based on a selection of 20 indexed journals about consumer behaviour, marketing, psychology, and neuroscience, considering a total of 49 articles. Lim (2018b) performed content analysis on a group of 78 articles from the Association of Business Schools (ABS) list of only 21 marketing publications. Despite the important literature reviews conducted in the past addressing the use of neuroscience methods, to the best of the authors' knowledge, no study has yet made a comprehensive and integrated review of all the vast and complex information on the topic.

Due to the exponential number of articles published in academic journals on consumer neuroscience and consumer behavior, the traditional or systematic literature review process is a very complex, voluminous, and time-consuming task (Delen & Crossland, 2008) generating a "data deluge" problem (the point where the amount of research on the topic exceeds the ability to manage so much information) (Ananiadou et al., 2009). Using a traditional approach, there is a need to conduct a manual screening of the literature to filter out less relevant papers (Thomas, McNaught, & Ananiadou, 2011), read every single article to identify the topics in a particular publication and evaluate the relevance of the published study (Griffiths & Steyvers, 2004). However, due to the growing number of articles available on several databases, important knowledge is potentially overlooked in the systematic review process (Delen &

Crossland, 2008). To overcome this issue, this paper aims to provide comprehensive knowledge on consumer neuroscience and neuromarketing by clustering and systematizing the complex and disperse textual information available. Therefore, in order to identify the main topics and theories discussed over more than 70 years of applying neuroscience within social sciences, this paper conducts a comprehensive review of the literature using a text mining (TM) technique.

TM is an efficient and accurate method to extract information, trends and patterns from large collections of documents (Ananiadou, Rea, Okazaki, Procter, & Thomas, 2009; Blei, 2012). This study employs the TM technique through R software, with application of the correlated topic model (CTM) algorithm due to its ability to model correlated topics, besides topic detection (S. Lee et al., 2010).

2. Theoretical Background on Consumer Neuroscience

Consumer neuroscience and neuromarketing are two terms used interchangeably in the literature though with subtle differences (Kenning & Plassmann, 2008; Lim, 2018; Reimann et al., 2011). Neuromarketing is a broader topic that entails the application of neuroscientific methods to understand conscious and unconscious consumer behavior in response to marketing stimuli (N. Lee et al., 2007, 2018; Solnais et al., 2013; Stipp, 2015). Formerly considered a branch of neuroeconomics (Camerer et al., 2005), the neuromarketing jargon was originally formulated in two papers published in 2007 (Fugate, 2007; Lee et al., 2007), but initially referred to by Ale Smidts in 2002 (Lim, 2018b). Despite the growing interest in and relevance of consumer neuroscience over almost two decades, the use of neuromarketing techniques is still quite controversial due to rising ethical issues, concerning the "(1) protection of various parties who may be harmed or exploited by neuromarketing and (2) protection of consumer autonomy" (Murphy et al., 2008, p. 294).

As for consumer neuroscience, Smidts et al. (2014) refer to it as a sub-field of neuromarketing, which applies neuroscience insights to study consumer behavior. Therefore, consumer neuroscience can be defined as an interdisciplinary field combining psychology, marketing, neuroscience and economics with the main goal of studying neural conditions and processes underlying consumption, physiological meaning and behavioral consequences (Lee et al., 2007; Reimann et al., 2011; Hansen, Kenning & Plassmann, 2010).

In consumer neuroscience the majority of studies on the impact of external stimuli on consumer emotions and behavior are grounded on the seminal framework proposed by Mehrabian and Russell (1974). The Stimulus-Organism-Response (S-O-R) model has been used as a way to explain the emotional reactions an individual or organism experiences after exposure to specific stimuli in a particular context. The stimuli is meant to create certain emotional traits in individuals that vary across different dimensions such as intensity, degree of pleasure and activation (Russell & Pratt, 1980). As far as responses are concerned, the primary emotions triggered will determine the approach-avoidance response (Vieira, 2013; Vinitzky & Mazursky, 2011) defined by the interest in exploring the environment, willingness to interact with others, or even the level of satisfaction that may lead to certain behavior such as purchase or recommendation. Vieira (2013) ran a meta-analysis identifying the most significant constructs for S-O-R, including brand commitment, attitude towards the advertisement, service quality, site entertainment, among others. Chan, Cheung, and Lee (2017) used the S-O-R framework to study the factors that trigger online impulse buying, and classified them into internal and external stimuli, organism, and online impulse-buying response. Wang, Chen, Ou, and Ren (2019) developed a research model grounded in S-O-R to analyze the impact of marketing and social media stimuli on participants' message reposting intention. Another example of an adaptive S-O-R framework has been proposed to study the components associated with the use of immersive technology (Suh & Prophet, 2018), concluding that both system features and content topics influence participants' cognitive and affective responses, but also identifying which stimuli typologies potentiated these responses.

The most common neuroscientific methods used by academics, researchers and business practitioners include functional resonance magnetic imaging (fMRI), electroencephalogram (EEG), eye tracking, magnetoencephalography among other psychophysiological and brain imaging tools (Lin et al., 2018) as described in *Table 1* and *Figure 1*.

INSERT TABLE 1

INSERT FIGURE 1

Biometrics are used to measure automatic responses to external stimuli (Venkatraman et al., 2015) as mechanisms to independently assess arousal. The heart rate is measured through Electrocardiogram (ECG) and is controlled by antagonistic systems, the sympathetic and parasympathetic nervous systems (Potter & Bolls, 2012). The sympathetic nervous system (SNS) increases heart and breathing rates showing evidence of arousal, while parasympathetic nervous system (PNS) activation leads to heart rate deceleration, enabling greater focus on the stimuli, and therefore is used as a measure of attention. In addition, SCR is employed to identify SNS activation from sweat level changes (Dimoka et al., 2012).

The main advantage of using psychophysiological tools, such as eye-tracking and facial electromyography (fEMG) is their low cost, accessibility, minor intervention and non-invasiveness. However, SCR has been criticized as having low reliability and small latency (Venkatraman et al., 2015) and ECG is difficult to interpret due to the numerous factors that can influence heart rate. The eye-tracking methodology benefits from the identification of visual activities that cannot be self-reported. Nevertheless, it can also be biased because a fixation does not mean the participant has paid attention to a specific stimulus (Dimoka et al., 2012). fEMG is widely used to measure participants' emotional valence (Lajante et al., 2017), in a continuous and precise way, but its limitations include the small number of muscles involved in research, the modification of natural expression as electrodes are positioned on an individual's face, and its susceptibility to bias in interpreting results.

As for brain imaging tools, EEG is the most widely used neurophysiological tool in advertising research (Y. J. Wang & Minor, 2008). EEG is a non-invasive technique with high temporal resolution, often used to assist in researching cause and effect relationships between several marketing stimuli and the associated cognitive response, providing close to real-time data, and enabling the understanding of how neurons communicate between each other. Event-Related Potentials (ERP) are a specific application of EEG in which trials are "time locked" aiming to uncover emotional and cognitive brain activity elicited by sensory stimuli (Lin et al., 2018). As ERP signals are small due to signal obstruction by the skull, electrical brain activity amplification is required. These signals are characterized by peaks and troughs, called ERP components (Bastiaansen et al., 2018). ERP has been employed in perception, attention and memory research (Rugg, 2009). When compared with fMRI, Positron Emission Tomography (PET) and Magnetoencephalography (MEG), EEG is cheaper, easily portable and tolerant to participants' movements. However, its major limitation is related to low spatial resolution as "it is restricted to measuring only cortical brain activity" (Venkatraman et al., 2015, p. 339).

In the field of consumer neuroscience research, fMRI has been recurrently used to measure brain activation to different marketing stimuli and in decision-making research (Smidts et al., 2014). This non-invasive technology measures the activation of specific brain regions with an excellent spatial resolution but lacks good temporal resolution, being a good complement to EEG and MEG due to their higher temporal resolution (Dimoka et al., 2012; Harris et al., 2018; Reimann, Schilke, Weber, Neuhaus, and Zaichkowsky, 2011). While EEG is mostly used to measure attention and affect, fMRI can also measure memory and desirability (Venkatraman et al., 2015). With a similar spatial resolution to fMRI, PET's temporal resolution is even lower (2 or 3 minutes) than fMRIs. Notwithstanding, PET is not commonly used in consumer neuroscience research due to its invasiveness, since subjects are injected with radioactive material (Dimoka et al., 2012; Harris et al., 2018). MEG has also been used to assess cognitive and affective stimuli in advertising research, but to a lesser extent than EEG or fMRI, as it is not a widely accessible tool, being comparable to EEG in terms of temporal resolution. Even though MEG is more effective than EEG in analyzing deeper brain structures, it is a quite costly and statistically complex device to work with. MEG also has a lower spatial resolution than fMRI (Dimoka et al., 2012).

The Single-Neuron Recording has some advantages over other neurophysiological methods due to its finer spatial resolution at a single neuron level (Cerf et al., 2015), but major disadvantages limit its use in neurosciences research, as it requires greater financial and human resources than EEG and fMRI, and because of its intrusiveness and restriction to patients with epilepsy and to a small set of neurons, in which implants are determined by "clinical criteria for epilepsy neurosurgery" (Cerf et al., 2015, p. 533).

3. Methodology

3.1. Systematic Review Design

Sytematic reviews can be classified in different categories (Paul & Criado, 2020), such as: a *structured review* when focusing on widely used methods, theories and constructs (Canabal & White, 2008; Kahiya, 2018; Paul & Singh, 2017; Rosado-Serrano et al., 2018); *framework-*

based when frameworks like ADO (Antecedents, Decisions, and Outcome) employed by Paul and Benito (2018), or TCCM (Theory, Context, Characteristics, and Methodology) developed by Paul and Rosado-Serrano (2019) are used; a *hybrid-narrative review* when a framework is integrated in a narrative discussion leading to a future research agenda (Bahoo et al., 2020; Dabić et al., 2020; A. Kumar et al., 2020; Paul et al., 2017); a *theory-based review* (Gilal et al., 2019; Paul & Rosado-Serrano, 2019); a *meta-analysis* (Barari et al., 2021a; Knoll & Matthes, 2017; Rana & Paul, 2020); a *bibliometric review* (Kumar et al., 2029, 2020; Randhawa et al., 2016); a *method-based review* (Sorescu et al., 2017); a *review aiming for model/framework development* (Paul, 2019; Paul & Mas, 2020); or a *text mining approach* (Bilro et al., 2021; Guerreiro & Rita, 2020; Loureiro, Guerreiro, & Han, 2021; Muñoz-Leiva et al., 2021). The current study is based on the text mining approach, which extracts useful information from a large collection of data in a semi-autonomic way, otherwise considered as humanly impossible or unrealistically time-consuming. This technique is much more efficient, accurate and objective, giving structure to unstructured data, and allows statistical analysis of the retrieved data (Blei, 2012; Griffiths & Steyvers, 2004; Guerreiro et al., 2016; Moro et al., 2017). Even though a bibliometric analysis also conducts a quantitative analysis of a large dataset and provides reliable indicators for quality, it does not analyze the textual information inside each article. Using a text mining approach, such information can be structured and clustered into different latent topics, which adds valuable context to a quantitative analysis. However, a hybrid approach between these two techniques can lead to results in much greater depth (Donthu et al., 2021; Islam et al., 2021; Paul et al., 2021). Even though this study is a review paper grounded on a text mining analysis, a section detailing future directions was conducted. This section was built upon the most cited articles from 2017 to 2021, in order to consider the most impactful studies up to date (Aria et al., 2020; Loureiro et al., 2020; Paul & Bhukya, 2021). As the total number of citations is correlated with year of publication, the Average Number of Citations per Year (AC_y) was calculated.

3.2. Text Mining

Text mining is an automated or semi-automated technique that extracts text from a large collection of unstructured documents (Delen & Crossland, 2008). The TM technique is a more efficient and accurate method than the traditional systematic literature review to extract information, select topics and studies of interest, and identify trends and patterns from a large collection of documents (Ananiadou et al., 2009; Blei, 2012). It reduces the time spent on identifying the relevant literature, its description, categorization and summarization. Considered as an extension of data mining (Ittoo et al., 2015), TM can lead to the discovery of new, hidden insights from unstructured documents. In TM, terms are usually represented as a *bag-of-words*, ignoring the lexical co-occurrence, i.e., assumed to occur independently, neglecting their context and order in sentences and documents (Blei et al., 2003; Yang, Wen, Kinshuk, Chen, and Sutinen, 2015). In this case, terms can be allocated into different topics. Each term frequency is then counted and stored in the Term-Document matrix (TDM). In order to deal with the *bag-of-words* approach, the importance of a term in a document and among documents can be calculated based on term frequency and inverse document frequency (*tf-idf*), which considers the relative frequency of a word within a document, and the length of that document (Karl et al., 2015), removing those terms which are frequent in a single document, but not frequent in other documents (Amado, Cortez, Rita, & Moro, 2018; Guerreiro, Rita, & Trigueiros, 2016). The conceptual text mining process encompasses several stages (Feinerer et al., 2008). After collecting the unstructured and heterogeneous corpora, the initial stage comprises preprocessing the dataset by tokenization, reformatting, stemming, punctuation and stop-word removal. Then, a TDM is generated, the most common textual data form for computation, and similar terms are clustered in the same groups, which will consist of the underlying topics (Cortez, Moro, Rita, King, & Hall, 2018; Guerreiro et al., 2016; Moro, Rita, & Cortez, 2017).

3.3. Clustering Text via Correlated Topic Models

Topic models are mathematical algorithms grounded on natural language processing and machine learning that cluster text into latent topics (Gutierrez & Nakai, 2016; Blei & Lafferty, 2006). The Latent Dirichlet Allocation (LDA) and the Correlated Topic Models (CTM) are the two topic model algorithms usally used to model large collections of documents, but they differ in the first step of the generative process. In the case of the topic model LDA, the topic proportions are assumed to follow a Dirichlet distribution (S. Lee et al., 2010). However, this model fails to incorporate the correlation of topics, due to the topic mixture proportion independence assumptions of the Dirichlet distribution for each document. This limitation does not allow the occurrence of a term in more than one topic, which is less realistic when analyzing a real collection of documents (Paisley et al., 2012). In order to overcome this limitation, CTM uses the logistic normal distribution to capture the relations among topics, enabling a covariance structure between the random variables topic mixture proportions (Blei & Lafferty, 2007).

Both CTM and LDA are classified as mixed-membership models, as documents are assumed not to belong to a single topic but to several topics simultaneously (Grün & Hornik, 2011), and grounded on Bayesian probabilistic modeling, aiming for decomposition of the large collection of textual data into multiple latent topics (Blei & Lafferty, 2007). CTM has been employed to accomplish different tasks such as topic extraction (Guerreiro et al., 2016; Loureiro et al., 2019, 2020), query classification (Zhai et al., 2009), motif finding (Gutierrez & Nakai, 2016), human action recognition (Tu et al., 2014), facial expression recognition (K.-

P. Chan et al., 2015), tracking scenes (Rodriguez et al., 2009), and image retrieval (Greif et al., 2008).

In their research, Blei and Lafferty (2007) highlighted the enhanced prediction performance of CTM over LDA, as well as the richer descriptive statistics available. The authors concluded that CTM fits the data better and supports more topics than LDA, using likelihood and *perplexity* metrics. The *perplexity* of a statistical model is a measure of the uncertainty of predicting a word in a document, evaluating a model's distribution accuracy to predict a sample, being equivalent to the geometric mean per-word likelihood. The lower the *perplexity*, the better the model fits the data (Gutierrez & Nakai, 2016). Blei and Lafferty (2007) found that under CTM, *perplexity* is nearly 10% lower than when using LDA. Therefore, the CTM algorithm is used in the current study to find hidden topics in the literature.

