Departamento de Comercialización e Investigación de Mercados

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CONSUMER BEHAVIOUR IN ELECTRONIC AND VIRTUAL COMMERCE: MERGING BEHAVIOURAL AND NEUROPHYSIOLOGICAL PERSPECTIVES

DOCTORAL DISSERTATION

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This thesis is a culmination of all our efforts.

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Preface

This PhD dissertation is a compendium of three published articles in internationally indexed journals. The first publication titled Interaction between extrinsic and intrinsic online review cues: perspectives from cue utilization theory (Chapter 2), is published in Springer's Electronic Commerce Research journal, which is indexed in Journal Citation Reports (JCR) of Web of Science database (IF: 3.46; Q3 in Business in 2021). The second article titled Heart rate variability in marketing research: A systematic review and methodological perspectives (Chapter 3), is published in Wiley's Psychology & Marketing journal, which is indexed in Journal Citation Reports (JCR) of Web of Science database (IF: 5.51; Q2 in Business, Q1 in Psychology, applied in 2021). The third article titled Cognitive load during planned and unplanned virtual shopping: Evidence from a neurophysiological perspective (Chapter 4), is published in Elsevier's International Journal of Information Management, which is indexed in Journal Citation Reports (JCR) of Web of Science database (IF: 18.95; Q1 in Information Science & Library Science in 2021) and is ranked 1 in the Marketing subcategory of Scopus database (Business, Management and Accounting). Additionally, the Appendix section contains three co-authored publications as well. The first article is titled How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach (Appendix 1), published in Elsevier's Journal of Business Research, which is indexed in Journal of Citation Reports (JCR) of Web of Science database (IF: 10.97; Q1 in Business in 2021). The second article titled Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket (Appendix 2), is published in Frontiers in Neuroscience, which is indexed in Journal of Citation Reports (JCR) of Web of Science database (IF: 5.15; Q2 in Neurosciences in 2021). The third article is titled as The Role of Stimuli-Driven and Goal-Driven Attention in Shopping Decision-Making Behaviors—An EEG and VR Study (Appendix 3), published in Brain sciences, which is indexed in Journal of Citation Reports (JCR) of Web of Science database (IF:3.33 ; Q3 in Neurosciences in 2021).

The overarching aim of this thesis is to extend academic scholarship on consumer behavior through novel theoretical frameworks and methodological techniques. From conceptual perspective, the studies move on to examining purchases behavior in e-commerce to virtual commerce environments. In the e-commerce format, analyzing the attributes of product reviews on purchases decisions for different product categories broadened the classical cue-utilization framework (Chapter 2). In virtual reality format, critical differences in planned and unplanned purchase behavior while shopping in a virtual supermarket are stated (Chapter 4). From a methodological point-of-view, this thesis incorporates implicit (neuro physiological) measurements along with traditional explicit (self-report) measurements. Utilizing neuroscientific tools served two interconnected goals for this thesis – (a) updating classical marketing frameworks for today's practitioners (Chapters 3 and 4); and (b) for evaluating the impact of marketing interventions (advertisement and retailing) on consumer purchase intentions (Chapter 4 and, in Appendix 1, 2 and 3). The usage of neuroscientific tools, in Chapter 3 and 4 (also in Appendix 1, 2 and 3) allowed for directly capturing real-time subconscious decision-making of consumers' during the purchase stage of consumer journey. This allowed for updating the classical consumer behavior models (e.g., stimulus-organism-response) to include both explicit and implicit (like Cognitive load) measurements. Therefore, rather than relying on a single technique, this dissertation also contributes to the growing awareness of the benefits of triangulating data to understand consumer decision-making at a more fundamental level in varied contexts.

The structure of this PhD thesis is as follows: Chapter 1 provides a general introduction to the topics of this thesis and highlights specific theoretical aspects, the key objectives, and methodological approaches. Subsequently, Chapters 2, 3 and 4, present the published articles with references as available online, in respective journals. Chapter 5 provides conclusion of this thesis by summarizing each study vis-à-vis their underlying theoretical perspectives, their implication for academic scholars and practitioners, and the limitations of our approaches and propose future line of research. Next, the Appendix section contains three published articles. Lastly, references all chapters can be viewed at the end of this thesis.

Abstract

In the last two decades, pragmatic shifts in technology have assisted Business-to-Consumers retailers to seek novel avenues for expanding their businesses and excite consumers with newer shopping experiences. On one hand, due to the continuous technological developments retailers have leveraged the power of Web 2.0 to make a shift from traditional brick-and-motor to e-commerce retail stores and empowered consumers with user-generated contents (UGC). With the advent of Web 3.0, retailers are attempting to set up stores in a three-dimensional space of extended reality by using virtual reality (VR), augmented reality (AR), or mixed reality (MR), thereby creating virtual world(s) for consumers to interact and share using Artificial Intelligence (AI). Evidently, this has resulted in a change of consumers' patterns of shopping and has directly necessitated the need for researchers to develop apparatus to capture and understand the ever-evolving nature of consumer behavior. Parallelly, marketing research has taken huge strides to incorporate tools and techniques to observe consumers' conscious and subconscious measurements. While conventional marketing techniques involved self-reports, focus group and panel data to understand explicitly stated observations, the advent of neurophysiological tools, such as Electroencephalography (EEG), Heart rate Variability (HRV) and Eye tracking (ET) has made it possible to record and quantify consumer's unstated subconscious observations vis-à-vis marketing stimulus. These advancements exhibit future course of research as well as carries with itself newfound challenges such as identifying critical aspects of UGC that influences purchase behavior, triangulating neurophysiological data with explicit measurements, and dynamic consumption patterns in immersive marketplaces. Therefore, the development of this thesis partakes various domains– retailing, neuromarketing and virtual reality – only to contribute a fresh perspective on understanding consumer behavior and therefore, overcoming some of the challenges.

Resumen

En las últimas dos décadas, los cambios pragmáticos en la tecnología han ayudado a los minoristas Business-to-Consumers a buscar vías novedosas para expandir sus negocios y entusiasmar a los consumidores con nuevas experiencias de compra. Por un lado, debido a los continuos desarrollos tecnológicos, los minoristas han aprovechado el poder de la Web 2.0 para hacer un cambio de las tiendas físicas tradicionales a las tiendas minoristas de comercio electrónico y empoderaron a los consumidores con contenido generado por el usuario (UGC). Con la llegada de la Web 3.0, los minoristas intentan establecer tiendas en un espacio tridimensional de realidad extendida mediante el uso de realidad virtual (VR), realidad aumentada (AR) o realidad mixta (MR), creando así mundos virtuales para que los consumidores interactúen y compartan usando Inteligencia Artificial (AI). Evidentemente, esto ha resultado en un cambio de los patrones de compra de los consumidores y ha hecho necesario directamente que los investigadores desarrollen aparatos para capturar y comprender la naturaleza en constante evolución del comportamiento del consumidor. Paralelamente, la investigación de mercados ha dado grandes pasos para incorporar herramientas y técnicas para observar las mediciones conscientes y subconscientes de los consumidores. Si bien las técnicas de marketing convencionales incluían autoinformes, grupos focales y datos de panel para comprender las observaciones explícitamente establecidas, la llegada de herramientas neurofisiológicas, como la electroencefalografía (EEG), la variabilidad de la frecuencia cardíaca (HRV), el seguimiento ocular (ET), etc., es posible registrar y cuantificar las observaciones subconscientes no declaradas del consumidor frente a estímulos de marketing. Estos avances muestran el curso futuro de la investigación y conllevan nuevos desafíos, como la identificación de aspectos críticos de UGC que influyen en el comportamiento de compra, la triangulación de datos neurofisiológicos con mediciones explícitas y patrones de consumo dinámicos en mercados inmersivos. Por lo tanto, el desarrollo de esta tesis participa en varios dominios (venta minorista, neuromarketing y realidad virtual) para contribuir con una nueva perspectiva para comprender el comportamiento del consumidor y, por lo tanto, superar algunos de los desafíos.

CHAPTER 1
INTRODUCTION

Introduction to the thesis

The last two decades have seen a change in shopping behavior from physical stores to digital stores. The rapid adoption of alternative channels (e-commerce and virtual reality-based stores) for sales has changed the consumption patterns of the consumers. In terms of global sales, e-commerce platforms are expected to contribute approximately $8 trillion[1]. By various reported estimates, it is anticipated that AR, VR and XR industry will showcase annual growth of 40%-80%[2], and clocking over $100 billion by 2026[3]. Thus, the understanding of consumer's explicit and implicit behavior in e-commerce and virtual commerce and the drivers of their consumptions have been focal point of marketing research. Through the compilation of the three studies as part of this thesis, we aim to extend the investigation of consumer behavior in different contexts. Figure 1 depicts the general overview of the thesis incorporating publication output. As part of this thesis, the articles (papers 1,2 and 3) are presented in Chapters 2,3 and 4, respectively.