3.4. Data Extraction

A query or search string using neuroscience and neuromarketing keywords was conducted on Scopus database. Scopus was used instead of Web of Science (WoS) due to its broader range of subject areas and categories (Alvino et al., 2020; Naz et al., 2021; Paul et al., 2021), providing a larger pool of articles, since our main goal is to provide a general overview of the topic. To obtain a sophisticated search string, the Boolean search operators AND and OR were added between different terms, and the search was restricted to specific parts of the article, such as title, abstract and keywords. The query was built in two parts. In the first part of the query, keywords about consumer neuroscience, neuromarketing and neuroscientific tools (including derivatives) were used. The second part of the query limited the search based on field specifications (marketing) and inner disciplines (e.g., advertising, branding, promotion). The keywords for the first part of the query were adapted from the studies by Cerf et al. (2015), Criado et al. (2008), Dimoka et al. (2012), Harris et al. (2018), Lim (2018), and Venkatraman et al. (2015). Regarding the keywords for the marketing part of the query, we considered the journals from the Association of Business Schools' (ABS) Academic Journal Guide (AJG, 2021) rated with 4*, 4 and 3 in the field of Marketing, such as Journal of Marketing, Journal of Marketing Research, International Journal of Research in Marketing, Psychology and Marketing, and European Journal of Marketing, amongst others. We built a database with all the keywords, analysed their frequencies, and considered the top 4 terms, namely, Marketing, Advertising, Promotion, and Brand.

The search query retrieved a total of 2,386 articles that were later narrowed down to the results of the top 4 areas, Neuroscience (330), Psychology (260), Business, Management, and Accounting (259), and Social Sciences (254), which generated the following query:

> (TITLE-ABS-KEY ("NEUROSCIENCE*" OR "NEUROMARKETING" OR "NEUROMANAGEMENT" OR "NEUROECONOMIC*" OR "NEUROTOURISM" OR "NEUROETHIC*" OR "NEUROPHYSIOLOG*" OR "NEUROIMAG*" OR "NEUROIS" OR "EYE-TRACK*" OR "FUNCTIONAL MAGNETIC RESONANCE IMAGING" OR "FMRI" OR "ELECTRO-ENCEPHALOGRA*" OR "EEG" OR "ELECTROCARDIOGRA*" OR "ECG" OR "ELECTROMYOGRA*" OR "FEMG" OR "SKIN CONDUCTANCE" OR "SCR" OR "ELECTRODERMAL" OR "EDA" OR "EDR" OR "GALVANIC SKIN*" OR "GSR" OR "BIOMETRIC" OR "HEART-RATE") AND TITLE-ABS-KEY ("MARKETING" OR "ADVERTIS*" OR "PROMOTIONS" OR "BRAND*")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ip")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "NEUR") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "PSYC") OR LIMIT-TO (SUBJAREA, "SOCI"))

The query revealed a total of 893 articles, which were manually screened to reduce all possible noise and achieve a more robust analysis and coherent results (Ashraf et al., 2018; Moro et al., 2015a). This screening procedure followed the quality criteria used by Loureiro et al. (2021, p. 922), adapted from Macpherson and Holt (2007), and present in Table 2. In fact, some terms in the string are also used in different contexts with different meanings. Hence, there was a need to identify and remove articles that were not related to the topic. A final set of 469 articles met all the criteria and were later analyzed using R software. Figure 2 shows the process followed to achieve the final set of articles.

INSERT FIGURE 2

INSERT TABLE 2

Articles were copied into a txt file format (the most transversally accepted text format by the different platforms). The text of the articles was either copied directly from the publishers' website or extracted using optical character recognition procedures (OCR).

3.5. Data Pre-Processing and Model Parameters Estimation

The collected dataset with all the text of the articles was pre-processed in order to remove punctuation, white spaces, numbers, and stop-words. A stemming algorithm was also applied to each word in the documents (see *Fig. 3*). Stemming consists of reducing inflected and derived terms into their root base form (Moro et al., 2015a; Richardson et al., 2014). Besides stop-word removal, other terms such as, "first", "will", "may", "can", "one", "two", "also", "use", "increase", "however", "found", "find" were excluded from the analysis due to their high frequency in the documents, but meaningless for topic / terms interpretation (Guerreiro et al., 2016). The TDM was then created, in which the columns consisted of the different documents and the rows had the words and scores based on terms' frequencies. The TDM matrix had a high sparsity level (98% of the elements are zero), with 35,232 terms in 469 documents. To reduce matrix sparsity, a threshold of 90% was set to retain only the terms that occured at least 10% of the time, returning a much less sparse set of terms. In order to reduce terms that were very frequent in one document but not in others, the term frequency and inverse document frequency (*tf-idf*) approach was employed, and set to values greater than .00260 (*tf-idf* > .0026), which was slightly lower than the median value (.00266) to guarantee the omission of high frequency terms (Grün & Hornik, 2011; Guerreiro et al., 2016). The new TDM matrix had 1,856 terms in 469 documents.

INSERT FIGURE 3

Before proceeding with the CTM estimation, the appropriate number of topics (*k*) had to be determined. Instead of selecting a *k* value randomly, several simulations were undertaken to find the optimal number of topics using three different approaches simultaneously. Griffiths and Steyvers (2004) employed Gibbs sampling algorithm by computing the approximated likelihood of the data for each *k*, selecting the *k* value that maximizes the harmonic mean of the log-likelihoods. Cao, Xia, Li, Zhang, and Tang (2009) used the pairwise average cosine distance (ACD) among topics, reporting the optimal number of topics as the one that minimizes this indicator. In turn, Arun, Suresh, Veni Madhavan, and Narasimha Murthy (2010) minimized the symmetric Kullback-Lieber divergence between the singular values of the matrix factors. The results of these three metrics are plotted in *Fig. 4*. Cao's and Griffiths' measures point to a number of topics of *k* = 140, while Arun's suggest *k* = 145. The existence of multiple inflexion points is quite common in cluster analysis (Greene et al., 2014), and it shows different appropriate solutions or topic structures. Several *k* values have been tested, comparing topics' structure for each *k* to identify the most consensual and stable topics among the different analyses, which depicted much broader topics when selecting lower values for *k*, while higher values returned highly-specific and rather similar topics, making it difficult to distinguish some of them, an "over-clustering" situation similar to the findings of Greene et al. (2014).

INSERT FIGURE 4

To sustain the number of topics selected, the CTM was iteratively estimated for different *k*, storing the mean log-likelihood and *perplexity* metrics of each model. The *k*-value that fits the corpus best was chosen based on metrics' variability as *k* increased. The method used to fit the CTM was the Variational EM algorithm as the marginal likelihood of the data could not be calculated (Blei & Lafferty, 2007; Grün & Hornik, 2011; Wainwright & Jordan, 2007).

Both log-likelihood and *perplexity* scores show consistency regarding $k = 23$, as for a higher number of topics the changes in log-likelihood and *perplexity* were quite insignificant, and the increase in explained variability was marginal. The selection of *k* was also sustained by the results described in Figure 4, in which $k = 23$ was identified as one of the first inflexion points. Thus, the current paper explored and analyzed 23 topics hidden in the text.

4. Results

4.1. Descriptive Analysis of the Literature

The top 5 most frequent terms were the stemmed terms *studi*, *advertis*, *brand*, *particip*, and *attent*, with an occurrence frequency above 10.000 (see *Fig. 5* and *Table 3*), whereas 35 terms presented a frequency above 4.000. The first term *studi* was quite broad and not specific to any area, and related with academic journals (Guerreiro et al., 2016).

INSERT FIGURE 5

INSERT TABLE 3

The second most frequent stemmed term *advertis* comes as no surprise given the focus of the query on Marketing and as one of the major concerns in this field has been advertising effectiveness (e.g., Daugherty et al., 2016; Li, Huang, & Bente, 2016; Russell, Russell, Morales, & Lehu, 2017) as well as brand attention and memory as the third and fifth most recurrent terms (e.g., Pieters, Warlop, & Wedel, 2002; Plassmann, Ramsøy, & Milosavljevic, 2012; Shang, Pei, Dai, & Wang, 2017). Neurosciences research is highly experiment-driven, so *participants* exposed to a stimulus are overtly present in the collected *corpus*. The interdisciplinary stemmed term *effect* was expected to occur frequently, and was related with cause-effect analysis, e.g., whether creative advertising has a positive effect on brand memory.

Publications classified as Q1 according to Scimago Journal Rank (SJR) Best Quartile (Scimago, 2018) represented 73,56%, against Q2 (14,07%), Q3 (8,32%), Q4 (3,20%), and unindexed articles (0,85%). Results show a 5-Year Journal Impact Factor of 3,36 on average (except for the unindexed 72 articles), with a 2,24 standard deviation (see *Table 4*).

INSERT TABLE 4

The period from 2013 to 2018 accounted for 58,8% of the articles included in this analysis, showing the emergence, importance and acceptance of this field. Figure 6 shows the number of articles by year.

INSERT FIGURE 6

The five main terms most correlated with each topic in Table 5 were used to classify each topic with a different name. Table 6 shows how each topic evolved over time.

INSERT TABLE 5

INSERT TABLE 6

Tables 7 and *8* show the ranking of the articles by posterior probability regarding their correlation with each topic. Although we only included in the next section a comprehensive profiling for the top 10 topics ranked by number of articles, the classification of topics was created for the first twenty-two. However, a name was not given to Topic 23 as this topic was found to be quite broad. Indeed, the article with the highest posterior probability of belonging to this topic showed a value of only 6.3%. Therefore, no articles were assigned to this topic.

INSERT TABLE 7

INSERT TABLE 8

The most mentioned topic (Topic 1) discusses consumer neuroscience, which corroborates the CTM analysis employed, as the identified main subject of this study. This emerging field of study was first discussed in 1984 (Weinstein et al., 1984), and more frequently in 2016.

The second topic (Topic 2) focused on brand memory research mainly using eye tracking data to acknowledge the process of generating attention and memory towards brands. This has been an active discussion since 1999 but still relevant in 2018, while the third most frequent topic (Topic 3) is related to willingness to buy, with increasing frequency since 2007, being a major concern from 2015 onwards.

The year 2007 became an important milestone with a 240% increase in articles published on the subject from 2006, and a 120% increase in the number of active topics. Indeed, topics such as Willingness to Buy (topic number 3), Models of Data Processing (topic number 6), Visual Attention (topic number 11), Semiotics (topic number 15), and Measuring Emotional vs. Cognitive Appraisal (topic number 18) originated in 2007. Another important milestone was 2015, when consumer neuroscience received great attention with special editions from several top journals. By then, twenty out of the twenty-two profiled topics were active, with a 50% increase in published articles.

4.2. Topics Description

Topic 1 – Consumer Neuroscience

The most correlated terms among the articles in the current topic were *research*, *consum*, *neurosci*, *studi*, and *brain*. The relevant articles discussed the emergence of *consumer neuroscience*, addressing future challenges, and its potential contribution to marketing theory and practice (Plassmann et al., 2015) (post. prob. = 0.604). Hubert (2010) (post. prob. = 0.772) posited *consumer neuroscience* as a breakthrough in consolidating, validating or extending economic theories. This author claimed that its conceivable acceptance and integration as a branch of economic and *consumer research* relied on the ability to deal both with methodological hitches and practical implementation of outcomes by corporations. Rimkute et al. (2016) (post. prob. = 0.529) developed a systematic literature review on the effects of scent on consumer behavior, identifying thematic areas and a major gap related to consumers' scent perception and to what extent it might stimulate their behavior.

Topic 2 – Brand Memory

The terms *brand*, *memori*, *process*, *attent*, and *inform* were highly correlated with the current topic. Due to the boom in advertising competition Pieters, Warlop, and Wedel (2002) (post. prob. = 0.661) discussed the effects of advertisement originality and familiarity on *brand attention* and *memory*. Through eye fixation data collection, the authors showed that original and familiar ads would grab the greatest *brand attention*, and subsequently *brand memory*. In addition, eye movements and fixations also have a major role in understanding the *process* by which advertised *brands* are *memorized*, with Wedel and Pieters (2000) (post. prob. = 0.636) finding evidence related to the amount of *information* obtained during eye fixation on an advertisement and the inner negative impact on latency of *brand memory*.

Neuroscience has had a major impact on brand memory studies (Venkatraman et al., 2021) by measuring unconscious responses and thus collecting more credible and effective results for improved ad recall (Plassmann et al., 2015).

Topic 3 – Willingness to Buy

The articles with higher posterior probability within this topic were related to *consumer's choice* of *products* researched in different contexts, using eye-tracking devices. This topic grouped the correlated terms *product*, *consum*, *choic*, *price*, and *inform*. The first article analysed the influence of *products'* label elements such as production method, origin, and nutritional composition, on the willingness to pay for processed foods (Rihn & Yue, 2016) (post. prob. = 0.660), suggesting that *consumers* might be influenced in their *product* selection through the additional *information* about important *product* attributes displayed on labels and on in-store promotions. *Consumers' product* preferences for brands, *prices*, and dietary restrictions are often in juxtaposition to what retailers want them to buy (Gidlöf et al., 2017) (post. prob. = 0.597). *Product* packages and in-store displays contain tailored *information* on attributes to increase *consumer* attention, as visual attention was identified by the authors as the prime purchase predictor. Waechter, Sütterlin, and Siegrist (2017) (post. prob. = 0.628) focused on energy-friendly *product choices*, and their reliance on lexicographic strategies. The correct and current *information* on energy consumption leads to easy identification of energy-friendly products, while ambiguous *information* like energy efficiency might result in non-optimal *product choices*. As for online shopping, Liu, Hsieh, Lo, and Hwang (2017) (post. prob. = 0.626) concluded that brand awareness had a null effect when *consumers* browse with no time pressure.

Applying neuroscientific tools, we were able to move from simply predicting behavior to measuring actual behavior (Ozkara & Bagozzi, 2021). By understanding actual behavior, brand strategies are adapted in ways that will enhance consumers' persuasion and willingness to buy (Harris et al., 2018; Zhang et al., 2021).

Topic 4 – Hedonic vs. Utilitarian Products

The main terms identified with stronger correlations were *activ*, *brain*, *brand*, *studi*, and *cortex*. This topic encompassed fMRI *studies* analyzing subjects' *brain response* when exposed to favorite or familiar *brands* recognized as culturally-based symbols (Schaefer & Rotte, 2007a) (post. prob. = 0.868). The authors acknowledged the activation of reward-related areas when individuals were exposed to favorite brands by *studying* cortical *activity* using *brand* logos as stimulus. *Activity* on the striatum was verified for favorite sports and luxury *brands* (hedonic), but the opposite was registered for rational *brands* (utilitarian). In the case of culturally familiar brands, Schaefer, Berens, Heinze, and Rotte (2006) (post. prob. = 0.829) reported *activation* in the medial prefrontal *cortex*, also for *brands* highly rated in "social competence" (Schaefer &

Rotte, 2010) (post. prob. = 0.753), as well as for sports and luxury *brands* which improved participants' "self-relevant thoughts" (Schaefer & Rotte, 2007b, p. 101) (post. prob. = 0.824), while familiar *brands* revealed *activation* of the bilateral superior frontal gyri, hippocampus and posterior cingulate. As for value *brands*, the left superior frontal gyrus and anterior cingulate *cortex* were *activated*, which is hypothesized as being relevant for associating actions with consequences. Thus, by applying neuroscienctific tools, academics and practitioners are able to identify brain responses and triggers upon hedonic and/or utilitarian brand exposure (Audrin et al., 2018; Bettiga et al., 2020; Hubert et al., 2018).

Topic 5 – Visual and Neural Cognition for Memory Detection

The five most correlated terms in this topic were *memori*, *use*, *imag*, *face*, and *perform*. The literature on this topic examined visual cognition together with neural pattern classifiers and neural response decoding. Uncapher, Boyd-Meredith, Chow, Rissman, and Wagner (2015) (post. prob. = 0.878) tested the vulnerability of *memory* detection with fMRI *using* different strategies to mask *memory* signal (countermeasures). Participants were exposed to several *images* of male *faces* and measures were undertaken to guarantee a suitable behavioral *performance*. The authors concluded that when *memory* was truly reported by participants, the multivoxel pattern analysis (MVPA) classifiers accurately decoded their *memory* state, but still cognitive strategies could bias classifiers' efficiency for *memory* detection. Visual stimuli were also *used* by Jiang, Summerfield, and Egner (2013) (post. prob. = 0.777) describing attention and expectation as the "main determinants of visual cognition" (p. 18438). Moreover, attended and expected stimuli increased neural selectivity in the visual cortex. The authors grounded their research on the relationship between attention and perceptual prediction error (PE) hypotheses. Using not only *images* of *faces* but also outdoor and indoor scenes, the fMRI data revealed attention as an enhancer of neural pattern classifiers' *performance* to distinguish expected from unexpected stimuli, while improving the accuracy of prediction errors.

Topic 6 – Models of Data Processing

Model, *refer*, *data*, *size*, and *featur* were the most correlated terms in this topic, discussing several approaches to enhance information understanding and its effects, through eye-tracking *data* and statistical *modeling*. The article published by Brocher, Chiriacescu, and von Heusinger (2018) (post. prob. = 0.831) aimed to study both conception and *referent* activation in discourse comprehension and planning. To deal with the dynamic process of language use, these authors developed the Dual-Process Activation *Model*, which proved to be effective in *referent* management. Feature advertising effectiveness was also a subject studied by Zhang, Wedel, and Pieters (2009) (post. prob. = 0.654) due to the recognized lack of knowledge on how *feature* ad characteristics, such as *size*, color, and location of the advertisement impact sales. The authors proposed a Bayesian statistical *model* accommodating variables' endogeneity and relevant for meditating analyses, showing the positive and considerable effect on sales outcomes of gaze duration on feature advertisements. Yang, Toubia, and De Jong (2015) (post. prob. = 0.550) proposed a "dynamic discrete choice model of information search and choice under bounded rationality" (p.166), which showed greater predictive and discriminative performance when compared with benchmarks.

Topic 7 – Emotional Responses to Advertisements

This topic addressed one major purpose of consumer neuroscience, which consists of *measuring consumers'* emotional responses to different advertising *messages* and content. The combination of methods enables the measurement of emotional experiences through three types of data, behavioral (e.g., facial *responses*), self-report (e.g., verbal or written reports), and physiological (e.g., HR, SCR, fEMG) (Bolls et al., 2001) (post. prob. = 0.671). This topic grouped *messag*, *arous*, *measur*, *respons*, and *particip* as the most correlated terms. Emotions such as fear and disgust were often analyzed in the context of anti-tobacco advertisements (Leshner et al., 2009) (post. prob. = 0.766). Through HR data, the authors found evidence of effects on cognitive resources allocated to encoding the *message* and on brand recognition in the presence of fear- and disgust-based *message* content. Self-reported emotional *arousal* and valence was also *measured* through the Self-Assessment Mannequin (SAM), a technique employed by Lee and Shin (2011) (post. prob. = 0.730) and also in combination with fEMG to test the emotional responses to anti-alcohol advertisements, using fear- and humor-related appeals. Individuals with heterogenous sensation-seeking levels *responded* differently to anti-alcohol abuse advertisements. Self-reports and physiological *measures* were used simultaneously (Yegiyan, 2015) (post. prob. = 0.707). In terms of neurophysiological *measures*, fEMG was used to assess appetitive and aversion activation, while SCR was added to infer about the magnitude of activation, and *participants' arousal* level during exposure to stimuli.

Stimulating emotional responses is one key element of success, as emotional cues influence brand memory, ad recall, and hence, future brand choices (Pozharliev et al., 2017). Neuroscience enabled the study of consumers' reactions, providing trustworthy and relevant information, so that advertisers can adapt their strategy to increase brand engagement through emotions (Barari et al., 2021b; Venkatraman et al., 2021).

Topic 8 – Advertising Effectiveness

The most correlated terms within this topic were *advertis*, *effect*, *commerci*, *attitud*, and *brand*. In growing and saturated markets, organizations are pursuing crucial factors for *advertising effectiveness* (Grigaliunaite & Pileliene, 2016) (post. prob. = 0.704). In their research, eye-tracking, implicit-association test (IAT), and questionnaires were used to study the *attitude* toward advertisement, *attitude* toward the *brand*, and purchase intentions. *Attitude* regarding emotional advertisements for convenience products in print / outdoor media had a much more positive effect than rational advertisement. Moreover, rational advertisement led to a stronger probability of purchasing convenience products. Russell, Swasy, Russell, and Engel (2017) (post. prob. = 0.646) tested the hedonic contamination process, i.e., how an entertainment experience was influenced by the presence of *advertisements* in different contexts (in-theater *commercials*, or watching television), measuring the *attitude* toward the movie using eye-tracking devices. Pre-exposure to *advertising* jeopardized participants' entertainment experience, and they were less receptive to product placement. This type of communication was also studied by Boerman, van Reijmersdal, and Neijens (2015) (post. prob. = 0.593), also using eye-tracking data. This research provided evidence that textual and pictorial disclosure of product placement was most effective for brand memory but indirectly less promising for *brand attitude*.

Advertisers' effectiveness has been a major subject in consumer neuroscience research (Couwenberg et al., 2017; S et al., 2020). Applying neuroscientific tools, useful data on consumer attitudes towards the advertisement and the brand have been collected. This can improve campaigns' effectiveness, unveiling unconscious emotions and preferences (Cummins et al., 2021; Pleyers & Vermeulen, 2021; Simola et al., 2020), also using several measures such as brand memory to predict this (Pieters & Wedel, 2020).

Topic 9 – Neural Activity in Behavioral Research

The terms *food*, *use*, *activ*, *behavior*, and *neural* had the highest correlation within this topic. Falk, Berkman, Whalen, and Lieberman (2011) (post. prob. = 0.710) looked for evidence on whether *neural activity* could predict some smoking reduction among participants exposed to specific campaigns designed to help smokers to quit. The authors found a positive relationship between *neural activity* in the medial prefrontal cortex (data being collected with fMRI) and *behavior* change (successful quitting), reinforcing the prominence of neuroimaging in health promotion, and also that neural activity is a valuable complement to self-report measures. Falk et al. (2016) (post. prob. = 0.505) corroborated these results. Public organizations frequently *use* fear appeals in their communication (Cerf et al., 2015) (post. prob. = 0.506). By using the single-neuron method, the authors concluded that messages stimulating consumers' feeling of fear through explicit instructions in the ad, would turn out to be effective. These authors stated that these insights would be difficult to obtain with self-report measures.

Topic 10 – Reliability of Eye-Tracking Data

This topic has *eye*, *fixat*, *search*, *user*, and *use* as the most correlated terms related to neuroscience studies using *eye*-tracking devices. Niehorster, Cornelissen, Holmqvist, Hooge, and Hessels (2018) (post. prob. = 0.912) explored the *use* of remote *eye*-tracker, analyzing the performance of five different devices to help researchers choose the most suitable device when unrestrained *users* were their target. Eye-tracking was also used quite frequently in online *searching* either through mobile (Domachowski et al., 2016) (post. prob. = 0.743) or desktop devices. These authors found that the reliability and validity of eye-tracking data can be estimated with behavioral patterns. Linked to online *search* and product display, thumbnails were a useful resource (Lam et al., 2007) (post. prob. = 0.718) complemented with a short product description. These authors *used eye*-tracking to analyze *users*' *search* behavior, the results not revealing any relevant differences in *users' fixation* patterns, even with different reading directions. Consumers tended to address their focus to the middle of the thumbnail, then to the left, and finally to the right region. The authors also stated that eye-movement data is important "for studying consumers' information search and processing behaviors in the Web environment" (p. 43). In fact, eye-movements are an accurate indicator of stimulus processing intensity.

5. Future Research Directions and Research Questions

Although consumer neuroscience research is still in its early days, it has already captured the interest of 80% of the market (Ramsøy, 2019). The use of neuroscience techniques can shed further insights into consumer behavior studies and recent articles have discussed some future research avenues. The current section (1) explores these future research proposals and (2) suggests other research questions that can move beyond the existing literature. To summarize the most relevant future research topics discussed in the literature, the articles collected in the current paper, published between 2017 to 2021, were ranked by the Average Number of Citations per Year (AC_y). Then, the top 10 cited articles were selected for further analysis (Aria et al., 2020; Loureiro et al., 2020) (see *Table* 9).

INSERT TABLE 9

The study by Szabo and Webster (2021) on perceived greenwashing using neuroscience tools achieved the highest AC_y score with 22.0 average citations per year. The authors suggest the use of neuroscience techniques to go further in the context of green marketing, namely the impact of green content on interactivity and ethical concerns when green marketing is used to persuade consumers. Niehorster et al. (2018) achieved the second highest average score in terms of citations per year (AC_y = 21.0). In their research, the authors stress the need to extend studies using eye-trackers in non-optimal conditions in in-depth studies. Muñoz-Leiva et al. (2019) (AC_y = 20.5) analyzed advertising effectiveness in social media, in the context of tourism. The authors suggested the study of advertising effectiveness while surfing the web versus during goal-oriented navigation, also highlighting the importance of extending eye-tracking techniques specifically for smartphones. Meyerding and Mehlhose (2020) (AC_y = 20.0) examined the feasibility of mobile functional near-infrared spectroscopy (fNIRS) systems in the context of food products. These authors suggested that fNIRS using a cap instead of a headband provides more accurate results, and that it should be combined with other methods in the future (e.g, eye-tracking, questionnaires, EEG). Kahn (2017) (average score of 19.3 citations per year) explored the patterns of attention on small screens. More specifically, the study shows how visual design decisions affect consumers' reactions in online environments. These authors propose additional moderators of attention toward small screens such as consumer expectations, individual differences, and expertise. Lee et al. (2020) (AC_y = 18.0) studied green marketing practices in the fashion context using fMRI, and suggested that consumer attitudes should be compared between luxury and mass-market fashion using neuroscience techniques. Machín et al. (2020) (AC_y = 18.0) explored how consumers make in-store food purchase decisions and identify which information they look for during that process. For future research, these authors suggested scholars should test the impact of in-store environments (e.g., changing the packaging, shelf position, logos, and colours) on change habits, to persuade consumers to have a healthier lifestyle. Calogiuri et al. (2018) achieved 17.7 average citation score. These authors suggest the use of immersive virtual environments (IVE) to promote green exercise through simulating outdoor environments. The study by Lim (2018b) (AC_y = 17.3) acted as a roadmap in the neuromarketing context, as it explored what has already been studied and the main priorities for the future. The author stressed the need to further address the ethical issues surrounding consumer neuroscience. Finally, van Reijmersdal et al. (2020) (AC_y = 17.0) conducted an experiment using eye-tracking methods to analyze children's ability to understand sponsored social influencer videos, highlighting the need for more longitudinal studies instead of studies focused only on immediate effects.

Using the previous suggestions for further studies, we categorized the main future research topics into three dimensions and present additional research questions: (1) green marketing / sustainability; (2) new technology developments; and (3) privacy and ethical concerns.

First, green marketing/sustainability was identified as an emerging topic in neuroscience. Green marketing strategies are becoming important to align the company with consumer expectations (Lee et al., 2020). Such strategies can be applied in different contexts, such as: (i) the luxury industry (perceived as one of the least sustainable industries), in the use of vegetarian leather instead of real leather; (ii) the inclusion of negative environmental cues in ads (Szabo & Webster, 2021); and also (iii) in anti-consumption ads. Using neuroscience techniques, researchers can efficiently study consumers' unconscious responses to such stimuli (Bettiga et al., 2020; Ozkara & Bagozzi, 2021). Hence, we suggest that future studies can explore such problems from a neuroscience perspective.

In the future, brands will increasingly use digital channels to connect with consumers (Hackl, 2021). From blockchain technology to metaverse, integration of the virtual world will allow organizations to bring together larger audiences in a unified virtual location (Cook & Kuczer, 2021; Gleim & Stevens, 2021; Sheth & Kellstadt, 2021). The metaverse arises as the most important futuristic digital environment, combining Artificial Intelligence (AI), Augmented Reality (AR) and Virtual Reality (VR) in one digital-place. These engagement-facilitating technologies are emerging and evolving, bringing a revolutionary arena in which brands can enhance their interactivity with customers (Hollebeek et al., 2022). Consumer Brand Engagement (CBE) is a pivotal element in marketing strategies, able to foster positive attitudes and behaviors towards the brands (Hollebeek et al., 2014; Hollebeek & Belk, 2021). Recent studies suggest that as interaction experiences increase through AI, AR, and VR, customer engagement is potentiated (Chen et al., 2021; Kull et al., 2021; Mostafa & Kasamani, 2021). Even though digital channels provide multiple ways of engagement (e.g., likes, comments, public sharing information), for emerging technologies such as AI, VR, AR, 5G, and blockchain (the metaverse subset technologies), the engagement potential is far greater, allowing consumers to playfully experience a brand and explore the space virtually (McLean et al., 2021; Rauschnabel et al., 2022). It is crucial for marketing practitioners and academics to understand which are the groundbreaking technologies for CBE optimization, as well as those that will become obsolete. Furthermore, the ultimate integration of AI and anthropomorphism such as Ameca, a humanoid with fascinating facial expressions, is also expected to transform the way companies and brands engage with their customers (Hollebeek et al., 2021).

Neuroscience techniques are crucial to identify and explore users' interactions, predict behaviors and choices (Alsharif et al., 2021; Vences et al., 2020). The use of such techniques can enable researchers to collect insights and behavioral responses to understand how consumers react in such virtual environments.

Finally, even though neuroscience is an emerging field with several advantages for brands and advertisers, it can also have negative impacts on consumers (Stanton et al., 2017). One such effect derives from potential bad use of private information which can lead to confidentiality issues. Second, using fMRI and EEG techniques, brands are able to understand how consumers´ brains react to different stimuli even before they rationalize such intentions, which can eventually lead to consumer manipulation (Aicardi et al., 2020; Rainey & Erden, 2020). Third, there is a need to address how to make such important and private information secure (Tham et al., 2021). Potential breaches in data security can represent a major obstacle to further developments in consumer neuroscience research.

Table 10 summarizes the proposed research questions.

INSERT TABLE 10

6. Conclusions

This study is based on an analysis of the literature on consumer neuroscience and focuses on identifying the prominent trends and topics in this area. Consumer neuroscience has been paid great attention as consumer attitudes, emotions and the decision making process are becoming overly complex (Plassmann, Ambler, Braeutigam, & Kenning, 2007; Steenkamp & Maydeu-Olivares, 2015). This field of consumer research has been mostly devoted to (1) the preference for objective versus subjective measurement, and (2) a more cost-effective way to develop new products and advertising material more likely to engage consumers (Ariely & Berns, 2010; Daugherty et al., 2016). Further advances in consumer neuroscience will depend on the success of its translation into practice both for marketing academics and business practitioners (Levallois et al., 2012).

The paper's contribution is threefold: (i) it provides a structured overview on how consumer neuroscience has been evolving over time, (ii) identifies the prominent trends and topics in this field through topic modeling, and, (iii) addresses future directions and research questions, not only for theoretical purposes, but also with practical implications.

A text mining technique was employed to analyze the literature using the correlated topic model algorithm. A total of twenty three topics emerged from the literature review on consumer neuroscience and neuromarketing. Each topic was then profiled exhaustively with the five most relevant terms and the most relevant articles. The results show that "consumer neuroscience", "brand memory", and "willingness to buy" are the most relevant topics in the field. This study also reveals that the literature has focused on ethical concerns and on controversial concerns in the use of consumer neuroscience techniques.

The current paper is the first to group such a large number of papers on the topic of consumer neuroscience and neuromarketing. Despite the important literature reviews that have been conducted in the past, no study has yet performed a comprehensive and integrated review of the vast and complex information around the topic. The paper also contributes to the literature by suggesting research questions on three dimensions: green marketing / sustainability; new technology developments; and privacy and ethical concerns.