To conduct the objectives of each study, this thesis received financial support from the Rhumbo project (European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie Grant Agreement No 813234). This project provided the shape and scope for the studies of this thesis. The project suggests applying mixed reality technologies (MRT) and advanced biometric signals processing to develop our understanding of the role implicit processes play in human decision-making.

The unique contribution of this thesis lies in examining consumer's purchase behavior in both e-commerce and virtual commerce, as well as using multi-method approaches to collect explicit and implicit consumer responses. In the following sections we provide detailed overview of the chapters as part of this thesis. First, we provide necessary background information for electronic word of mouth and Chapter 2. Next, we provide literature on the use of neurophysiological tools in marketing research which provides basis

[1] https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

[2] https://medium.com/xrbootcamp/a-summary-of-augmented-reality-and-virtual-reality-market-size-predictions-4b51ea5e2509

[3] https://www.statista.com/statistics/591181/global-augmented-virtual-reality-market-size/

for Chapter 3 and 4, respectively. Lastly, we showcase the increasing use of virtual reality in marketing research as the basis for Chapter 4.

eWOM and consumer behavior

Online consumer reviews are an essential part of the electronic word-of- mouth (eWOM) that shapes consumers purchase behavior. According to statistics published by various market research firms convey that almost 95% of consumers view other consumer reviews before buying a product on e-commerce website[1]. To understand the influence of online reviews in consumer's purchase behavior, previous studies have applied various theoretical perspectives such as Elaboration likelihood model (ELM), Heuristic-Systematic model (HSM), Signaling theory, and Revealed preference theory. In Chapter 2, we use cue-utilization framework to examine the interactive effects of intrinsic and extrinsic aspect of online reviews on consumer purchase behavior. Based on previous studies, we examined three types of extrinsic cues of online consumer reviews. (i) content style of the reviews which explores the linguistic expression i.e., denotes the way a review has been written by the consumer either in general or specific way. General content style describes the consumption experience with high focus on subjective evaluation with suppressing objective or technical information. On the other hand, a specific content style describes the consumption experience of the product with high focus on specification of the products. (ii) Presence or absence of a label or badge that indicates verification of a purchase in online reviews i.e., cues indicating if the reviews are genuine and posted by reviewers who have purchased and used the product from the platform. (iii) Valence of the online review i.e., positive, or negative. It indicates the subjective polarity of the consumer having used the product. Usually, a positive set of reviews lead to higher purchase intentions and vice versa. Derived from previous studies, we examined two types of intrinsic cues: search and experiential good. In search goods, consumers process objective cues of the product which are accessible before purchasing the product, whereas in experiential products consumers look for sensorial cues for subjective evaluation before making the purchase. The study incorporated mixed design with 8 combinations of extrinsic cues, for both the intrinsic cues. The stimulus of the study was derived after pre-testing on a limited set of participants. Quantitative analysis using frequentist and Bayesian statistical analysis to examine the interactions between the cues found review valence to supersede other extrinsic cues for search and experiential products.

Cues embedded in product reviews that influence purchase decisions have attracted a lot of attention due to the exponential growth of e-commerce. Although the current study examines several cues, earlier research has neglected the interaction between the linguistic content of product reviews and the presence or absence of verified reviews on consumers' purchase intentions, even though consumers are constantly exposed to these cues. Examining this novel interaction of cues is essential for developing frameworks to understand consumer's purchase behavior in e-commerce.

Neuroscience and consumer behavior

Since the dawn of the present century, there has been a rapid increase in the usage of neuroscience-centric methods to examine consumer decision making (García-Madariaga et al., 2020). These neuroscience-centric methods, alternatively neuromarketing tools, capture and quantify consumers' subconscious or implicit responses. These responses are deemed to be more objective than explicit or self-report-based responses influenced by social desirability bias. In a recent literature review, Casado-Aranda et al. (2023) consolidated 861 studies to present an trends pertaining to neuromarketing tools in marketing research. Functional magnetic resonance imaging (fMRI), Electroencephalogram (EEG) and Eye tracking (ET) with 36%, 25.7% and 16% were the most used neurophysiological tool for recording implicit responses. Conversely, other tools such as Electroencephalogram (ECG), Galvanic skin response (GSR), and Electromyogram (EMG) were the least used in studies with 4.2%, 3.7% and 2.3%, respectively.

Heart rate variability captures consumers' psychophysiological variations i.e., time variation between the heartbeats due to the interplay of parasympathetic- and sympathetic- nervous system. Analysis of heart rate variability can be done in a variety of domains, including time, frequency, and nonlinear. Difference-based indices used in time domain metrics, which capture periods of different lengths, are suggestive of strong short-term variations. The heart rate variability series is divided into three main frequency components: very low frequency (VLF), low frequency (LF), and high frequency (HF). Frequency domain metrics are derived from spectral analysis. Nonlinear indices characterise the predictability inherent to cardiovascular regulation. Most used heart rate variability indices are heart rate, standard deviation of RR intervals (SDRR), ratio of low frequency and high frequency, and sample entropy.

In Chapter 3, we conducted a systematic literature review to highlight the use and potential of Heart rate variability in consumer research. The study developed conceptual framework by merging stimulus-organism-response (SOR) theory (Mehrabian & Russell, 1974) with classic marketing mix. The proposed framework will allow researchers to establish links between environmental factors with consumer's heart rate variability, and thereby, correlations between heart rate variability and their responses. Interestingly, the study found that heart rate variability was used alongside other neurophysiological tools to assess consumer's subconscious responses such as galvanic skin response and eye tracking. Bibliometric analysis of the database informed that heart rate variability highly correlated with three clusters. The first cluster showcased the usage of heart rate variability with other explicit and implicit tools. Second cluster highlighted its usage for understanding consumer emotions. Third cluster showed its usage for capturing consumer responses towards promotional stimulus. The study also proposed three broad research directions (theory, characteristics, methodology) for the use of heart rate variability in marketing research. Lastly, Chapter 3 establishes guidelines for the use of heart rate variability tool for future studies.

EEG is a non-invasive tool to capture electrical neuronal activity of the brain. EEG captures brain activity via electrodes placed on the scalp and a higher number of electrodes provides better spatial details. EEG devices can be portable (wireless) or non-portable. EEG provides better temporal resolution compared to other neurophysiological tools. Previous research in marketing has used EEG to capture consumer's cognitive (e.g., attention, memory) and affective (e.g., emotion, arousal, valence, excitement) responses in response to marketing stimulus such as advertisement, product experience and branding. Typical measures recorded in EEG are segregated between time-based (i.e., event related potentials) and frequency-based (i.e., frequency bands). In their systematic reviews of 113 articles, Bazzani et al. (2020) found that most studies have used EEG to examine promotion-based topics (e.g., advertising) involving audio-visual stimulus.

In Chapter 4, and Appendix 1 and 2, we used EEG to examine consumers' cognitive load. Cognitive load is a multidimensional construct that informs mental effort imposed on the individual performing a particular task. Previous studies in consumer research have commonly observed cognitive load as explicit responses via questionnaires. However, in few studies in consumer research have used EEG to capture cognitive load (e.g., García-Madariaga et al., 2020). In Chapter 4, we observed differences in consumer's cognitive load during planned and unplanned shopping tasks. Cognitive load was higher during planned shopping as compared to unplanned shopping. This was directly associated with the time spent shopping. In Appendix 1, we used EEG measurements to capture cognitive load of the consumers while they were viewing user generated content on TripAdvisor. Cognitive load does not change due to the presence (or absence) of information in the embedded ad on social media. In Appendix 2, we used theta-alpha ratio (TAR) metric to capture the cognitive load from frontal and parietal brain regions of consumers while shopping. In Appendix 3, we used EEG to investigate the differences between consumers' goal-driven and stimulus-driven attention while shopping in virtual reality. The study revealed the involvement of goal-driven and stimulus-driven attention in planned and unplanned purchase behavior. EEG observations revealed differences in alpha and theta bands over frontal and parietal lobes while making planned vs. unplanned purchases.