As for practical implications, our research acknowledges the importance of neuroscience for practitioners. Through studying conscious and unconscious responses, managers can adapt their future strategy to meet their target expectations (Ozkara & Bagozzi, 2021). This text mining analysis unveiled the most relevant topics in the literature, some of them receiving more attention from researchers than others. No immersive technology research, whether virtual, augmented or mixed reality, has been captured by the search string developed for this study, revealing a substantial gap for future research.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

References

Aicardi, C., Akintoye, S., Fothergill, B. T., Guerrero, M., Klinker, G., Knight, W., Klüver, L., Morel, Y., Morin, F. O., Stahl, B. C., & Ulnicane, I. (2020). Ethical and Social Aspects of Neurorobotics. *Science and Engineering Ethics*, *26*(5), 2533–2546. https://doi.org/10.1007/s11948-020-00248-8

Alsharif, A. H., Salleh, N. Z. M., Baharun, R., Hashem E, A. R., Mansor, A. A., Ali, J., & Abbas, A. F. (2021). Neuroimaging Techniques in Advertising Research: Main Applications, Development, and Brain Regions and Processes. *Sustainability*, *13*(11), 6488. https://doi.org/10.3390/su13116488

Alvino, L., Pavone, L., Abhishta, A., & Robben, H. (2020). Picking Your Brains: Where and How Neuroscience Tools Can Enhance Marketing Research. *Frontiers in Neuroscience*, *14*, 577666. https://doi.org/10.3389/fnins.2020.577666

Amado, A., Cortez, P., Rita, P., & Moro, S. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. *European Research on Management and Business Economics*, *24*(1), 1–7. https://doi.org/10.1016/j.iedeen.2017.06.002

Ananiadou, S., Rea, B., Okazaki, N., Procter, R., & Thomas, J. (2009). Supporting Systematic Reviews Using Text Mining. *Social Science Computer Review*, *27*(4), 509–523. https://doi.org/10.1177/0894439309332293

Aria, M., Misuraca, M., & Spano, M. (2020). Mapping the Evolution of Social Research and Data Science on 30 Years of Social Indicators Research. *Social Indicators Research*, *149*(3), 803–831. https://doi.org/10.1007/s11205-020-02281-3

Ariely, D., & Berns, G. S. (2010). Neuromarketing: The hope and hype of neuroimaging in business. *Nature Reviews Neuroscience*, *11*(4), 284–292. https://doi.org/10.1038/nrn2795

Arun, R., Suresh, V., Veni Madhavan, C. E., & Narasimha Murthy, M. N. (2010). On Finding the Natural Number of Topics with Latent Dirichlet Allocation: Some Observations. In M. J. Zaki, J. X. Yu, B. Ravindran, & V. Pudi (Eds.), *Advances in Knowledge Discovery and Data Mining* (pp. 391–402). Springer Berlin Heidelberg.

Ashraf, H., Sodergren, M. H., Merali, N., Mylonas, G., Singh, H., & Darzi, A. (2018). Eye-tracking technology in medical education: A systematic review. *Medical Teacher*, *40*(1), 62–69. https://doi.org/10.1080/0142159X.2017.1391373

Audrin, C., Brosch, T., Sander, D., & Chanal, J. (2018). More Than Meets the Eye: The Impact of Materialism on Information Selection During Luxury Choices. *Frontiers in Behavioral Neuroscience*, *12*, 172. https://doi.org/10.3389/fnbeh.2018.00172

Bahoo, S., Alon, I., & Paltrinieri, A. (2020). Corruption in international business: A review and research agenda. *International Business Review*, *29*(4), 101660. https://doi.org/10.1016/j.ibusrev.2019.101660

Barari, M., Ross, M., Thaichon, S., & Surachartkumtonkun, J. (2021a). A meta-analysis of customer engagement behaviour. *International Journal of Consumer Studies*, *45*(4), 457–477. https://doi.org/10.1111/ijcs.12609

Barari, M., Ross, M., Thaichon, S., & Surachartkumtonkun, J. (2021b). A meta-analysis of customer engagement behaviour. *International Journal of Consumer Studies*, *45*(4), 457–477. https://doi.org/10.1111/ijcs.12609

Bastiaansen, M., Straatman, S., Driessen, E., Mitas, O., Stekelenburg, J., & Wang, L. (2018). My destination in your brain: A novel neuromarketing approach for evaluating the effectiveness of destination marketing. *Journal of Destination Marketing & Management*, *7*, 76–88. https://doi.org/10.1016/j.jdmm.2016.09.003

Bettiga, D., Bianchi, A. M., Lamberti, L., & Noci, G. (2020). Consumers Emotional Responses to Functional and Hedonic Products: A Neuroscience Research. *Frontiers in Psychology*, *11*, 559779. https://doi.org/10.3389/fpsyg.2020.559779

Bilro, R. G., Loureiro, S. M. C., & Santos, J. F. (2021). Masstige strategies on social media: The influence on sentiments and attitude toward the brand. *International Journal of Consumer Studies*, ijcs.12747. https://doi.org/10.1111/ijcs.12747

Blei, D. M. (2012). Introduction to Probabilistic Topic Modeling. *Communications of the ACM*, *55*, 77–84. https://doi.org/10.1145/2133806.2133826

Blei, D. M., Edu, B. B., Ng, A. Y., Edu, A. S., Jordan, M. I., & Edu, J. B. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022. https://doi.org/10.1162/jmlr.2003.3.4-5.993

Blei, D. M., & Lafferty, J. D. (2006). Correlated Topic Models. *Advances in Neural Information Processing Systems 18*, 147–154. https://doi.org/10.1145/1143844.1143859

Blei, D. M., & Lafferty, J. D. (2007). A Correlated Topic Model of Science. *The Annals of Applied Statistics*, *1*(1), 17–35. https://doi.org/10.1214/07-AOAS136

Boerman, S. C., van Reijmersdal, E. A., & Neijens, P. C. (2015). Using Eye Tracking to Understand the Effects of Brand Placement Disclosure Types in Television Programs. *Journal of Advertising*, *44*(3), 196–207. https://doi.org/10.1080/00913367.2014.967423

Bolls, P. D., Lang, A., & Potter, R. F. (2001). The Effects of Message Valence and Listener Arousal on Attention, Memory, and Facial Muscular Responses to Radio Advertisements. *Communication Research*, *28*(5), 627–651. https://doi.org/10.1177/009365001028005003

Brocher, A., Chiriacescu, S. I., & von Heusinger, K. (2018). Effects of Information Status and Uniqueness Status on Referent Management in Discourse Comprehension and Planning. *Discourse Processes*, *55*(4), 346–370. https://doi.org/10.1080/0163853X.2016.1254990

Calogiuri, G., Litleskare, S., Fagerheim, K. A., Rydgren, T. L., Brambilla, E., & Thurston, M. (2018). Experiencing Nature through Immersive Virtual Environments: Environmental Perceptions, Physical Engagement, and Affective Responses during a Simulated Nature Walk. *Frontiers in Psychology*, *8*, 2321. https://doi.org/10.3389/fpsyg.2017.02321

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How Neuroscience Can Inform Economics. *Journal of Economic Literature*, *43*(1), 9–64. https://doi.org/10.1257/0022051053737843

Camerer, C., & Yoon, C. (2015). Introduction to the *Journal of Marketing Research* Special Issue on Neuroscience and Marketing. *Journal of Marketing Research*, *52*(4), 423–426. https://doi.org/10.1509/0022-2437-52.4.423

Canabal, A., & White, G. O. (2008). Entry mode research: Past and future. *International Business Review*, *17*(3), 267–284. https://doi.org/10.1016/j.ibusrev.2008.01.003

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing*, *72*(7–9), 1775–1781. https://doi.org/10.1016/j.neucom.2008.06.011

Cerf, M., Greenleaf, E., Meyvis, T., & Morwitz, V. G. (2015). Using Single-Neuron Recording in Marketing: Opportunities, Challenges, and an Application to Fear Enhancement in Communications. *Journal of Marketing Research*, *52*(4), 530–545. https://doi.org/10.1509/jmr.13.0606

Chan, K.-P., Xinxin Zhan, & Jiali Wang. (2015). Facial expression recognition by correlated Topic Models and Bayes modeling. *2015 International Conference on Image and Vision Computing New Zealand (IVCNZ)*, 1–5. https://doi.org/10.1109/IVCNZ.2015.7761546

Chan, T. K. H., Cheung, C. M. K., & Lee, Z. W. Y. (2017). The state of online impulse-buying research: A literature analysis. *Information & Management*, *54*(2), 204–217. https://doi.org/10.1016/j.im.2016.06.001

Chen, Y. H., Keng, C.-J., & Chen, Y.-L. (2021). How interaction experience enhances customer engagement in smart speaker devices? The moderation of gendered voice and product smartness. *Journal of Research in Interactive Marketing*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/JRIM-03-2021-0064

Cook, A., & Kuczer, K. (2021). *A brave new world with virtual worlds*. Deloitte. https://www2.deloitte.com/us/en/insights/topics/emerging-technologies/virtual-world-for-business.html

Cortez, P., Moro, S., Rita, P., King, D., & Hall, J. (2018). Insights from a text mining survey on Expert Systems research from 2000 to 2016. *Expert Systems*, *35*(3), e12280. https://doi.org/10.1111/exsy.12280

Couwenberg, L. E., Boksem, M. A. S., Dietvorst, R. C., Worm, L., Verbeke, W. J. M. I., & Smidts, A. (2017). Neural responses to functional and experiential ad appeals: Explaining ad effectiveness. *International Journal of Research in Marketing*, *34*(2), 355–366. Scopus. https://doi.org/10.1016/j.ijresmar.2016.10.005

Criado, J. M., de la Fuente, A., Heredia, M., Riolobos, A. S., & Yajeya, J. (2008). Single-cell recordings: A method for investigating the brain's activation pattern during exercise. *Methods*, *45*(4), 262–270. https://doi.org/10.1016/j.ymeth.2008.05.007

Cruz, C. M. L., Medeiros, J. F. D., Hermes, L. C. R., Marcon, A., & Marcon, É. (2016). Neuromarketing and the advances in the consumer behaviour studies: A systematic review of the literature. *International Journal of Business and Globalisation*, *17*(3), 330. https://doi.org/10.1504/IJBG.2016.078842

Cummins, R. G., Gong, Z. H., & Reichert, T. (2021). The impact of visual sexual appeals on attention allocation within advertisements: An eye-tracking study. *International Journal of Advertising*, *40*(5), 708–732. https://doi.org/10.1080/02650487.2020.1772656

Dabić, M., Vlačić, B., Paul, J., Dana, L.-P., Sahasranamam, S., & Glinka, B. (2020). Immigrant entrepreneurship: A review and research agenda. *Journal of Business Research*, *113*, 25–38. https://doi.org/10.1016/j.jbusres.2020.03.013

Daugherty, T., Hoffman, E., & Kennedy, K. (2016). Research in reverse: Ad testing using an inductive consumer neuroscience approach. *Journal of Business Research*, *69*(8), 3168–3176. https://doi.org/10.1016/j.jbusres.2015.12.005

Delen, D., & Crossland, M. D. (2008). Seeding the survey and analysis of research literature with text mining. *Expert Systems with Applications*, *34*(3), 1707–1720. https://doi.org/10.1016/j.eswa.2007.01.035

Dimoka, A., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Riedl, R., vom Brocke, J., & Weber, B. (2012). On the Use of Neurophysiological Tools in IS Research: Developing a Research Agenda for NeuroIS. *MIS Quarterly*, *36*(3), 679–702.

Domachowski, A., Griesbaum, J., & Heuwing, B. (2016). Perception and effectiveness of search advertising on smartphones: Perception and Effectiveness of Search Advertising on Smartphones. *Proceedings of the Association for Information Science and Technology*, *53*(1), 1–10. https://doi.org/10.1002/pra2.2016.14505301074

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Falk, E. B., Berkman, E. T., Whalen, D., & Lieberman, M. D. (2011). Neural activity during health messaging predicts reductions in smoking above and beyond self-report. *Health Psychology*, *30*(2), 177–185. https://doi.org/10.1037/a0022259

Falk, E. B., O'Donnell, M. B., Tompson, S., Gonzalez, R., Dal Cin, S., Strecher, V., Cummings, K. M., & An, L. (2016). Functional brain imaging predicts public health campaign success. *Social Cognitive and Affective Neuroscience*, *11*(2), 204–214. https://doi.org/10.1093/scan/nsv108

Feinerer, I., Hornik, K., & Meyer, D. (2008). Text Mining Infrastructure in R. *Journal Of Statistical Software*, *25*(5), 1–54. https://doi.org/citeulike-article-id:2842334

Fisher, R. J. (1993). Social Desirability Bias and the Validity of Indirect Questioning. *Journal of Consumer Research*, *20*(2), 303–315.

Fugate, D. L. (2007). Neuromarketing: A layman's look at neuroscience and its potential application to marketing practice. *Journal of Consumer Marketing*, *24*(7), 385–394. https://doi.org/10.1108/07363760710834807

Gidlöf, K., Anikin, A., Lingonblad, M., & Wallin, A. (2017). Looking is buying. How visual attention and choice are affected by consumer preferences and properties of the supermarket shelf. *Appetite*, *116*, 29–38. https://doi.org/10.1016/j.appet.2017.04.020

Gilal, F. G., Zhang, J., Paul, J., & Gilal, N. G. (2019). The role of self-determination theory in marketing science: An integrative review and agenda for research. *European Management Journal*, *37*(1), 29–44. https://doi.org/10.1016/j.emj.2018.10.004

Gleim, M. R., & Stevens, J. L. (2021). Blockchain: A game changer for marketers? *Marketing Letters*, *32*(1), 123–128. https://doi.org/10.1007/s11002-021-09557-9

Greene, D., O'Callaghan, D., & Cunningham, P. (2014). How Many Topics? Stability Analysis for Topic Models. In T. Calders, F. Esposito, E. Hüllermeier, & R. Meo (Eds.), *Machine*

Learning and Knowledge Discovery in Databases (Vol. 8724, pp. 498–513). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-44848-9_32

Greif, T., Hörster, E., & Lienhart, R. (2008). Correlated Topic Models for Image Retrieval. *Technical Report TR2008-09, University of Augsburg*.

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, *101*(Supplement 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Grigaliunaite, V., & Pileliene, L. (2016). Emotional or rational? The determination of the influence of advertising appeal on advertising effectiveness. *Scientific Annals of Economics and Business*, *63*(3), 391–414. Scopus. https://doi.org/10.1515/saeb-2016-0130

Grün, B., & Hornik, K. (2011). **topicmodels**: An *R* Package for Fitting Topic Models. *Journal of Statistical Software*, *40*(13). https://doi.org/10.18637/jss.v040.i13

Guerreiro, J., & Rita, P. (2020). How to predict explicit recommendations in online reviews using text mining and sentiment analysis. *Journal of Hospitality and Tourism Management*, *43*, 269–272. https://doi.org/10.1016/j.jhtm.2019.07.001

Guerreiro, J., Rita, P., & Trigueiros, D. (2016). A Text Mining-Based Review of Cause-Related Marketing Literature. *Journal of Business Ethics*, *139*(1), 111–128. https://doi.org/10.1007/s10551-015-2622-4

Gutierrez, J. B., & Nakai, K. (2016). A study on the application of topic models to motif finding algorithms. *BMC Bioinformatics*, *17*(S19), 129–138. https://doi.org/10.1186/s12859-016-1364-3

Hackl, C. (2021, November 23). *Value Creation In The Metaverse: A Utility Framework For NFTs*. Forbes. https://www.forbes.com/sites/cathyhackl/2021/11/23/value-creation-in-the-metaverse-a-utility-framework-for-nfts/amp/

Harris, J. M., Ciorciari, J., & Gountas, J. (2018). Consumer neuroscience for marketing researchers. *Journal of Consumer Behaviour*, *17*(3), 239–252. https://doi.org/10.1002/cb.1710

Hollebeek, L. D., & Belk, R. (2021). Consumers' technology-facilitated brand engagement and wellbeing: Positivist TAM/PERMA- vs. Consumer Culture Theory perspectives.

International Journal of Research in Marketing, *38*(2), 387–401. https://doi.org/10.1016/j.ijresmar.2021.03.001

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer Brand Engagement in Social Media: Conceptualization, Scale Development and Validation. *Journal of Interactive Marketing*, *28*(2), 149–165. https://doi.org/10.1016/j.intmar.2013.12.002

Hollebeek, L. D., Sharma, T. G., Pandey, R., Sanyal, P., & Clark, M. K. (2022). Fifteen years of customer engagement research: A bibliometric and network analysis. *Journal of Product & Brand Management*, *31*(2), 293–309. https://doi.org/10.1108/JPBM-01-2021-3301

Hollebeek, L. D., Sprott, D. E., & Brady, M. K. (2021). Rise of the Machines? Customer Engagement in Automated Service Interactions. *Journal of Service Research*, *24*(1), 3–8. https://doi.org/10.1177/1094670520975110

Hubert, M. (2010). Does neuroeconomics give new impetus to economic and consumer research? *Journal of Economic Psychology*, *31*(5), 812–817. https://doi.org/10.1016/j.joep.2010.03.009

Hubert, M., Hubert, M., Linzmajer, M., Riedl, R., & Kenning, P. (2018). Trust me if you can – neurophysiological insights on the influence of consumer impulsiveness on trustworthiness evaluations in online settings. *European Journal of Marketing*, *52*(1/2), 118–146. https://doi.org/10.1108/EJM-12-2016-0870

Islam, A., Hassini, S., & El-Dakhakhni, W. (2021). A systematic bibliometric review of optimization and resilience within low impact development stormwater management practices. *Journal of Hydrology*, *599*, 126457. https://doi.org/10.1016/j.jhydrol.2021.126457

Ittoo, A., Nguyen, L. M., & van den Bosch, A. (2015). Text analytics in industry: Challenges, desiderata and trends. *Computers in Industry*, *78*, 96–107. https://doi.org/10.1016/j.compind.2015.12.001

Jiang, J., Summerfield, C., & Egner, T. (2013). Attention Sharpens the Distinction between Expected and Unexpected Percepts in the Visual Brain. *Journal of Neuroscience*, *33*(47), 18438–18447. https://doi.org/10.1523/JNEUROSCI.3308-13.2013

Kahiya, E. T. (2018). Five decades of research on export barriers: Review and future directions. *International Business Review*, *27*(6), 1172–1188. https://doi.org/10.1016/j.ibusrev.2018.04.008

Kahn, B. E. (2017). Using Visual Design to Improve Customer Perceptions of Online Assortments. *Journal of Retailing*, *93*(1), 29–42. https://doi.org/10.1016/j.jretai.2016.11.004

Karl, A., Wisnowski, J., & Rushing, W. H. (2015). A practical guide to text mining with topic extraction. *Wiley Interdisciplinary Reviews: Computational Statistics*, *7*(5), 326–340. https://doi.org/10.1002/wics.1361

Kenning, P. H., & Plassmann, H. (2008). How Neuroscience Can Inform Consumer Research. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*, 532–538. https://doi.org/10.1109/TNSRE.2008.2009788

Knoll, J., & Matthes, J. (2017). The effectiveness of celebrity endorsements: A meta-analysis. *Journal of the Academy of Marketing Science*, *45*(1), 55–75. https://doi.org/10.1007/s11747-016-0503-8

Kull, A. J., Romero, M., & Monahan, L. (2021). How may I help you? Driving brand engagement through the warmth of an initial chatbot message. *Journal of Business Research*, *135*, 840–850. https://doi.org/10.1016/j.jbusres.2021.03.005

Kumar, A., Paul, J., & Unnithan, A. B. (2020). 'Masstige' marketing: A review, synthesis and research agenda. *Journal of Business Research*, *113*, 384–398. https://doi.org/10.1016/j.jbusres.2019.09.030

Kumar, P., Sharma, A., & Salo, J. (2019). A bibliometric analysis of extended key account management literature. *Industrial Marketing Management*, *82*, 276–292. https://doi.org/10.1016/j.indmarman.2019.01.006

Lajante, M. M. P., Droulers, O., & Amarantini, D. (2017). How reliable are "state-of-the-art" facial EMG processing methods?: Guidelines for improving the assessment of emotional valence in advertising research. *Journal of Advertising Research*, *57*(1), 28–37. Scopus. https://doi.org/10.2501/JAR-2017-011

Lam, S. Y., Chau, A. W.-L., & Wong, T. J. (2007). Thumbnails as online product displays: How consumers process them. *Journal of Interactive Marketing*, *21*(1), 36–59. https://doi.org/10.1002/dir.20073

Lee, E.-J., Choi, H., Han, J., Kim, D. H., Ko, E., & Kim, K. H. (2020). How to "Nudge" your consumers toward sustainable fashion consumption: An fMRI investigation. *Journal of Business Research*, *117*, 642–651. https://doi.org/10.1016/j.jbusres.2019.09.050

Lee, M. J., & Shin, M. (2011). Fear versus humor: The impact of sensation seeking on physiological, cognitive, and emotional responses to antialcohol abuse messages. *Journal of Psychology: Interdisciplinary and Applied*, *145*(2), 73–92. Scopus. https://doi.org/10.1080/00223980.2010.532519

Lee, N., Broderick, A. J., & Chamberlain, L. (2007). What is 'neuromarketing'? A discussion and agenda for future research. *International Journal of Psychophysiology*, *63*(2), 199–204. https://doi.org/10.1016/j.ijpsycho.2006.03.007

Lee, N., Chamberlain, L., & Brandes, L. (2018). Welcome to the jungle! The neuromarketing literature through the eyes of a newcomer. *European Journal of Marketing*, *52*(1/2), 4–38. https://doi.org/10.1108/EJM-02-2017-0122

Lee, S., Song, J., & Kim, Y. (2010). An Empirical Comparison of Four Text Mining Methods. *Journal of Computer Information Systems*, *51*(1), 1–10. https://doi.org/10.1109/HICSS.2010.48

Leshner, G., Bolls, P., & Thomas, E. (2009). Scare' Em or Disgust 'Em: The Effects of Graphic Health Promotion Messages. *Health Communication*, *24*(5), 447–458. https://doi.org/10.1080/10410230903023493

Levallois, C., Clithero, J. A., Wouters, P., Smidts, A., & Huettel, S. A. (2012). Translating upwards: Linking the neural and social sciences via neuroeconomics. *Nature Reviews Neuroscience*, *13*(11), 789–797. https://doi.org/10.1038/nrn3354

Li, K., Huang, G., & Bente, G. (2016). The impacts of banner format and animation speed on banner effectiveness: Evidence from eye movements. *Computers in Human Behavior*, *54*, 522–530. https://doi.org/10.1016/j.chb.2015.08.056

Lim, W. M. (2018a). What will business-to-business marketers learn from neuro-marketing? Insights for business marketing practice. *Journal of Business-to-Business Marketing*, *25*(3), 251–259. https://doi.org/10.1080/1051712X.2018.1488915

Lim, W. M. (2018b). Demystifying neuromarketing. *Journal of Business Research*, *91*, 205–220. https://doi.org/10.1016/j.jbusres.2018.05.036

Lin, M.-H. (Jenny), Cross, S. N. N., Jones, W. J., & Childers, T. L. (2018). Applying EEG in consumer neuroscience. *European Journal of Marketing*, *52*(1/2), 66–91. https://doi.org/10.1108/EJM-12-2016-0805

Liu, C.-W., Hsieh, A.-Y., Lo, S.-K., & Hwang, Y. (2017). What consumers see when time is running out: Consumers' browsing behaviors on online shopping websites when under time pressure. *Computers in Human Behavior*, *70*, 391–397. https://doi.org/10.1016/j.chb.2016.12.065

Loureiro, S. M. C., Guerreiro, J., & Ali, F. (2020). 20 years of research on virtual reality and augmented reality in tourism context: A text-mining approach. *Tourism Management*, *77*, 104028. https://doi.org/10.1016/j.tourman.2019.104028

Loureiro, S. M. C., Guerreiro, J., Eloy, S., Langaro, D., & Panchapakesan, P. (2019). Understanding the use of Virtual Reality in Marketing: A text mining-based review. *Journal of Business Research*, *100*, 514–530. https://doi.org/10.1016/j.jbusres.2018.10.055

Loureiro, S. M. C., Guerreiro, J., & Han, H. (2021). Past, present, and future of pro-environmental behavior in tourism and hospitality: A text-mining approach. *Journal of Sustainable Tourism*, 1–21. https://doi.org/10.1080/09669582.2021.1875477

Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. *Journal of Business Research*, *129*, 911–926. https://doi.org/10.1016/j.jbusres.2020.11.001

Machín, L., Curutchet, M. R., Gugliucci, V., Vitola, A., Otterbring, T., de Alcantara, M., & Ares, G. (2020). The habitual nature of food purchases at the supermarket: Implications for policy making. *Appetite*, *155*, 104844. https://doi.org/10.1016/j.appet.2020.104844

Macpherson, A., & Holt, R. (2007). Knowledge, learning and small firm growth: A systematic review of the evidence. *Research Policy*, *36*(2), 172–192. https://doi.org/10.1016/j.respol.2006.10.001

Mandolfo, M., & Lamberti, L. (2021). Past, Present, and Future of Impulse Buying Research Methods: A Systematic Literature Review. *Frontiers in Psychology*, *12*, 687404. https://doi.org/10.3389/fpsyg.2021.687404

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement? – Examining the role of AI powered voice assistants in influencing consumer brand engagement. *Journal of Business Research*, *124*, 312–328. https://doi.org/10.1016/j.jbusres.2020.11.045

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

Meyerding, S. G. H., & Mehlhose, C. M. (2020). Can neuromarketing add value to the traditional marketing research? An exemplary experiment with functional near-infrared spectroscopy (fNIRS). *Journal of Business Research*, *107*, 172–185. https://doi.org/10.1016/j.jbusres.2018.10.052

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, *6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moro, S., Cortez, P., & Rita, P. (2015a). Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation. *Expert Systems with Applications*, *42*(3), 1314–1324. https://doi.org/10.1016/j.eswa.2014.09.024

Moro, S., Cortez, P., & Rita, P. (2015b). Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation. *Expert Systems with Applications*, *42*(3), 1314–1324. https://doi.org/10.1016/j.eswa.2014.09.024

Moro, S., Rita, P., & Cortez, P. (2017). A text mining approach to analyzing Annals literature. *Annals of Tourism Research*, *66*, 208–210. https://doi.org/10.1016/j.annals.2017.07.011

Mostafa, R. B., & Kasamani, T. (2021). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/EJM-02-2020-0084

Muñoz-Leiva, F., Hernández-Méndez, J., & Gómez-Carmona, D. (2019). Measuring advertising effectiveness in Travel 2.0 websites through eye-tracking technology. *Physiology & Behavior*, *200*, 83–95. https://doi.org/10.1016/j.physbeh.2018.03.002

Muñoz-Leiva, F., Rodríguez López, M. E., Liebana-Cabanillas, F., & Moro, S. (2021). Past, present, and future research on self-service merchandising: A co-word and text mining approach. *European Journal of Marketing*, *55*(8), 2269–2307. https://doi.org/10.1108/EJM-02-2019-0179

Murphy, E. R., Illes, J., & Reiner, P. B. (2008). Neuroethics of neuromarketing. *Journal of Consumer Behaviour*, *7*(4–5), 293–302. https://doi.org/10.1002/cb.252

National Research Council. (2008). *Human Behavior in Military Contexts*. The National Academies Press. https://doi.org/10.17226/12023

Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2021). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research. *Operations Management Research*. https://doi.org/10.1007/s12063-021-00208-w

Niehorster, D. C., Cornelissen, T. H. W., Holmqvist, K., Hooge, I. T. C., & Hessels, R. S. (2018). What to expect from your remote eye-tracker when participants are unrestrained. *Behavior Research Methods*, *50*(1), 213–227. https://doi.org/10.3758/s13428-017-0863-0

Ozkara, B. Y., & Bagozzi, R. (2021). The use of event related potentials brain methods in the study of Conscious and unconscious consumer decision making processes. *Journal of Retailing and Consumer Services*, *58*, 102202. https://doi.org/10.1016/j.jretconser.2020.102202

Paisley, J., Wang, C., & Blei, D. M. (2012). The discrete infinite logistic normal distribution. *Bayesian Analysis*, *7*(4), 997–1034. https://doi.org/10.1214/12-BA734

Paul, J. (2019). Marketing in emerging markets: A review, theoretical synthesis and extension. *International Journal of Emerging Markets*, *15*(3), 446–468. https://doi.org/10.1108/IJOEM-04-2017-0130

Paul, J., & Benito, G. R. G. (2018). A review of research on outward foreign direct investment from emerging countries, including China: What do we know, how do we know and where should we be heading? *Asia Pacific Business Review*, *24*(1), 90–115. https://doi.org/10.1080/13602381.2017.1357316

Paul, J., & Bhukya, R. (2021). Forty-five years of International Journal of Consumer Studies: A bibliometric review and directions for future research. *International Journal of Consumer Studies*, *45*(5), 937–963. https://doi.org/10.1111/ijcs.12727

Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? *International Business Review*, *29*(4), 101717. https://doi.org/10.1016/j.ibusrev.2020.101717

Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, *45*(4). https://doi.org/10.1111/ijcs.12695

Paul, J., & Mas, E. (2020). Toward a 7-P framework for international marketing. *Journal of Strategic Marketing*, *28*(8), 681–701. https://doi.org/10.1080/0965254X.2019.1569111

Paul, J., Parthasarathy, S., & Gupta, P. (2017). Exporting challenges of SMEs: A review and future research agenda. *Journal of World Business*, *52*(3), 327–342. https://doi.org/10.1016/j.jwb.2017.01.003

Paul, J., & Rosado-Serrano, A. (2019). Gradual Internationalization vs Born-Global/International new venture models: A review and research agenda. *International Marketing Review*, *36*(6), 830–858. https://doi.org/10.1108/IMR-10-2018-0280

Paul, J., & Singh, G. (2017). The 45 years of foreign direct investment research: Approaches, advances and analytical areas. *The World Economy*. https://doi.org/10.1111/twec.12502

Pieters, R., Warlop, L., & Wedel, M. (2002). Breaking through the clutter: Benefits of advertisement originality and familiarity for brand attention and memory. *Management Science*, *48*(6), 765–781. Scopus. https://doi.org/10.1287/mnsc.48.6.765.192

Pieters, R., & Wedel, M. (2020). Heads up: Head movements during ad exposure respond to consumer goals and predict brand memory. *Journal of Business Research*, *111*, 281–289. Scopus. https://doi.org/10.1016/j.jbusres.2018.11.031

Plassmann, H., Ambler, T., Braeutigam, S., & Kenning, P. (2007). What can advertisers learn from neuroscience? *International Journal of Advertising*, *26*(2), 151–175. https://doi.org/10.1080/10803548.2007.11073005

Plassmann, H., Ramsøy, T. Z., & Milosavljevic, M. (2012). Branding the brain: A critical review and outlook. *Journal of Consumer Psychology*, *22*(1), 18–36. https://doi.org/10.1016/j.jcps.2011.11.010

Plassmann, H., Venkatraman, V., Huettel, S., & Yoon, C. (2015). Consumer Neuroscience: Applications, Challenges, and Possible Solutions. *Journal of Marketing Research*, *52*(4), 427–435. https://doi.org/10.1509/jmr.14.0048

Pleyers, G., & Vermeulen, N. (2021). How does interactivity of online media hamper ad effectiveness. *International Journal of Market Research*, *63*(3), 335–352. https://doi.org/10.1177/1470785319867640

Potter, R. F., & Bolls, P. D. (2012). *Psychophysiological measurement and meaning: Cognitive and emotional processing of media.* Routledge/Taylor & Francis Group.