Eye tracking is a non-invasive and inexpensive that allows for quantitatively measuring the eye gaze, pupil dilation, and saccades. It provides heat maps and gaze plot. Due to its portability and temporal superiority, it has been widely used in consumer research to examine the relationship between consumer's cognitive processes i.e., visual attention and engagement, vis-à-vis marketing applications such as advertisement, retail experience and online shopping (García-Madariaga et al., 2020; Royo-Vela & Varga, 2022).

In Appendix 1, we used eye tracking. In our study, we used it to examine the difference in visual attention in a TripAdvisor webpage. We used heuristic-systematic model as basis of our study. Eye tracker was used to observe areas of interest (AOIs), time to first fixation (TIFF), number of fixation and number of visits. The eye tracker showed no differences in aforementioned metrics in ad-context (in-)congruence conditions.

Virtual reality and consumer behavior

Virtual-, augmented-, or mixed- reality are characterized by three-dimensional virtual spaces built upon the advancements in artificial intelligence and Web 3.0 in the last decade, with a purpose of promoting social interaction and experiences between individuals and establishing marketplaces for consumption of digital objects. The increase in usage of these technologies for the purpose of retailing, also known as metaverse retailing (Dwivedi, Hughes, Wang, et al., 2022) is an upcoming distribution channel for marketers which also offers novel opportunity for researchers and practitioners to leverage its potential to transform consumer shopping experiences. Initial work involving the use of virtual reality as a commercial channel was demonstrated in the work by Martínez-Navarro et al. (2019).

Extension or replacement of local physical environment determines the primary difference between augmented reality and virtual reality. In augmented reality, physical environment is either extended or diminished leading to local presence, whereas in virtual reality, the physical environment is replaced by virtual environment leading to telepresence (Rauschnabel et al., 2022). In their work, Xi & Hamari (2021) reviewed 72 articles on the use of virtual reality in consumer shopping research. Predominantly, 42% of the studies used experimental method in their research with 25% of overall studies using head-mounted displays. Presence theory and Technology acceptance model were the commonly used theories. 31 studies used retail environments, 25 studies used food and beverages as the most used product type. Most commonly used constructs were perceived usability (n= 19), enjoyment (n= 11), perceived presence (n= 14), and behavioral intention of purchase or visit (n= 17) (Xi & Hamari, 2021).

In Chapter 4, the study examined how shopper’ impulsivity and their unplanned purchases are associated while shopping in a virtual retail store. The virtual retail store closely resembled a traditional supermarket in terms of its layout and variety of product offerings with their digital price tags. Similar to a traditional supermarket, participants could move around the entire supermarket using teleporting technique (Prithul et al., 2021), and interact with the product shelves by bending down or extending their arms to retrieve the items. To closely resemble a regular shopping trip, participants were not restricted by time limit and a budget of 260 Danish kroner (approx. 35 euros) was provided to them.

From a conceptual perspective, the study expanded the classic stimulus-organism-response framework to evaluate how planned and unplanned behavior differ using explicit and implicit measures. Stimulus component include sense of presence whereas Organism component includes consumer's impulsiveness and their flow experience. Response component included unplanned products and their cumulative expenses, desire to stay, store satisfaction, budget deviation, basket-size deviation, time duration during planned and unplanned purchases and cognitive load experienced during planned and unplanned purchases. From a methodological perspective, we used a multi-method approach i.e., combined self-reports and electroencephalography. The study found that cognitive load, captured via EEG, differed between planned and unplanned shopping phases. Through mediational analysis, the study found flow experience to partially mediate between sense of presence and the desire to stay. Additionally, the desire to stay construct positively influences consumers' satisfaction with the store and basket-size and budget deviation. This study is published in the International Journal of Information Management.

The findings of Chapter 4 are complemented by Appendix 2 and 3. In Appendix 2, the study examined differences in frontal asymmetry captured via EEG, during while consumers shopped in virtual retail store. Study found differences in gamma-band during planned vs. unplanned purchase phases. In Appendix 3, the study examined differences in alpha and theta frequency band planned vs. unplanned purchase phases. The study found higher alpha and theta power during planned purchases (vs. unplanned purchases) suggesting higher cognitive engagement during shopping.

In these three publications, participants followed their regular purchasing sequence i.e., planned purchases and then unplanned purchases, in virtual reality-based supermarket. Appendix 2 was published in the Decision Neuroscience section of Frontiers in Neuroscience and Appendix 3 was published in Brain Sciences in MDPI.

CHAPTER 2

INTERACTION BETWEEN EXTRINSIC AND INTRINSIC ONLINE REVIEW CUES: PERSPECTIVES FROM CUE UTILIZATION THEORY

This is the first out of three complied publications. The aim of the paper was to examine the interplay between extrinsic cues of online reviews such as valence, content style and verification, on intrinsic cues such as search and experiential products. It has been accepted and published online at Electronic Commerce Research (Springer): Kakaria, S., Simonetti, A., & Bigne, E. (2023). Interaction between extrinsic and intrinsic online review cues: perspectives from cue utilization theory. *Electronic Commerce Research.* 1-29. https://doi.org/10.1007/s10660-022-09665-2

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Interaction between extrinsic and intrinsic online review cues: perspectives from cue utilization theory

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Abstract
We examine the interaction effects of linguistic style and verification of online reviews in terms of their valence on purchase intention for search and experiential products. We adopt the cue utilization framework to examine the interplay between the extrinsic cues of online reviews—content style (general versus specific), verified purchase (VP) badge (present versus absent), and valence (positive versus negative)—in two product categories—search product (tablet) and experiential product (trip package)—using an experimental design. The findings of the frequentist and Bayesian analyses show that valence supersedes other attributes' impacts on purchase intention in both product categories. Variations in the content style of the reviews have minor influences on purchase intention. The presence of a VP badge on a review has a negligible influence on purchase intention across both product categories. Valence-content style and valence-VP badge interactions significantly affect purchase intention. Based on these findings, implications are discussed.

Keywords E-commerce platforms · Online consumer reviews · Purchase intention · Cue utilization theory · Consumer behavior

1 Introduction

Product ratings and reviews are considered to be the second most important attribute of online shopping experiences [1] as well as the second most important source of specific information on products [2]. Consumers seek online consumer reviews (OCRs) in order to guide their intended purchasing behavior [3] and attitudes toward products, brands, and services, which impacts sales [4, 5]. However, consumers may be exposed to multiple types of cues, both intrinsic and extrinsic, that with their interactions ultimately lead to consumer decision making.

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1. Introduction

Product ratings and reviews are considered to be the second most important attribute of online shopping experiences (S. Chevalier, 2021a) as well as the second most important source of specific information on products (Kunst, 2020). Consumers seek online consumer reviews (OCRs) in order to guide their intended purchasing behavior (Z. Chen & Yuan, 2020) and attitudes toward products, brands, and services, which impacts sales (Floyd et al., 2014; Rosario et al., 2016). However, consumers may be exposed to multiple types of cues, both intrinsic and extrinsic, that with their interactions lead to consumer decision making.

A diverse range of online review cues are available on e-commerce websites and social media sites, such as product evaluations (e.g., valence, star ratings), review verification (e.g., badges), or a combination of the two, and they help consumers make purchase decisions (Moore & Lafreniere, 2020; Purnawirawan et al., 2015; Srivastava & Kalro, 2019). The increasing amount of research on OCRs reveals that, in addition to the volume, variance, or average star ratings of reviews (Moore & Lafreniere, 2020), two additional cues influence prospective consumers' judgments and product sales (Kaushik et al., 2018): the way in which comments are made (the text's linguistic style) (H. Huang et al., 2022; S. Q. Liu et al., 2018) and trust of an actual purchase (purchase verification) (J. He et al., 2020). Linguistic style and purchase verification might influence consumers' assessments as seen in established knowledge in consumer research that is informed by cognitive and affective processing. However, despite extensive examination of the influence of OCRs on consumer behavior, studies on how consumers evaluate the influence of the content style (i.e., the linguistic style of the review) (Moore & Lafreniere, 2020) and verified purchases in online reviews (Bigné et al., 2020; Figini et al., 2020) in terms of their product evaluations (Moore & Lafreniere, 2020) remain inconclusive. In this view, we address two understudied gaps. Firstly, although content style is an integral part of online reviews as they disseminate information and persuade readers, their influence on purchase intention (PI) remains understudied. Content style in OCRs has been recently approached from different perspectives: (i) natural language processing for examining the content of featured words, such as nouns or adjectives, which then leads to sentiment analysis or assessing the affective content in order to detect emotions (Ludwig et al., 2013); and (ii) the influence of the text type, such as the use of concrete versus abstract language or explicit versus implicit language (H. Huang et al., 2022; Packard & Berger, 2017). In recent years, the availability of digital text data and improvements in computational linguistics techniques has resulted in an incredible amount of studies using automated text analysis to provide understanding of psychological constructs of consumer behavior (Berger et al., 2020; Humphreys & Wang, 2018). Despite the high value of these studies, they do not provide answers on the persuasiveness of a limited number of online reviews. When consumers are looking for specific content instead of using other heuristics such as online ratings, they tend to read only a few comments (Bigne et al., 2020). Therefore, the analysis of the featured online reviews should be approached by searching for a specific type of content through other methodologies, such as an experimental design. Furthermore, the value of online reviews is driven by multiple factors, such as source credibility (Q. Xu, 2013), which leads to the second point: Source credibility comprises both sender and platform issues. A mixed path for reducing uncertainty of a post's credibility is the verification of the comment by the platform. In a nutshell, certain platforms grant credibility to online reviews by certifying or verifying that the product in question was actually purchased. But the evidence for how verified purchases (VPs) translate into PI remains inconclusive due to a lack of comparisons between either positive or negative valence of OCRs and the type of products analyzed. The literature shows varied online consumer behavior patterns between search and experiential product types (Kukar-Kinney & Xia, 2017)(Li et al., 2020). Based on these two research gaps of content style and VPs, this study aims to analyze the direct and interaction effects of these cues in both positive and negative online reviews in terms of consumers' PI for two distinct types of products: search and experiential products.