Pozharliev, R., Verbeke, W. J. M. I., & Bagozzi, R. P. (2017). Social Consumer Neuroscience: Neurophysiological Measures of Advertising Effectiveness in a Social Context. *Journal of Advertising*, *46*(3), 351–362. https://doi.org/10.1080/00913367.2017.1343162

Rainey, S., & Erden, Y. J. (2020). Correcting the Brain? The Convergence of Neuroscience, Neurotechnology, Psychiatry, and Artificial Intelligence. *Science and Engineering Ethics*, *26*(5), 2439–2454. https://doi.org/10.1007/s11948-020-00240-2

Ramsøy, T. Z. (2019). Building a Foundation for Neuromarketing And Consumer Neuroscience Research: How Researchers Can Apply Academic Rigor To the Neuroscientific Study of Advertising Effects. *Journal of Advertising Research*, *59*(3), 281–294. https://doi.org/10.2501/JAR-2019-034

Rana, J., & Paul, J. (2020). Health motive and the purchase of organic food: A meta-analytic review. *International Journal of Consumer Studies*, *44*(2), 162–171. https://doi.org/10.1111/ijcs.12556

Randhawa, K., Wilden, R., & Hohberger, J. (2016). A Bibliometric Review of Open Innovation: Setting a Research Agenda: A BIBLIOMETRIC REVIEW OF OPEN INNOVATION. *Journal of Product Innovation Management*, *33*(6), 750–772. https://doi.org/10.1111/jpim.12312

Rauschnabel, P. A., Babin, B. J., tom Dieck, M. C., Krey, N., & Jung, T. (2022). What is augmented reality marketing? Its definition, complexity, and future. *Journal of Business Research*, *142*, 1140–1150. https://doi.org/10.1016/j.jbusres.2021.12.084

Reimann, M., Schilke, O., Weber, B., Neuhaus, C., & Zaichkowsky, J. (2011). Functional magnetic resonance imaging in consumer research: A review and application. *Psychology and Marketing*, *28*(6), 608–637. https://doi.org/10.1002/mar.20403

Richardson, G. M., Bowers, J., Woodill, A. J., Barr, J. R., Gawron, J. M., & Levine, R. A. (2014). Topic Models: A Tutorial with R. *International Journal of Semantic Computing*, *08*(01), 85–98. https://doi.org/10.1142/S1793351X14500044

Rihn, A. L., & Yue, C. (2016). Visual Attention's Influence on Consumers' Willingness-to-Pay for Processed Food Products. *Agribusiness*, *32*(3), 314–328. https://doi.org/10.1002/agr.21452

Rimkute, J., Moraes, C., & Ferreira, C. (2016). The effects of scent on consumer behaviour: The effects of scent. *International Journal of Consumer Studies*, *40*(1), 24–34. https://doi.org/10.1111/ijcs.12206

Rodriguez, M., Ali, S., & Kanade, T. (2009). Tracking in unstructured crowded scenes. *2009 IEEE 12th International Conference on Computer Vision*, 1389–1396. https://doi.org/10.1109/ICCV.2009.5459301

Rosado-Serrano, A., Paul, J., & Dikova, D. (2018). International franchising: A literature review and research agenda. *Journal of Business Research*, *85*, 238–257. https://doi.org/10.1016/j.jbusres.2017.12.049

Rugg, M. D. (2009). Event-Related Potentials (ERPs). In *Encyclopedia of Neuroscience* (pp. 7–12). Elsevier. https://doi.org/10.1016/B978-008045046-9.00752-X

Russell, C. A., Russell, D., Morales, A., & Lehu, J.-M. (2017). Hedonic contamination of entertainment: How exposure to advertising in movies and television taints subsequent entertainment experiences. *Journal of Advertising Research*, *57*(1), 38–52. Scopus. https://doi.org/10.2501/JAR-2017-012

Russell, C. A., Swasy, J. L., Russell, D. W., & Engel, L. (2017). Eye-tracking evidence that happy faces impair verbal message comprehension: The case of health warnings in direct-to-consumer pharmaceutical television commercials. *International Journal of Advertising*, *36*(1), 82–106. https://doi.org/10.1080/02650487.2016.1196030

Russell, J. A., & Pratt, G. (1980). A Description of the Affective Quality Attributed to Environments. *Journal of Personality and Social Psychology*, *38*(2), 311–322.

S, S., Paul, J., Strong, C., & Pius, J. (2020). Consumer response towards social media advertising: Effect of media interactivity, its conditions and the underlying mechanism. *International Journal of Information Management*, *54*, 102155. https://doi.org/10.1016/j.ijinfomgt.2020.102155

Schaefer, M., Berens, H., Heinze, H.-J., & Rotte, M. (2006). Neural correlates of culturally familiar brands of car manufacturers. *NeuroImage*, *31*(2), 861–865. https://doi.org/10.1016/j.neuroimage.2005.12.047

Schaefer, M., & Rotte, M. (2007a). Favorite brands as cultural objects modulate reward circuit: *NeuroReport*, *18*(2), 141–145. https://doi.org/10.1097/WNR.0b013e328010ac84

Schaefer, M., & Rotte, M. (2007b). Thinking on luxury or pragmatic brand products: Brain responses to different categories of culturally based brands. *Brain Research*, *1165*, 98–104. https://doi.org/10.1016/j.brainres.2007.06.038

Schaefer, M., & Rotte, M. (2010). Combining a semantic differential with fMRI to investigate brands as cultural symbols. *Social Cognitive and Affective Neuroscience*, *5*(2–3), 274–281. https://doi.org/10.1093/scan/nsp055

Shang, Q., Pei, G., Dai, S., & Wang, X. (2017). Logo Effects on Brand Extension Evaluations from the Electrophysiological Perspective. *Frontiers in Neuroscience*, *11*. https://doi.org/10.3389/fnins.2017.00113

Sheth, J., & Kellstadt, C. H. (2021). Next frontiers of research in data driven marketing: Will techniques keep up with data tsunami? *Journal of Business Research*, *125*, 780–784. https://doi.org/10.1016/j.jbusres.2020.04.050

Shiv, B., Bechara, A., Levin, I., Alba, J., Bettman, J., Dube, L., Isen, A., Mellers, B., Smidts, A., Grant, S., & McGraw, P. (2005). Decision Neuroscience. *Marketing Letters: A Journal of Research in Marketing*, *16*(3–4), 375–386. https://doi.org/10.1007/s11002-005-5899-8

Simola, J., Kuisma, J., & Kaakinen, J. K. (2020). Attention, memory and preference for direct and indirect print advertisements. *Journal of Business Research*, *111*, 249–261. Scopus. https://doi.org/10.1016/j.jbusres.2019.06.028

Smidts, A., Hsu, M., Sanfey, A. G., Boksem, M. A. S., Ebstein, R. B., Huettel, S. A., Kable, J. W., Karmarkar, U. R., Kitayama, S., Knutson, B., Liberzon, I., Lohrenz, T., Stallen, M., & Yoon, C. (2014). Advancing consumer neuroscience. *Marketing Letters*, *25*(3), 257–267. https://doi.org/10.1007/s11002-014-9306-1

Solnais, C., Andreu-Perez, J., Sánchez-Fernández, J., & Andréu-Abela, J. (2013). The contribution of neuroscience to consumer research: A conceptual framework and empirical review. *Journal of Economic Psychology*, *36*, 68–81. https://doi.org/10.1016/j.joep.2013.02.011

Sorescu, A., Warren, N. L., & Ertekin, L. (2017). Event study methodology in the marketing literature: An overview. *Journal of the Academy of Marketing Science*, *45*(2), 186–207. https://doi.org/10.1007/s11747-017-0516-y

Stanton, S. J., Sinnott-Armstrong, W., & Huettel, S. A. (2017). Neuromarketing: Ethical Implications of its Use and Potential Misuse. *Journal of Business Ethics*, *144*(4), 799–811. https://doi.org/10.1007/s10551-016-3059-0

Steenkamp, J.-B. E. M., & Maydeu-Olivares, A. (2015). Stability and Change in Consumer Traits: Evidence from a 12-Year Longitudinal Study, 2002–2013. *Journal of Marketing Research*, *52*(3), 287–308. https://doi.org/10.1509/jmr.13.0592

Stipp, H. (2015). The Evolution of Neuromarketing Research: From Novelty to Mainstream: How Neuro Research Tools Improve Our Knowledge about Advertising. *Journal of Advertising Research*, *55*(2), 120–122. https://doi.org/10.2501/JAR-55-2-120-122

Suh, A., & Prophet, J. (2018). The state of immersive technology research: A literature analysis. *Computers in Human Behavior*, *86*, 77–90. https://doi.org/10.1016/j.chb.2018.04.019

Szabo, S., & Webster, J. (2021). Perceived Greenwashing: The Effects of Green Marketing on Environmental and Product Perceptions. *Journal of Business Ethics*, *171*(4), 719–739. https://doi.org/10.1007/s10551-020-04461-0

Tham, A., Schaffer, V., & Sinay, L. (2021). The ethics of experimental research employing intrusive technologies in tourism: A collaborative ethnography perspective. *Tourism and Hospitality Research*, *21*(3), 303–316. https://doi.org/10.1177/1467358421993893

Thomas, J., McNaught, J., & Ananiadou, S. (2011). Applications of text mining within systematic reviews. *Research Synthesis Methods*, *2*(1), 1–14. https://doi.org/10.1002/jrsm.27

Tu, H. Bin, Xia, L. M., & Wang, Z. W. (2014). The complex action recognition via the correlated topic model. *The Scientific World Journal*, *2014*. https://doi.org/10.1155/2014/810185

Uncapher, M. R., Boyd-Meredith, J. T., Chow, T. E., Rissman, J., & Wagner, A. D. (2015). Goal-Directed Modulation of Neural Memory Patterns: Implications for fMRI-Based Memory Detection. *Journal of Neuroscience*, *35*(22), 8531–8545. https://doi.org/10.1523/JNEUROSCI.5145-14.2015

van Reijmersdal, E. A., Rozendaal, E., Hudders, L., Vanwesenbeeck, I., Cauberghe, V., & van Berlo, Z. M. C. (2020). Effects of Disclosing Influencer Marketing in Videos: An Eye Tracking Study Among Children in Early Adolescence. *Journal of Interactive Marketing*, *49*, 94–106. https://doi.org/10.1016/j.intmar.2019.09.001

Vences, N. A., Díaz-Campo, J., & Rosales, D. F. G. (2020). Neuromarketing as an Emotional Connection Tool Between Organizations and Audiences in Social Networks. A Theoretical Review. *Frontiers in Psychology*, *11*, 1787. https://doi.org/10.3389/fpsyg.2020.01787

Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H. E., Ishihara, M., & Winer, R. S. (2015). Predicting advertising success beyond traditional measures: New insights from neurophysiological methods and market response modeling. *Journal of Marketing Research*, *52*(4), 436–452. Scopus. https://doi.org/10.1509/jmr.13.0593

Venkatraman, V., Dimoka, A., Vo, K., & Pavlou, P. A. (2021). Relative Effectiveness of Print and Digital Advertising: A Memory Perspective. *Journal of Marketing Research*, *58*(5), 827–844. https://doi.org/10.1177/00222437211034438

Vieira, V. A. (2013). Stimuli–organism-response framework: A meta-analytic review in the store environment. *Journal of Business Research*, *66*(9), 1420–1426. https://doi.org/10.1016/j.jbusres.2012.05.009

Vinitzky, G., & Mazursky, D. (2011). The effects of cognitive thinking style and ambient scent on online consumer approach behavior, experience approach behavior, and search motivation. *Psychology and Marketing*, *28*(5), 496–519. https://doi.org/10.1002/mar.20398

Waechter, S., Sütterlin, B., & Siegrist, M. (2017). Decision-Making Strategies for the Choice of Energy-friendly Products. *Journal of Consumer Policy*, *40*(1), 81–103. Scopus. https://doi.org/10.1007/s10603-016-9328-6

Wainwright, M. J., & Jordan, M. I. (2007). Graphical Models, Exponential Families, and Variational Inference. *Foundations and Trends® in Machine Learning*, *1*(1–2), 1–305. https://doi.org/10.1561/2200000001

Wang, W., Chen, R. R., Ou, C. X., & Ren, S. J. (2019). Media or message, which is the king in social commerce?: An empirical study of participants' intention to repost marketing messages on social media. *Computers in Human Behavior*, *93*, 176–191. https://doi.org/10.1016/j.chb.2018.12.007

Wang, Y. J., & Minor, M. S. (2008). Validity, reliability, and applicability of psychophysiological techniques in marketing research. *Psychology and Marketing*, *25*(2), 197–232. https://doi.org/10.1002/mar.20206

Wedel, M., & Pieters, R. (2000). Eye fixations on advertisements and memory for brands: A model and findings. *Marketing Science*, *19*(4), 297–312. Scopus. https://doi.org/10.1287/mksc.19.4.297.11794

Weinstein, S., Drozdenko, R., & Weinstein, C. (1984). Brain wave analysis in advertising research. Validation from basic research & independent replications. *Psychology & Marketing*, *1*(3–4), 83–95. Scopus. https://doi.org/10.1002/mar.4220010309

Yang, G., Wen, D., Kinshuk, Chen, N. S., & Sutinen, E. (2015). A novel contextual topic model for multi-document summarization. *Expert Systems with Applications*, *42*(3), 1340–1352. https://doi.org/10.1016/j.eswa.2014.09.015

Yang, L., Toubia, O., & De Jong, M. G. (2015). A Bounded Rationality Model of Information Search and Choice in Preference Measurement. *Journal of Marketing Research*, *52*(2), 166–183. https://doi.org/10.1509/jmr.13.0288

Yegiyan, N. S. (2015). Explicating the Emotion Spillover Effect: At the Intersection of Motivational Activation, Resource Allocation, and Consolidation. *Journal of Media Psychology*, *27*(3), 134–145. https://doi.org/10.1027/1864-1105/a000164

Yoon, C., Gonzalez, R., Bechara, A., Berns, G. S., Dagher, A. A., Dubé, L., Huettel, S. A., Kable, J. W., Liberzon, I., Plassmann, H., Smidts, A., & Spence, C. (2012). Decision neuroscience and consumer decision making. *Marketing Letters*, *23*(2), 473–485. https://doi.org/10.1007/s11002-012-9188-z

Zhai, H., Guo, J., Wu, Q., Cheng, X., Sheng, H., & Zhang, J. (2009). Query classification based on Regularized Correlated Topic Model. *Proceedings - 2009 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2009*, *1*, 552–555. https://doi.org/10.1109/WI-IAT.2009.91

Zhang, J., Wedel, M., & Pieters, R. (2009). Sales Effects of Attention to Feature Advertisements: A Bayesian Mediation Analysis. *Journal of Marketing Research*, *46*(5), 669–681. https://doi.org/10.1509/jmkr.46.5.669

Zhang, J., Yun, J. H., & Lee, E.-J. (2021). Brain buzz for Facebook? Neural indicators of SNS content engagement. *Journal of Business Research*, *130*, 444–452. https://doi.org/10.1016/j.jbusres.2020.01.029

Tables

Table 1. Most common neuroscientific methods: description and applications

	Neuroscientific Methods	Measurement	Application
Non-Neuroimaging Tools	Eye-Tracking	Eye pupil's and cornea's position (eye position) or eye motion relative to the head (eye movement)	Cognitive studies, computer usability, product development, virtual reality, advertising, web usability and design, sponsorship, shelf displays, sporting events, media usage, and human-computer interaction
	Skin Conductance Response (SCR) (Also known as Electrodermal Response or Galvanic Skin Response)	Sympathetic nervous system that changes the sweat levels in eccrine glands of the palms or feet	Arousal, emotion, fear, excitement, and attention
	Electrocardiogram (ECG)	Electrical activity of the heart on the skin, and heart rate (heart beats in a minute)	Anxiety, effort, stress, and arousal evaluation
	Facial Electromyography (fEMG) (Facial Coding)	Muscle activity through electrical impulses caused by muscle fibers during the contraction of the two main facial muscles (the corrugator and the zygomaticus)	Emotional reactions - Activity in the corrugator muscle: negative emotional stimuli and mood states (e.g., anger and disgust) - Activity in the zygomatic muscle: correlated with positive stimuli and mood states (e.g., pleasure and enjoyment)
Neuroimaging Tools	Electroencephalography (EEG)	Electrical brain activity through the multiple electrodes placed on the scalp, revealing electrical signals of cortical brain areas	Neuroscience, cognitive science, cognitive psychology, and psychophysiological research, including attention, recall, judgement, emotional engagement, choice behavior, preference ranking, sleeping disorder, coma, and epilepsy
	Magnetoencephalography (MEG)	Magnetic fields induced by synchronized neuronal electrical potentials occurring naturally in the brain	Consumer preferences, reactions, tastes, and choice behavior. Sensory and cognitive brain functions, including perception and memory. It is often used for neuronal changes examination after stroke, trauma or drug administration
	Single-Neuron Recording	Isolated spike potentials of single neurons, recorded with microelectrodes implanted into the nervous tissue	Memory consolidation, fear and social behavior, high-level perception, navigation, perception of specific concepts, high-level cognitive control, motor planning
	Functional Magnetic Resonance Imaging (fMRI)	Neural activity by changes in blood oxygenation (blood flow) during cognitive tasks	Value perception, conflict resolution, fear, reward processing, risk perception, prediction, decision making, self-reflection, disgust, anger, memory and emotions. Analysis of social perceptions such as trust, envy, cooperation, and reciprocity
	Positron Emission Tomography (PET)	Metabolic activity representing neurochemical changes by means of radioactive tracer isotopes	Humans' brain patterns that occur over a long period of time