This study contributes to the growing amount of research on the effectiveness of online reviews in the following ways. Firstly, based on cue utilization theory, we account for the individual and interaction effects of content style, VPs, and valence on consumers' PI for two distinctive product categories. Cue utilization theory has been adopted in marketing, psychology, and consumer behavior studies to facilitate understanding of how products' quality perception is affected by cues (Chi et al., 2021; Chonpracha et al., 2020; Richardson et al., 1994). As online product reviews consist of multiple cues that interact and impact consumers' decision making (Floyd et al., 2014), understanding the effects of their interaction curbs the overestimation of a single cue's independent effect (Rosario et al., 2016). Consumers who judge products based on the cues contained within a single online review make incorrect inferences (Langan et al., 2017). Secondly, the present work extends the sparse literature on review verification. Review verification is a platform-specific process that verifies that the reviews posted are indeed from the consumers that bought the product from the platform and that they are expressing their opinions (Bigné et al., 2020; Figini et al., 2020). Using revealed preference theory, He et al. (J. He et al., 2020) analyze a dataset comprising a focal product's reviews obtained from a single source (Amazon), from which an established positive relationship between the proportion of verified reviews and sales was determined. In contrast, our study explores the effect of review verification across two distinctive product categories that are generally available on different platforms. Thirdly, for robust measurement of the effect of OCR cues on PI, our analysis uses the Bayesian approach in addition to conventional frequentist analysis. Previous electronic word-of-mouth (eWOM) research has predominantly used a single methodology (e.g., fuzzy-set qualitative comparative analysis, analysis of variance, and structural equation modeling (SEM)) to investigate the influence of online reviews on purchases (Ismagilova et al., 2020a), while Bayesian statistics has been rarely used. Under Bayesian analysis, it is assumed that consumers have prior expectations of the variables examined in the study (Rossi & Allenby, 2003). This approach is essential in an e-commerce context as prospective buyers read product reviews with certain prior expectations. To the best of the authors' knowledge, this is the first study to apply Bayesian statistics to the examination of the influence of OCR cues on PI.

The paper is organized as follows. Firstly, we present a literature review on the relevant topics in our study and list the hypotheses based on the cue utilization approach. Next, we describe the methodology, followed by the results derived from the frequentist and Bayesian analyses, after which a discussion of the results is provided. Lastly, we conclude our findings and provide the theoretical and practical implications of this study as well as future research directions.

2. Literature review

2.1 Cue utilization framework

Previous research on OCR cues have pivoted around the signaling theory (Choi et al., 2018), heuristic-systematic model (S. Park & Nicolau, 2015), elaboration likelihood model

(Aghakhani et al., 2020), and revealed preference theory (J. He et al., 2020). We employ the cue utilization theory wherein consumers evaluate product quality by utilizing a series of cues or information related to the products (Olson & Jacoby, 1972). This array of product cues is classified into intrinsic and extrinsic cues (Szybillo & Jacoby, 1974). Intrinsic cues are inherently related to the unalterable physical attributes of the focal product. Extrinsic cues are not inherently part of a product's characteristics and can be minimally altered (Richardson et al., 1994). The cue utilization theory states that prospective consumers might utilize intrinsic and extrinsic cues in e-commerce purchases before purchasing products. The intrinsic cue of the product refers to its inherent nature (e.g., search or experiential) while extrinsic cues are the varied forms of information regarding the product (e.g., online product reviews). For instance, when one is seeking to purchase a vacation or tablet, specifications regarding the tourism destination and tablet screen size can be considered intrinsic cues while reviews regarding the product or service can be considered extrinsic cues (Choi et al., 2018). Consumers utilize extrinsic and intrinsic cues in parallel when evaluating products (Szybillo & Jacoby, 1974). When intrinsic cues are difficult to access or are scarce, salient extrinsic cues help consumers make evaluations (Miyazaki et al., 2005). To investigate the independent and interactive effects of various cues on consumers' decisions, consumer researchers have adopted the cue utilization framework across a range of domains (see Table 1).

We searched for "cue utilization" in journal articles published from 2000 to 2022 in the Business, Management, and Accounting category in the Scopus database and found 92 articles in English. We then manually inspected each article and, after removing non-empirical studies and review papers, 64 articles were shortlisted for use in this study (see Appendix A). Figure 1 provides the keyword co-occurrence network (Donthu, Kumar, Mukherjee, et al., 2021) that was created from the 100 most common keywords obtained from the 64 papers' abstracts using VOSviewer software in order to identify the theme of each cluster, called the cluster identity (van Eck & Waltman, 2010). Co-occurrence networks represent the intellectual structures of the topic, which indicates the conceptual relationship between keywords used in eWOM literature (Donthu, Kumar, Pandey, et al., 2021).

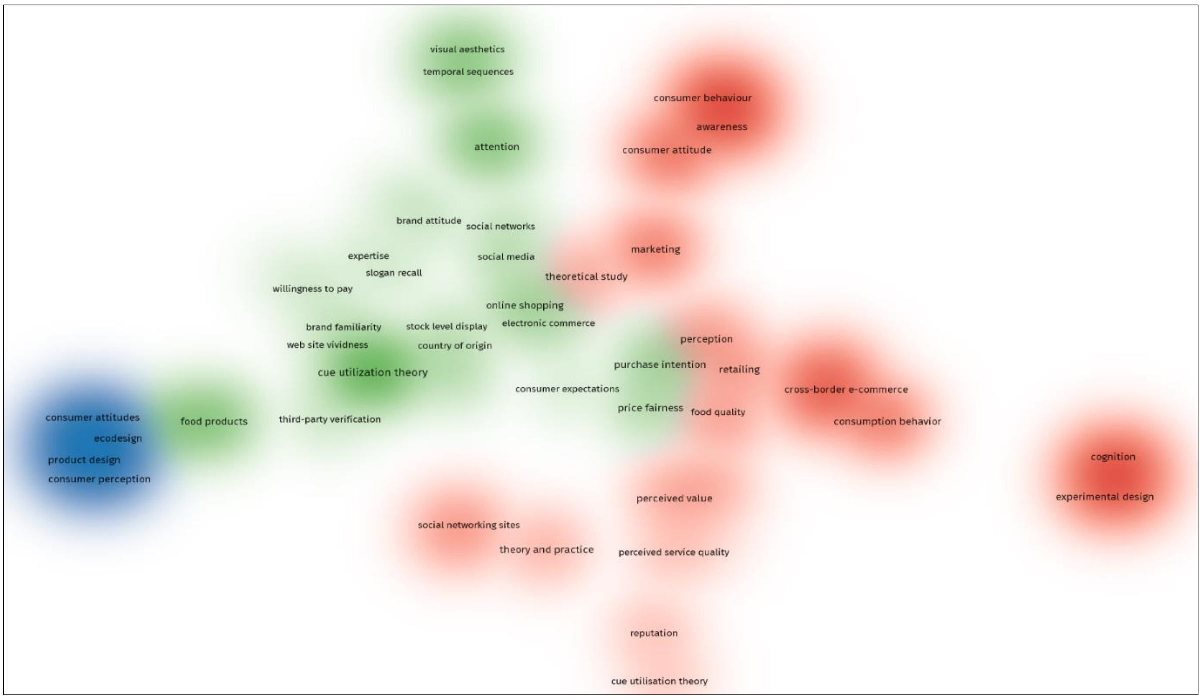

Fig 1 Cluster identity of the keywords extracted from the database. This word map visualizes three interconnected clusters, with each color representing a theme

Additionally, in Table 1, we provide a summary of selected articles that can be divided across stimulus type. Although researchers have previously used cue typology in the eWOM context, studies have predominantly used either search or experiential goods, but rarely both.

Table 1 Recent papers on cue utilization theory

Author (Year)	Intrinsic cue (Stimulus type)	Extrinsic cue	Findings
Roy & Attri (2022) (Roy & Attri, 2022)	Experiential (Destination)	Physimorphic and typographic brand logo.	Physimorphic logos have a greater tendency to generate positive attitudes and intention to visit a destination than typographic logos do.

Halkias et al. (2022) (Halkias et al., 2022)	Search (16 assorted products)	Country of origin (COO)	COO labels influence behavioral intention depending on the duration and dwell time length.
Gabriela et al. (2022) (Lelo de Larrea et al., 2022)	Experiential (Crowdfunding campaign)	Number of rewards	A campaign should be seen as neutral and conservative in style with an optimal range of pictures, videos, and record of rewards.
Nie et al. (2022) (Nie et al., 2022)	Search (Packaging)	Food certification label	Consumers show differences in their willingness to pay based on labels caused by their purchase motivations.
Konuk (2021) (Konuk, 2021)	Experiential (Food taste)	Taste award	Using the Stimulus-Organism-Response model, SEM reveals a positive relationship between perceived taste, award, quality, and brand trust.
Chi et al. (2021) (Chi et al., 2021)	Experiential (Accommodation listings)	Guest review and textual color cues	The textual cues related to color in pictures impact consumers' inclination to rent a property.
Sun et al. (2020) (Sun et al., 2020)	Search (Giveaways value)	Cuteness and unexpectedness of meeting giveaways	High value giveaways render higher levels of word-of-mouth (WOM) intention. Cute and unexpected gifts moderate the value of gifts in terms of WOM intention.
Yang et al. (2020) (Yang et al., 2020)	Search (Apparel)	Post popularity and quality	Both Instagram posts' popularity cues and argument quality cues reduce uncertainty in online apparel purchases.

He & Oppewal (2018) (Y. He & Oppewal, 2018)	Studies 1,2: Search (Book and chocolates)	Sales and stock levels	The effect of sales and stock level on subsequent choice is mediated by product popularity and quality. In addition, sales level supersedes stock level when both cues are available.
Konuk (2019) (Konuk, 2019)	Experiential (Food quality)	Price fairness	A perceived food quality cue positively impacts price fairness and perceived value.
Kinney & Xia (2017) (Kukar-Kinney & Xia, 2017)	Studies 1, 3, 4: Experiential (Local restaurant) Study 2: Search and Experiential (Hair dryer and hair styling)	Number of deals	Social extrinsic cues (the number of deals) impact evaluations and intentions when the intrinsic product, the deal cues (good versus service, discount size), and consumers' characteristics (familiarity with provider) are inadequate for determining deal attractiveness.
Bruwer et al. (2017) (Bruwer et al., 2017)	Experiential (Wine)	Variety, wine style, and packaging	Product knowledge positively impacts products' intrinsic cues.

2.2 Online reviews as extrinsic cues

In the digital marketplace, a product's perceived performance is gauged from OCRs of firms, brands, products, or services that are shared by consumers (Koh et al., 2010). As a form of eWOM, OCRs have a significant influence on PI (Ismagilova et al., 2020a). However, previous studies have rarely used cue utilization theory to understand OCRs (see Table 1). Langan et al. [5] reveal that high review variance decreases PI for utilitarian (versus hedonic) products. Additionally, they report that when brand equity is stronger, the impact of OCRs decreases. In their work, Sun et al. (Sun et al., 2020) sought to examine the perceived value of giveaways on word of mouth (WOM) intentions. They used cuteness of gifts and unexpectedness as extrinsic cues while manipulating the intrinsic cue, that is, the value of giveaways. High-value giveaways positively influenced attendees' WOM intention, while extrinsic cues moderated the effect of giveaways on WOM intentions. However, neither study used distinctive products to understand the interaction effects of extrinsic and intrinsic cues. Nevertheless, these studies facilitate an interesting discussion on the dynamics of extrinsic and intrinsic cues of products in the digital marketplace.

2.3 Search and experiential product categories as intrinsic cues

As demonstrated in Table 1, only a few studies address more than one product type in their analyses using the cue utilization framework. The search and experiential classification paradigm is useful for elucidating consumers' evaluations of OCRs (Jiménez & Mendoza, 2013; Mudambi & Schuff, 2010). Nelson (P. Nelson, 1970) demarcates products' characteristics based on the quality of attributes that can be evaluated prior to the purchase and the quality of those attributes that can only be determined post-purchase or during consumption. For search products (e.g., smartphones and dishwashers), the product cues (e.g., size and color) are easier to obtain before the purchase. Objective cues chiefly determine product evaluations of search products, limiting the role of sensory experiences in purchase decisions. On the contrary, consumers find it difficult to evaluate the subjective cues (e.g., flavor and pleasure) of experiential products (e.g., tourist destinations and movies) that are derived from sensory evaluation prior to making purchases (P. Nelson, 1970). While shopping online, consumers spend a relatively longer amount of time per webpage for experiential products than search products, but they view more webpages for search products than experiential products (P. Huang et al., 2009). Researchers show that OCRs are important for influencing sales across search and experiential product categories, such as cellphones (Jiménez & Mendoza, 2013) and digital games (Choi et al., 2018).

3. Hypothesis development

3.1 Content style in online reviews

A growing stream of marketing literature has shown that the way in which OCRs are expressed (i.e., the content style) drives reviewers' credibility (Hamilton et al., 2014), reviews' helpfulness (Moore, 2015), and persuasion (H. Huang et al., 2022) and they have demonstrated that they are important for product or service evaluations (S. Q. Liu et al., 2018). These findings support the theoretical framework of heuristic and systematic information processing (Chaiken et al., 1989). Researchers have examined the consequences of linguistic expression on purchase behavior and PI, including the use of implicit or explicit endorsement language (Packard & Berger, 2017), tentative wordings (Ordenes et al., 2017), action or reaction explanations (Moore, 2015), textual parawordings (A. W. Luangrath et al., 2017), specific or vague styles (Bigne et al., 2019), language mimicry (Moore & McFerran, 2017), benefits or attributes (Z. Zhang et al., 2021), assertiveness (H. Huang et al., 2022), divided or mixed narratives (Lu et al., 2021), powerful or powerless markers (J. Chen et al., 2021), and figurative or literal language (Kronrod & Danziger, 2013).

In the present study, we extend the line of inquiry by exploring the persuasiveness of general or specific information in reviews. A review's content serves as a factor in the persuasion process because the evaluation contained therein may reduce consumers' uncertainty and ambiguous feelings regarding the product (Bigne et al., 2019). An OCR can describe the specific features of the focal product during the consumption experience without highlighting feelings associated with the consumption. Conversely, it can narrate general aspects of the consumption experience of the focal product but suppress specific information. For experiential products, consumers have limited product information to inspect that could help in decision-making. Understandably, consumers rely more on other consumers' subjective evaluations than objective reviews for experiential products (Z. Liu et al., 2020). Contextually, a general review will offer valuable expressions of subjective feelings experienced while using the focal product or service. OCRs are generally voluntarily written to express personal experiences, opinions, and recommendations (J. A. Chevalier & Mayzlin, 2006). Thus, specific details are expected less frequently for experiential products because subjective information cannot be provided for these products before consumption. Alternatively, for search products, consumers can verify the focal product's readily available information cues and form objective criteria for evaluation of the products (Z. Liu et al., 2020). In this regard, specific reviews include objective facts about the product from which consumers can scrutinize information more accurately than a general review, thereby aiding their subsequent purchase (see Figure 2). Consequently, we expect the following:

H1a: General (versus specific) review content increases PI for experiential products.

H1b: Specific (versus general) review content increases PI for search products.