Adapted from Cerf et al., 2015; Criado et al., 2008; Dimoka et al., 2012; Harris et al., 2018; Lim, 2018; Venkatraman et al., 2015

Table 2. Quality criteria for manual article screening (Loureiro, Guerreiro, & Tussyadiah, 2021, p. 922; Macpherson & Holt, 2007)

Elements	**0: Absence**	**1: Low Level**	**2: Medium Level**	**3: High Level**	**Not Applicable**
1. Directly related to the objective of the research	There is not enough information to evaluate this criterion	Not related	Somehow related	Totally related	Not Applicable
2. Theory robustness	There is not enough information to evaluate this criterion	Weak development of literature	Superficial development of theories and constructs within existing literature	Robust use of theory	Not Applicable
3. Congruence of theory, methodology and findings	There is not enough information to evaluate this criterion	Incomplete data and not related to theory	Data somehow related to the arguments	Strong link between the arguments presented and data	Not Applicable
4. Contributions to theory and/or practice	There is not enough information to evaluate this criterion	Makes a low contribution	Makes a medium contribution	Makes a high contribution	Not Applicable

Table 3. Top 36 most frequent stemmed terms

Nr.	Term	Frequency	Nr.	Term	Frequency
1	studi	12,731	19	time	6,425
2	advertis	12,454	20	respons	6,422
3	brand	12,164	21	data	5,710
4	particip	11,111	22	signific	5,696
5	attent	10,732	23	market	5,504
6	effect	10,560	24	experi	5,454
7	use	10,321	25	brain	5,426
8	product	9,790	26	present	5,209
9	research	9,688	27	model	5,139
10	consum	9,410	28	posit	4,922
11	differ	9,030	29	subject	4,504
12	process	8,743	30	relat	4,494
13	activ	8,305	31	behavior	4,443
14	measur	8,172	32	imag	4,434
15	inform	7,662	33	show	4,296
16	result	7,431	34	condit	4,282
17	emot	6,811	35	test	4,037
18	visual	6,451	36	stimuli	3,903

Table 4. Ranking of journals by number of articles (excluding those with 2 or fewer articles)

Journal	**Number of Articles**	**5-Year Impact Factor**	**SJR Best Quartile**	**H index**
Journal of Marketing Research	19	5.678	Q1	141
Journal of Advertising Research	14	2.709	Q1	71
Computers in Human Behavior	11	4.417	Q1	123
Journal of Neuroscience, Psychology, and Economics	11	1.265	Q1	19
Journal of Advertising	10	3.846	Q1	85
Frontiers in Psychology	10	2.749	Q1	66
International Journal of Advertising	8	2.475	Q1	35
Social Cognitive and Affective Neuroscience	7	4.941	Q1	79
Journal of Consumer Psychology	7	4.427	Q1	84
Journal of Neuroscience	6	6.517	Q1	409
NeuroImage	6	7.079	Q1	307
Journal of Product and Brand Management	6	N/A	Q1	64
Frontiers in Human Neuroscience	6	4.022	Q1	73
NeuroReport	6	1.493	Q3	176
Journal of Business Research	6	3.689	Q1	144
Journal of Consumer Marketing	6	N/A	Q1	79
Frontiers in Behavioral Neuroscience	5	3.553	Q1	50
Journal of Retailing and Consumer Services	5	N/A	Q1	57
Journal of Consumer Behaviour	5	2.270	Q2	28
Neuroscience Letters	5	2.124	Q2	153
Journal of Brand Management	5	N/A	Q2	33
Psychology and Marketing	5	2.631	Q1	90
European Journal of Marketing	5	2.545	Q1	71
Appetite	5	3.691	Q1	110
Journal of the Academy of Marketing Science	4	9.810	Q1	139
Journal of Marketing	4	9.592	Q1	208
Frontiers in Neuroscience	4	4.294	Q1	58
Qualitative Market Research	4	N/A	Q3	42
Journal of Interactive Marketing	4	9.472	Q1	82
Journal of Economic Psychology	4	2.197	Q1	77
Body Image	3	3.534	Q1	62
Marketing Science	3	3.918	Q1	108
Cerebral Cortex	3	6.800	Q1	216

Communication Research	3	4.024	Q1	84
Cogent Psychology	3	N/A	Q3	5
Comunicar	3	3.285	Q1	20
Journal of Marketing Management	3	N/A	Q1	41
Consumption Markets and Culture	3	2.197	Q1	19
Marketing Letters	3	2.080	Q1	55
International Journal of Psychophysiology	3	3.311	Q2	106
Neuropsychological Trends	3	N/A	Q4	4
Journal of Consumer Research	3	6.022	Q1	146
Psychology and Marketing	3	2.631	Q1	90
Applied Cognitive Psychology	3	1.988	Q1	81
Social Neuroscience	3	3.182	Q1	53

Note: N/A = Not Applicable

Table 5. The 23 topics and the most frequent terms in each topic

Topic	Nr. Articles	1st Term	2nd Term	3rd Term	4th Term	5th Term
1 - Consumer Neuroscience	21	research	consum	neurosci	studi	brain
2 - Brand Memory	10	brand	memori	process	attent	inform
3 - Willingness to Buy	34	product	consum	choic	price	inform
4 - Hedonic vs. Utilitarian Products	30	activ	brain	brand	studi	cortex
5 - Visual and Neural Cognition for Memory Detection	15	memori	use	imag	face	perform
6 - Models of Data Processing	8	model	refer	data	size	featur
7 - Emotional Responses to Advertisements	20	messag	arous	measur	respons	particip
8 - Advertising Effectiveness	23	advertis	effect	commerci	attitud	brand
9 - Neural Activity in Behavioral Research	13	food	use	activ	behavior	neural
10 - Reliability of Eye-Tracking Data	25	eye	fixat	search	user	use
11 - Visual Attention	23	attent	fixat	visual	gaze	text
12 - Experiment Manipulation	12	particip	imag	use	behavior	studi
13 - Online Advertising	21	banner	anim	effect	game	user
14 - Ethical Concerns in Neuromarketing	51	market	research	neuromarket	brain	custom
15 - Semiotics	22	condit	particip	effect	stimuli	present
16 - Safety Measurements	29	particip	studi	risk	children	group
17 - Neural Response to Reward	20	activ	subject	choic	price	trial
18 - Measuring Emotional vs. Cognitive Appraisal	24	emot	measur	facial	express	use
19 - Visual Design Effects	19	visual	attent	design	effect	complex
20 - Social Comparison	13	social	women	polit	negat	model
21 - TV Commercials Stimuli	26	eeg	activ	commerci	subject	differ
22 - Individual Interaction in Structured Environment	10	focus	system	work	goal	individu
23 - (-)	0	studi	differ	particip	process	effect

Table 6. Relevant topics: yearly frequency evolution

Topic	#	1948	1950	1971	1972	1973	1984	1985	1989	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
1 - Consumer Neuroscience	21						1														1		2	1	2			4	6	3	1
2 - Brand Memory	10											1	1		1		2				1		1		1				1	1	
3 - Willingness to Buy	34																			1	1	1	1		2	3	3	7	4	9	2
4 - Hedonic vs. Utilitarian Products	30																	1	1	4	1	3	4	3	3	2	4	1	2	1	
5 - Visual and Neural Cognition for Memory Detection	15																		1			1	2	3		3	1	2		2	
6 - Models of Data Processing	8																			1		2			1			1	2		1
7 - Emotional Responses to Advertisements	20	1			1	1								1						1		2		2	1	1	2	2	2	3	
8 - Advertising Effectiveness	23		1						1			2									2		1		1	2	2	1	5	5	
9 - Neural Activity in Behavioral Research	13																							1			3	5	2	1	1
10 - Reliability of Eye-Tracking Data	25									1					1	1				2			1	6	1	2	2	1	4	3	
11 - Visual Attention	23																			1	1	1		3		2	2	5	3	4	1
12 - Experiment Manipulation	12							1																1	1	1	1	1	4	1	1
13 - Online Advertising	21															1	1					1	1	1	3	2	2	4	2	3	
14 - Ethical Concerns in Neuromarketing	51																	1	3	5	1	1		8	7	8	3	5	3	6	
15 - Semiotics	22																			2	1		2	1	3	1		4	6	2	
16 - Safety Measurements	29								1		3				1					2			1	3	1	2	2	3	7	3	
17 - Neural Response to Reward	20																1	1	1	3	2			1	3	1		2	1	3	1
18 - Measuring Emotional vs. Cognitive Appraisal	24																			2		1	1		1	1		3	6	7	2
19 - Visual Design Effects	19																1		1			1	1	1	2	2	4	1	1	3	1
20 - Social Comparison	13			1																			2			2	3	1	2	2	
21 - TV Commercials Stimuli	26						2										1				1		5	1	1		2	4	2	7	
22 - Individual Interaction in Structured Environment	10							1									2	1			1	1			1		1		1	1	
23 - (-)	0																														

Table 7. The core 3 articles from topic 1 to 12

Topic	Authors	Journal	Year	Posterior Probability
1	Hubert M.	Journal of Economic Psychology	2010	.772
	Plassmann H., Venkatraman V., Huettel S., et al.	Journal of Marketing Research	2015	.604
	Rimkute J., Moraes C., Ferreira C.	International Journal of Consumer Studies	2016	.529
2	Pieters R., Warlop L., Wedel M.	Management Science	2002	.661
	Wedel M., Pieters R.	Marketing Science	2000	.636
	Shang Q., Pei G., Dai S., et al.	Frontiers in Neuroscience	2017	.489
3	Rihn A.L., Yue C.	Agribusiness	2016	.66
	Waechter S., Sütterlin B., Siegrist M.	Journal of Consumer Policy	2017	.628
	Liu C.-W., Hsieh A.-Y., Lo S.-K., et al.	Computers in Human Behavior	2017	.626
4	Schaefer M., Rotte M.	NeuroReport	2007	.868
	Schaefer M., Berens H., Heinze H.-J., et al.	NeuroImage	2006	.829
	Schaefer M., Rotte M.	Brain Research	2007	.824
5	Uncapher M.R., Tyler Boyd-Meredith J., Chow T.E., et al.	Journal of Neuroscience	2015	.878
	Jiang J., Summerfield C., Egner T.	Journal of Neuroscience	2013	.777
	Harding G., Bloj M.	Journal of Vision	2010	.637
6	Brocher A., Chiriacescu S.I., von Heusinger K.	Discourse Processes	2016	.831
	Zhang J., Wedel M., Pieters R.	Journal of Marketing Research	2009	.654
	Yang L., Toubia O., De Jong M.G.	Journal of Marketing Research	2015	.55
7	Leshner G., Bolls P., Thomas E.	Health Communication	2009	.766
	Lee M.J., Shin M.	Journal of Psychology: Interdisciplinary and Applied	2011	.73
	Yegiyan N.S.	Journal of Media Psychology	2015	.707
8	Grigaliunaite V., Pileliene L.	Scientific Annals of Economics and Business	2016	.704
	Russell C.A., Russell D., Morales A., et al.	Journal of Advertising Research	2017	.646
	Boerman S.C., Van Reijmersdal E.A., Neijens P.C.	Journal of Advertising	2015	.593
9	Falk E.B., Berkman E.T., Whalen D., et al.	Health Psychology	2011	.71
	Cerf M., Greenleaf E., Meyvis T., et al.	Journal of Marketing Research	2015	.506
	Falk E.B., O'Donnell M.B., Tompson S., et al.	Social Cognitive and Affective Neuroscience	2016	.505
10	Niehorster D.C., Cornelissen T.H.W., Holmqvist K., et al.	Behavior Research Methods	2017	.912
	Domachowski A., Griesbaum J., Heuwing B.	Proceedings of the Association for Information Science and Technology	2016	.743
	Lam, S. Y., Chau, A. W.-L., & Wong, T. J.	Journal of Interactive Marketing	2007	.718
11	Li Q., Huang Z.J., Christianson K.	Tourism Management	2016	.648
	Hutton S.B., Nolte S.	Applied Cognitive Psychology	2011	.533
	Smit E., Boerman S., Meurs L.	Journal of Advertising Research	2015	.522
12	Hansen K.A., Hillenbrand S.F., Ungerleider L.G.	Frontiers in Neuroscience	2011	.717
	Starcke K., Wiesen C., Trotzke P., et al.	Frontiers in Psychology	2016	.552
	Hüsser A., Wirth W.	Journal of Financial Services Marketing	2014	.514

Table 8. The core 3 articles from topic 13 to 23

Topic	Authors	Journal	Year	Posterior Probability
13	Li K., Huang G., Bente G.	Computers in Human Behavior	2016	.818
	Jeong E., Bohil C., Biocca F.	Journal of Advertising	2011	.645
	Hamborg K.-C., Bruns M., Ollermann F., et al.	Computers in Human Behavior	2012	.629
14	Krausová A.	Lawyer Quarterly	2017	.776
	Trocchia P.J., Ainscough T.L.	International Journal of Retail and Distribution Management	2006	.756
	Nijboer F., Clausen J., Allison B.Z., et al.	Neuroethics	2013	.749
15	Mulders I., Szendroi K.	Frontiers in Psychology	2016	.769
	Thomas A., Hammer A., Beibst G., et al.	BMC Neuroscience	2013	.671
	Fudali-Czyz A., Ratomska M., Cudo A., et al.	Neuroscience Letters	2016	.641
16	Seneviratne D., Molesworth B.R.C.	Safety Science	2015	.696
	Dukic T., Ahlstrom C., Patten C., et al.	Traffic Injury Prevention	2013	.664
	Cavalari R.N.S., Romanczyk R.G.	Journal of Behavioral Decision Making	2015	.657
17	Bray S., Rangel A., Shimojo S., et al.	Journal of Neuroscience	2008	.702
	Scult M.A., Knodt A.R., Hanson J.L., et al.	Social Neuroscience	2017	.649
	Staudinger M.R., Erk S., Walter H.	Cerebral Cortex	2011	.62
18	Bellman S.	Australasian Marketing Journal	2007	.608
	Lewinski P.	Journal of Neuroscience, Psychology, and Economics	2015	.575
	Karim A.A., Lützenkirchen B., Khedr E., et al.	Frontiers in Psychology	2017	.572
19	Orth U.R., Crouch R.C.	Journal of Retailing	2014	.707
	Husić-Mehmedović M., Omeragić I., Batagelj Z., et al.	Journal of Business Research	2017	.596
	Kahn B.E.	Journal of Retailing	2017	.54
20	Mischner I.H.S., van Schie H.T., Engels R.C.M.E.	Body Image	2013	.804
	Bury B., Tiggemann M., Slater A.	Body Image	2016	.594
	Bury B., Tiggemann M., Slater A.	Body Image	2014	.588
21	Vecchiato G., Astolfi L., Fallani F.D.V., et al.	Brain Topography	2010	.882
	Vecchiato G., De Vico Fallani F., Astolfi L., et al.	Journal of Neuroscience Methods	2010	.761
	De Vico Fallani F., Astolfi L., Cincotti F., et al.	Clinical Neurophysiology	2008	.755
22	D'Aquili E.G.	Zygon®	1985	.584
	Gillingwater D., Gillingwater T.H.	International Journal of Business Science and Applied Management	2009	.505
	McKhann G.M.	Technology in Society	2004	.448
23	Kilboume W.E., Painton S., Ridley D.	Journal of Advertising	1985	.063
	Golin E., Lyerly S.B.	Journal of Applied Psychology	1950	.059
	Fletcher J.E.	Psychophysiology	1971	.057

Table 9. Top 10 articles (ordered by average citation score per year)