3.2 Verification of a purchase in online reviews

Consumers make inferences not only about the review but also the cues associated with the reviewer (Moore & Lafreniere, 2020; Zheng, 2021). The review credibility system incorporates feature labels or badges in the reviews, indicating that reviews of VPs (e.g., Amazon Verified Purchase or Expedia Verified Reviews) are posted by reviewers who have purchased the product from the platform in question (J. He et al., 2020). However, not all platforms (e.g., TripAdvisor) have adopted such a system (Bigné et al., 2020). As a review cue, the VP label discloses purchase information by endorsing reviewers' genuine experiences with the focal product or service. The literature reveals that VP reviews increase product ranks compared to non-VP reviews (Figini et al., 2020; Kokkodis & Lappas, 2016). However, this effect has not been confirmed in other studies based on multiple tourism platforms (Bigné et al., 2020), resulting in inconclusive findings. From another perspective, the related literature shows that a high percentage of VP reviews in a review set positively influences product sales and leads to the customer trusting the authenticity and credibility of reviews (Kaushik et al., 2018). Figini et al. (Figini et al., 2020) studied review platforms for an experiential product (i.e., hotel ratings) and found that OCR ratings on open platforms that accept non-VP OCRs have relatively higher ratings than the OCR ratings of VPs, thereby endorsing the use of closed platforms. Additionally, the presence of unsolicited, fake, and deceptive reviews reduces credibility (Dongyeon Kim et al., 2018) and the helpfulness of OCRs (Moore & Lafreniere, 2020), necessitating VP labels only being assigned to authentic reviews (Wu et al., 2020).

Source trustworthiness and expertise are acknowledged as determinants of persuasion in the source credibility scheme created by Hovland et al. (Hovland et al., 1953). The former dimension offers an adequate framework for supporting the influence of a VP as a relevant cue for assessing online reviews. Thus, VPs provide objective cues about the trustworthiness of the OCRs, which can result in the customer trusting the text. According to the trust transfer theory (Stewart, 2003), it is expected that a VP (e.g., an object) will transfer customers' trust for the comment to the product itself (see Figure 2). Based on these ideas, we propose the following hypothesis:

H2: The presence (versus absence) of a VP badge on reviews increases PI across product categories.

3.3 The persuasiveness of review valence

Review valence indicates the "evaluative direction" of the review and can be polarized (extremely positive or negative) or mixed (neutral) (Purnawirawan et al., 2012; Tsao & Tsao, 2014). Valence is regularly found to be one of the most helpful and persuasive cues in a review set (Ruiz-Mafe et al., 2020), yet it yields mixed effects on subsequent purchase probability (Ismagilova et al., 2020a; Purnawirawan et al., 2015). Positive valence reviews have "pleasant, vivid and romanticized" explanations, whereas negative valence reviews contain complaints and unpleasant explanations (Sparks & Browning, 2011). The influence of positive ratings on PI is greater than that of negative ratings (Ismagilova et al., 2020a). Alternatively, when exposed to negative information, consumers become motivated to seek additional information through OCRs, and their purchase likelihood is reduced (Varga & Albuquerque, 2019). Additionally, studies have shown that search and experiential products have a moderating effect on OCR valence (Hao et al., 2010; Xia & Bechwati, 2008).

Reviewers tend to post reviews only when they are extremely satisfied or dissatisfied, forming a J-shaped distribution (J. A. Chevalier & Mayzlin, 2006). As such, an improvement in positive ratings increases PI over time (Marchand et al., 2017). We expect that prospective consumers will utilize valence to narrow their consideration set in order to ease the uncertainty experienced before purchase (Vermeulen & Seegers, 2009). Arguably, a positive set of reviews will incentivize the consumer to make a purchase decision and vice versa (Tata et al., 2020). Consequently, we anticipate a positive association between a set of positive OCRs and PI across product categories, while negative OCRs will deter PI (see Figure 2). Hence, we propose the following hypothesis:

H3: Positive reviews lead to a higher PI for experiential and search products than negative reviews.

3.4 Interaction effects among extrinsic cues

Online reviews can be from a verified source or non-verified source, and they can use either specific or general content styles. The influence of content styles might vary depending on identification of the reviewer (J. Chen et al., 2021). OCRs are viewed as diagnostic when consumers perceive information as credible (Langan et al., 2017). To mitigate purchase uncertainty caused by unfamiliarity with the reviewer, consumers often look for other quality assessment cues, such as review credibility, before making purchases (Filieri, 2015; Ismagilova et al., 2020a). Source credibility—an elementary feature that helps purchasers evaluate eWOM communication—refers to consumers' evaluations of a source in terms of expertise, trustworthiness, credentials, and attractiveness, and it has a positive influence on PI (Ismagilova et al., 2020b). A source is considered trustworthy when consumers perceive the information as genuine and accurate, leading to a positive impact on their PI (Ismagilova et al., 2020a). Filieri (Filieri, 2016) reveals that consumers utilize cues such as valence, content, style, and review extremity to analyze trustworthiness. Building on the trust transfer theory (Stewart, 2003), we argue that trust for an OCR based on a VP will be transferred to the content of the OCR. In addition to the direct effect of VPs on PI (discussed in Section 3.2), further evidence on the interaction effects of VPs with content style and valence need further elaboration. The transferred trust of a VP on content style might be stronger depending on the type of text (either generic or specific). In line with hypotheses 1a and 1b, generic comments will have a stronger effect on PI for experiential products, while specific comments will have a stronger impact on PI for search products. Given the higher diagnosticity of VPs and general comments for experiential products, a stronger impact on PI is expected. Similarly, a stronger impact of VPs and specific comments on PI is expected in search products.

Regarding the effect of a review's polarity, its valence is perceived as less ambiguous, diagnostic, and helpful for the consumer than neutral reviews (Filieri, 2015; Langan et al., 2017), thereby ensuring that extreme valence—either positive or negative—is more credible than the valence of ambivalent reviews (Jimmy Xie et al., 2011). High variance in the review set diminishes the diagnosticity of information, leading to reduced source credibility (Langan et al., 2017). The provision of visual information with a review that indicates that the reviewer has genuine experience with the product adds credibility to the review (Filieri, 2016). Certainly, a VP badge can function as a proxy for visual evidence that indicates a reviewer has genuine experience with a product, thereby enhancing the quality of the information and improving their review credibility. Because review cues can move jointly through central and peripheral processing (Aghakhani et al., 2020), the interaction between OCR cues and PI is compelling to explore (see Figure 2). Therefore, we address these effects as follows:

H4a: Specific (versus general) review content and the presence (or absence) of a VP badge will lead to higher PI when a review's valence is positive (versus negative) for search products.

H4b: Specific (versus general) review content and presence (or absence) of a VP badge will lead to higher PI when a review's valence is positive (versus negative) for experiential products.

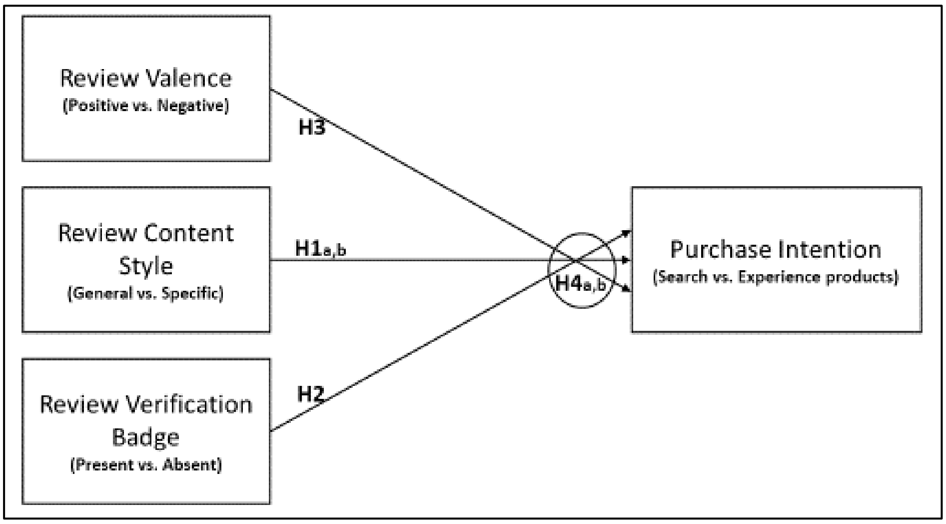

Fig 2. Schematic representation of hypotheses

4. Methodology

To effectively analyze the specific influence of the cues associated with online reviews, an experimental study was conducted. As discussed in the Introduction, experimental approaches capture the specific influence of the type of online reviews in comparison with automated text analysis. This study is an online behavioral study in which we manipulate: (i) the content style of the comments (hereafter referred to as "content"): (ii) the indication of a VP (hereafter referred to as a "badge"); and (iii) the valence of the OCR (hereafter referred to as the "valence").

4.1 Design and participants

A 2 x 2 x 2 mixed design experiment was chosen, with content (general versus specific), a badge (absence versus presence), and valence (positive versus negative) acting as independent variables (IVs) and PI acting as the dependent variable (DV). This design was used to examine the hypotheses. The United States of America (USA) was chosen as the context for this study because industry reports show that online ratings are widely used by American consumers when searching for information on a product prior to purchase (Kunst, 2020). Five hundred participants living in the USA were monetarily compensated for their participation through the crowdsourcing platform Clickworker. The main characteristics of the participants were as follows: 51.6% female; M_{age} = 36.61, SD = 8.31, age range: 20–71; 67% employed, 27% unemployed; 57% of the participants had university as their highest level of education (ongoing or completed); 51% had an annual gross income below US$40,000; 93% partook in online shopping in the past year, ranging in frequency from sometimes to all the time. The data were collected in May and June of 2020.

4.2 Stimulus

A pre-test with 44 consumers who did not participate in the main study was conducted online in order to select the comments for the products (see the Results and Discussion Section). For the main study, the stimulus resembled a webpage that contained online reviews from other consumers for two products in distinct categories: a tablet, representing a search product, and a trip package, representing an experiential product. The artificial webpage consisted of a generic picture of the products (a tablet with no brand information and a beach landscape), a sentence that provided context, and four comments with a star rating and the badge (when applied) (see Appendix B). We presented four comments for three reasons: (i) For a consumer, it is difficult to read all the reviews for a product or service. Most platforms usually provide consumers with either a default setting to view only relevant reviews or filters for positive or negative reviews (e.g., five-star rating systems) or to organize the reviews by date posted (e.g., most recent or oldest), which assists in consumers' decision-making; (ii) Generally, consumers read approximately four reviews (Spivack, 2019); and (iii) To avoid participants' fatigue and lack of engagement when reading the comments. The reviews were manipulated in the following ways: (i) content (general or specific content); (ii) badge (the presence or absence of the VP badge); and (iii) valence (the valence of the star rating and comments' content). The positive (five-stars and positive wording) and negative (one-star and negative wording) comments had the same content but were framed accordingly. The comments were adapted from actual online reviews and comprised 37 to 40 words (M = 38.25). There were 8 conditions for both products (see Table 2). The composition of the reviews was mixed to make them seem genuine and to allow for comparison of the review cues. For each condition, one review among the four had the opposite condition. For example, in condition 1, three comments had positive valence, general content, and the verified badge, and one (always placed in the third position) had a negative valence, specific content, and no badge (see Appendix B).

Table 2 Summary of the 8 conditions for both product categories and their descriptions

Condition	Description
1. PGV	Positive valence review with general content style and presence of verification badge
2. PSV	Positive valence review with specific content style and presence of verification badge
3. PGU	Positive valence review with general content style and absence of verification badge
4. PSU	Positive valence review with specific content style and absence of verification badge
5. NGV	Negative valence review with general content style and presence of verification badge
6. NSV	Negative valence review with specific content style and presence of verification badge
7. NGU	Negative valence review with general content style and absence of verification badge
8. NSU	Negative valence review with specific content style and absence of verification badge

4.3 Procedure and task

The participants answered the survey via the online platform Clickworker. Each participant was assigned to one of the eight conditions. The two products were presented in the same manipulation condition but in a randomized order. The procedure comprised the following: (i) a brief introduction; (ii) stimulus presentation (for the tablet, participants imagined finding the tablet's reviews on an e-commerce website and buying it, and, for the trip, they imagined planning their next vacation to Sri Lanka and finding reviews for an online provider of packages for this destination); (iii) the PI question of "What is the probability that you will purchase this tablet or purchase this trip?" being asked, for which the participants stated the probability in a percentage between 0 and 100%; and (v) demographics. The survey was self-paced.

4.4 Metrics and analysis

We used the continuous metric of PI as a DV for the frequentist statistical analysis and a binary PI metric for the Bayesian statistical analysis. The binary PI variable was created based on the continuous metric. We assigned participants that scored ≥ 60% to the "yes" group (i.e., a positive PI) and ≤ 40% to the "no" group (i.e., a negative PI). Participants who scored between 45% and 54% were excluded from the binary analysis due to their indecisiveness.

For ratings between 41% and 45% and 55% and 59%, a second metric that was not analyzed in this study was used in conjunction with the continuous metric in order to determine whether these participants would be included or excluded from the analysis. The final dataset for the binary variable consisted of 462 participants for the search product and 457 participants for the experiential product. The data were analyzed using IBM SPSS 26.0 for the frequentist inference analysis and R using the tidyverse, statsr, and Bayesian Adaptive Sampling packages for the Bayesian analysis. Each analysis is described in details in the results and discussion section.

5. Results and discussion

5.1 Pre-Test

Participants rated the eight comments for each product from 1 (mostly general content) to 5 (mostly specific content), with the middle point as neither general nor specific. The chosen comments had individual means below three for general comments and means above three for specific comments. The results of a related-samples Wilcoxon signed-rank test showed significant differences between general and specific comments for the tablet ($Z = 975$, $p < .001$) and trip ($Z = 935$, $p < .001$). The mean values were: $M_{general\text{-}tablet} = 1.75$, $SD = 0.82$; $M_{specific\text{-}tablet} = 4.48$, $SD = 0.98$; $M_{general\text{-}trip} = 1.80$, $SD = 0.84$; $M_{specific\text{-}trip} = 3.92$, $SD = 0.92$.

5.2 Frequentist inference analysis

A chi-square test confirmed that the eight groups were homogeneous in all socio-demographic variables ($p > .100$). The group sizes ranged from 61 to 65 participants each. A generalized linear model with a robust estimation procedure was used to assess the influence of the three IVs (valence, content, and badge), and their two-way and three-way interactions with PI (0–100%) for each product. In addition to a significant main effect of valence, the results reveal two significant two-way interactions: valence-content and valence-badge interaction. The other effects (three-way interaction, content-badge interaction, and content and badge main effects) were not statistically significant. The mean values for each condition and product are shown in Figure 3, and the significant interactions are shown in Figure 4.

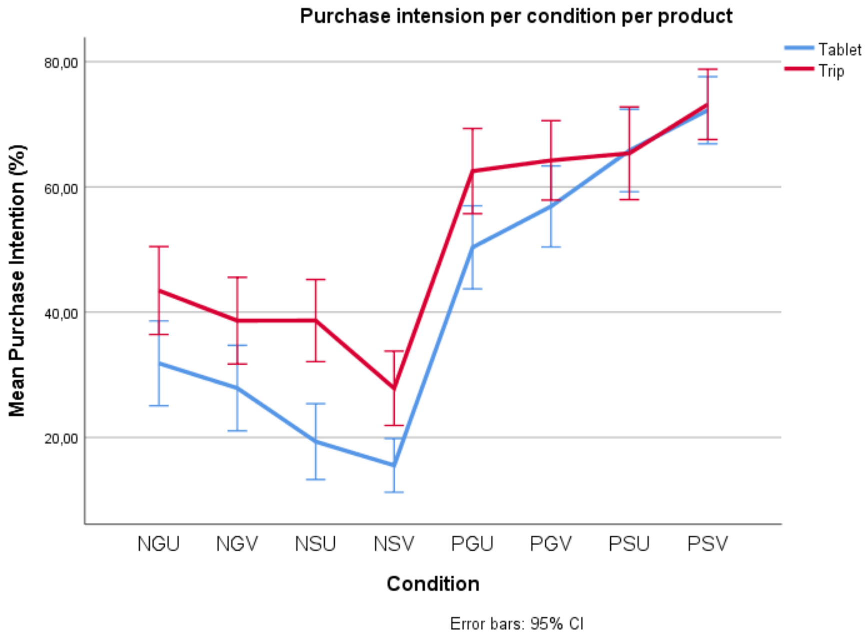

Fig. 3 Means of PI (%) for each product per condition. Key: The first letter represents the valence, with N = negative, P = positive; the second letter represents the content, with G = general, S = specific; and the third letter represents the badge, with U = unverified, V = verified.