Rank Position	Author	Journal	TC	CY	AC_y
1	Szabo, and Webster (2021)	Journal of Business Ethics	22	0	22.0
2	Niehorster, Cornelissen, Holmqvist et al. (2018)	Behavior Research Methods	63	3	21.0
3	Muñoz-Leiva, Hernández-Méndez, and Gómez-Carmona D. (2019)	Physiology and Behavior	41	2	20.5
4	Meyerding, and Mehlhose (2020)	Journal of Business Research	20	1	20.0
5	Kahn (2017)	Journal of Retailing	77	4	19.3
6	Lee, Choi, Han et al. (2020)	Journal of Business Research	18	1	18.0
7	Machín, Curutchet, Gugliucci et al. (2020)	Appetite	18	1	18.0
8	Calogiuri, Litleskare, Fagerheim et al. (2018)	Frontiers in Psychology	53	3	17.7
9	Lim (2018)	Journal of Business Research	52	3	17.3
10	van Reijmersdal, Rozendaal, Hudders et al. (2020)	Journal of Interactive Marketing	17	1	17.0

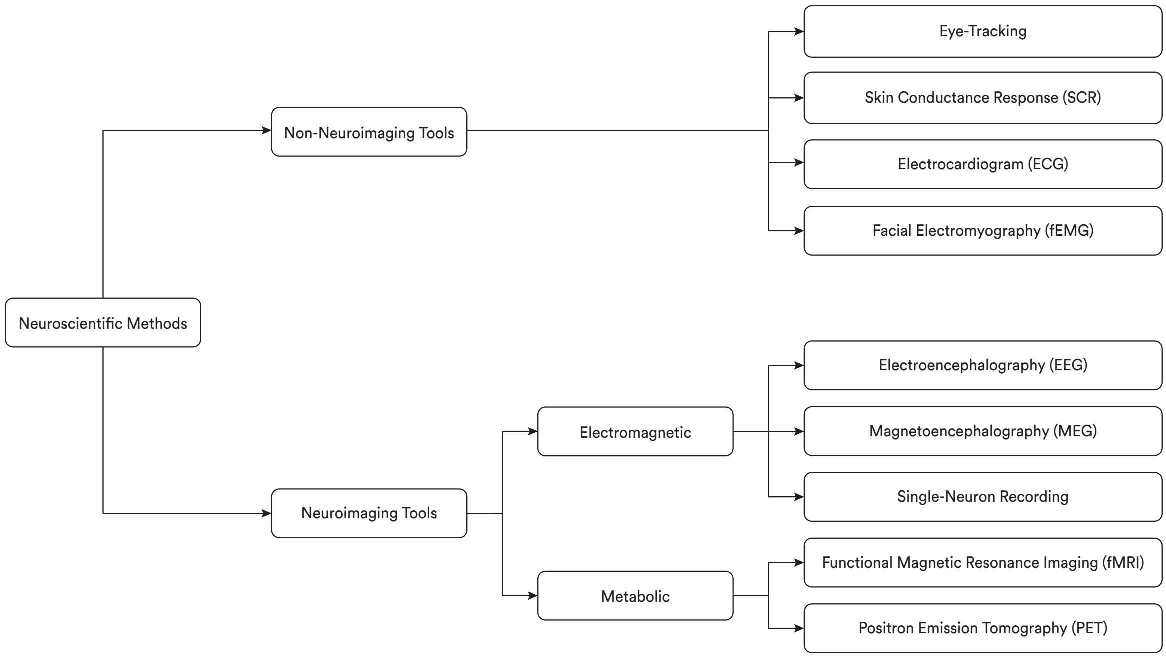
TC = Total Citations; CY = Citable Years; AC_y = Average Citations per Year

Table 10. Research Questions in Consumer Neuroscience

Future Research Avenues	**Dimensions**	**Research Questions**
Green Marketing / Sustainability	Consumer Behavior	– How will green labelling influence visual attention? – What emotional responses may arise in case of sustainable versus non-sustainable brands (e.g., vegetarian leather vs. real leather products)? – Are eco-friendly products more memorable than non-eco? – Are ads with sustainable practices more appealing than regular ads? – Do anti-consumption ads generate less arousal than traditional commercial ads?
	Luxury Marketing	– Which emotions do sustainable luxury advertising stimulate in individuals? – How will luxury brands' advertisements for sustainable products (e.g., vegetarian leather products by fashion designers) impact brand awareness and engagement?
	New Technology	– Which neuroscientific methods can convey effective messages regarding sustainability?
New Technology Developments	Blockchain	– How can neuroscience be used to assess the blockchain technology impact on perceived trust in retail? – How is blockchain affecting consumer brand attention, brand engagement and influencing purchasing intentions? – How will blockchain impact perceived risk and anonymity in financial contexts, whether through SCR or EEG measurement?
	Artificial Intelligence (AI)	– How does AI affect online shopping experience, using biometrics data? – How can neuroscience measure perceived cybersecurity risks with AI? – Is advertising through AI devices creating greater brand memory and attention than through traditional media? – Will we ever be able to measure emotions in AI devices?
	Metaverse	– How will brand engagement evolve within metaverse environment? – Will advertising within metaverse context trigger different brain responses from those from other social media? – How can eye-tracking devices be used to optimize social media interaction with metaverse technology?
	Virtual Worlds	– Will the lower physical presence in shops (higher immersive scenarios) cause lower levels of attention and engagement? – Will many-to-many group events improve direct attention and engagement? – Will virtual venues, such as music concerts, ease the relationship with the artists, and hence increase the level of emotions?
	Neuroscientific Tools	– Can mobile devices enabling eye-tracking via front-facing camera accurately measure visual attention? – Will eye-trackers on virtual reality glasses bring more insights to consumer neuroscience due to their portability and real life application? – Will facial coding softwares accurately measure other than basic emotions?
Privacy and Ethical Concerns		– Will privacy and anonymity concerns be a major obstacle for consumer neuroscience evolution? – How far can subliminal marketing go? – What shall remain as private data regarding data obtained through neuroscientific tools? – Will blockchain technology impact the definition of private data in consumer neuroscience?

Figures

Figure 1. Most common neuroscientific methods



Adapted from (Lim, 2018b)

Figure 2. Process to identify articles for the final dataset

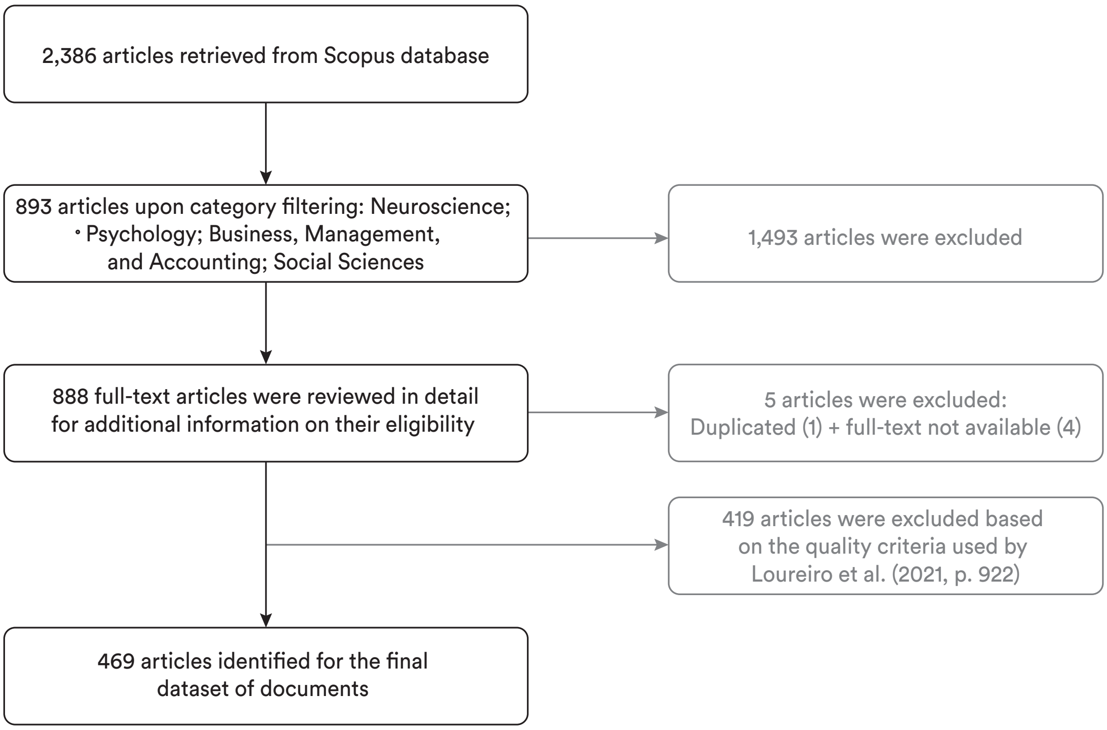


Figure 3. Text mining process, partially based on the framework of Guerreiro et al. (2016), and Moher, Liberati, Tetzlaff, Altman, and The PRISMA Group, (2009)

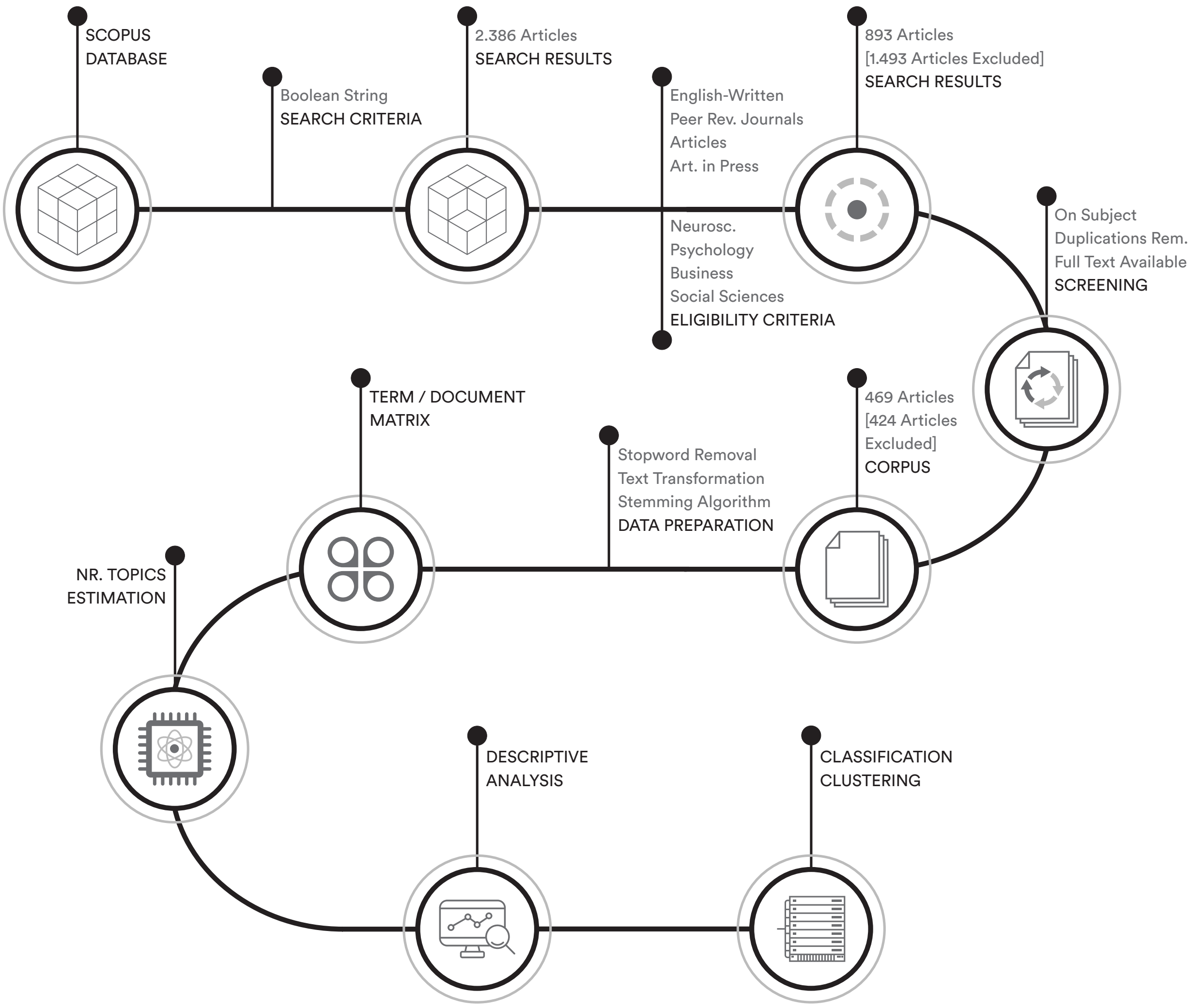


Figure 4. Number of topics estimation

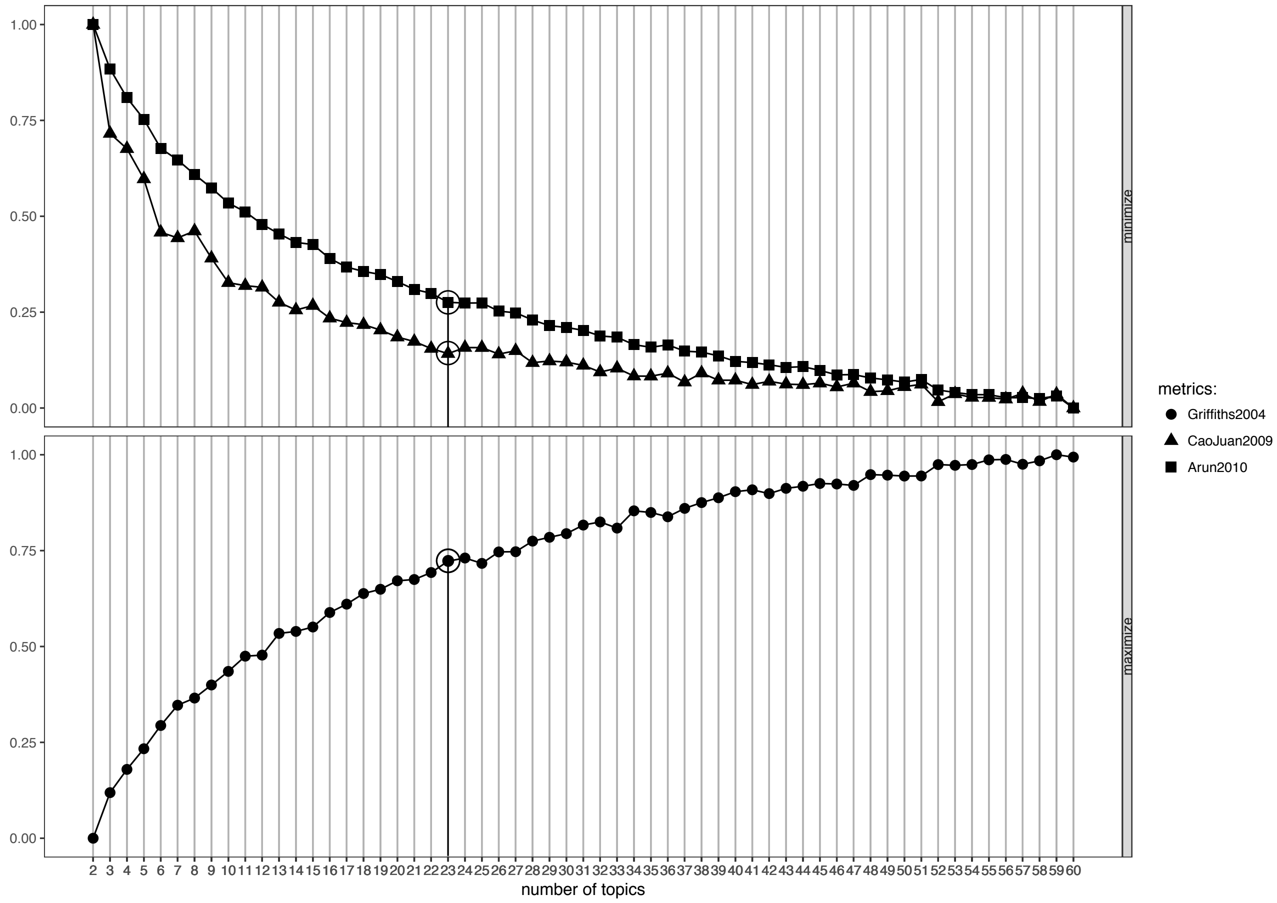


Figure 5. Word Cloud of the most frequent stemmed terms

Figure 6. Number of Articles per Period