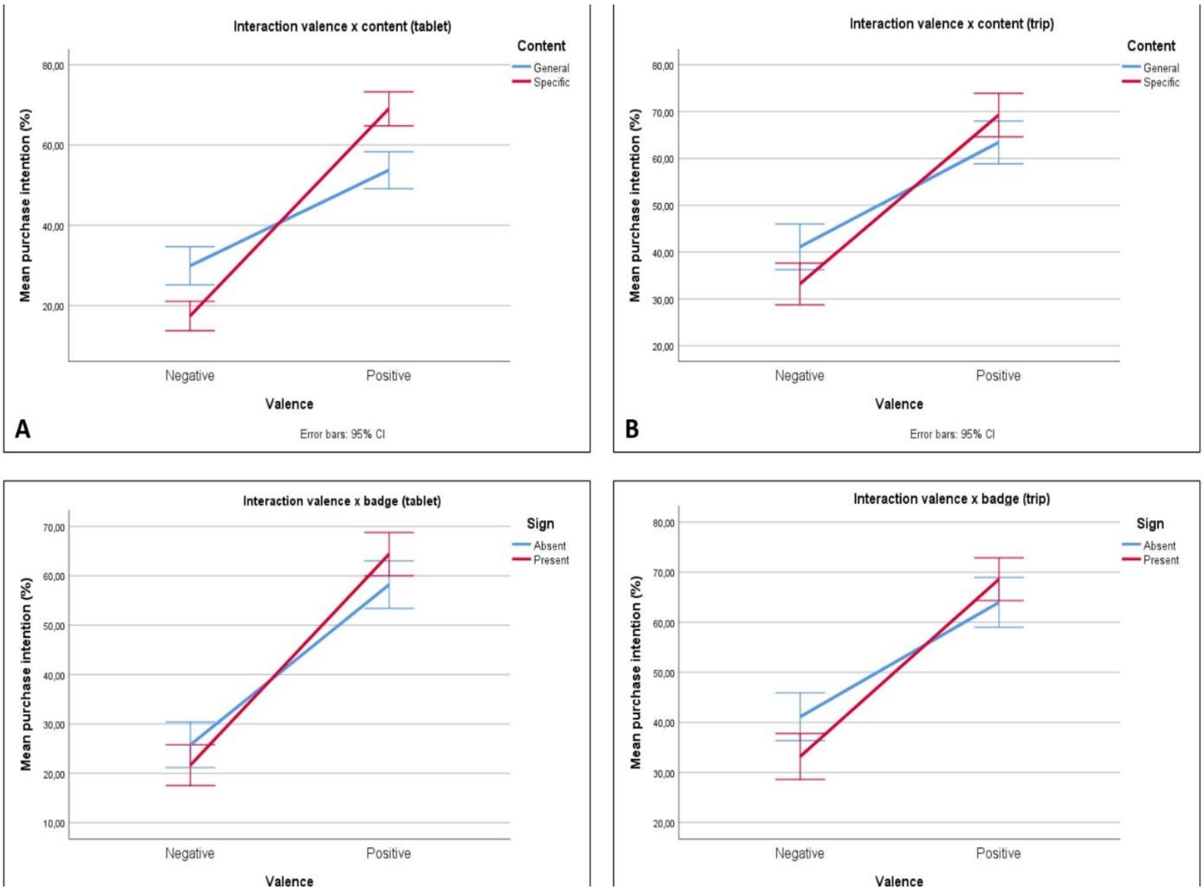

Fig. 4 Representation of the two-way interactions for the tablet (A, C) and trip (B, D)

Table 3 shows the main and interaction effects of the tablet, and Table 4 shows the main and interaction effects of the trip. The main effect of valence was derived from a higher PI for the positive valence than the negative valence in both products. The valence-content interaction showed that, for the negative valence condition, general content led to a higher PI than specific content, and, for the positive valence condition, general content led to a lower PI than specific content. The valence-badge interaction indicated that, for the negative valence condition, unverified content led to a higher PI than verified content, and, for the positive valence condition, unverified content led to a lower PI than verified content.

Table 3 Means, SD (in parenthesis), and significant statistical tests of PI (%) for the main and interaction effects of the tablet.

PI for the Search Product (Tablet)					
Variable	Condition	Positive valence	Negative valence	Statistical test	
				F (1, 492)	p-value
Valence	Main effect	61.33 (26.13)	23.74 (24.76)	302.09	< .001
Content	General	53.71 (26.11)	29.91 (26.96)	Valence-content interaction:	
	Specific	69.00 (23.90)	17.41 (20.52)	41.22	< .001
Badge	Absence	58.20 (27.06)	25.78 (26.26)	Valence-badge interaction:	
	Presence	64.38 (24.91)	21.65 (23.04)	5.71	.017

Table 4 Means, SD (in parenthesis), and significant statistical tests of PI (%) for the main and interaction effects of the trip.

PI for the Experiential Product (Trip)					
Variable	Condition	Positive valence	Negative valence	Statistical test	
				F (1, 492)	F (1, 492)
Valence	Main effect	66.31 (26.21)	37.21 (26.64)	158.95	< .001
Content	General	63.40 (25.96)	41.12 (27.70)	Valence-content interaction:	
	Specific	69.24 (26.23)	33.20 (25.00)	8.75	.003
Badge	Absence	63.97 (27.95)	41.13 (27.04)	Valence-badge interaction:	
	Presence	68.60 (24.29)	33.20 (25.72)	7.38	.007

We assessed whether the difference in PI across the two conditions of content and badge was statistically significant within each valence condition (simple effects). A nonparametric independent-sample Mann-Whitney U test was conducted due to the violation of the normality assumption of the DV. For the negative valence, there was a significant difference in content style for both products (U_{tablet} = 5,530.5, p < .001; U_{trip} = 6,458.5, p = .023). For the badge variable, there was a significant difference only for the trip and not for the tablet (U_{tablet} = 7,236.5, p = .366; U_{trip} = 6,432.5, p = .020). For the positive valence, there was a significant difference in content style for both products (U_{tablet} = 10,641.0, p < .001; U_{trip} = 9,247.0, p = .017). For the badge variable, there was a marginally significant difference only for the tablet and not for the trip (U_{tablet} = 8,975.5, p = .055; U_{trip} = 8,582.0, p = .218). The p-values are not corrected in order to allow for multiple comparisons.

The findings do not show a main effect of content style and the verification of reviews on PI. Therefore, we reject H1a, H1b, and H2. However, the null main effects for those variables (i.e., content and badge) are explained by their significant interactions with valence. Depending on whether the valence is positive or negative, the effects of content style and badge on PI is opposite (see Figure 4). Moreover, the results demonstrate that the valence of OCRs is the main factor impacting PI. Positive evaluations increase PI and vice versa. This confirms H3 and supports existing research on the impact of review valence on decision-making (Daugherty & Hoffman, 2014; Tata et al., 2020; Zablocki et al., 2019).

We answered H4a and H4b using the significant valence-content and valence-badge interactions. Reviews with general content led to a higher PI than reviews with specific content when their valence was negative and vice versa for both products. An explanation for this is that specific content evokes more critical evaluations of the product than general content. The description of a product's specific qualities enhances positive and negative perceptions thereof (as inferred from the revealed PI), depending on positive or negative framing, respectively. Our findings contradict those of Bigné et al. (Bigne et al., 2019), who analyzes the effects of this interaction on the visit intention and digital destination image in a different country with a larger sample size and a sole focus on tourism destinations. However, we agree with the authors that "specific content is more trustworthy and thus more persuasive than general content" (Bigne et al., 2019). Moreover, we posit that this persuasiveness effect follows the valence of the comment. When a review is negative, specific comments reinforce the negative aspects of the product and decreases the PI, whereas, when a review is positive, the specificity strengthens the positive perceptions of the product and increases the PI.

Concerning the valence-badge interaction, our data show a tendency of higher PI when the badge is absent in negative comments and present in positive comments. This tendency is seen in both products, but the differences in PI are statistically significant in the negative condition only for the trip package and in the positive condition only for the tablet. It seems that, when the comments are negative for search products (i.e., the tablet), participants give them equal weight, regardless of the presence of the badge, indicating that they have low PI. However, when encountering positive comments, they find the verified comments more persuasive than the unverified ones. These effects are the opposite for experiential products (i.e., the trip). Therefore, we infer that search versus experiential products induce different judgment mechanisms depending on the type of information presented. He et al. (J. He et al., 2020) investigate whether verified online reviews on Amazon's website impact tablet sales. The authors find a positive correlation between the proportion of verified comments and sales rankings. However, they also find that the ratings of the VP reviews do not impact sales. Our data support the positive effect of the badge on PI, albeit only when the review is positive.

5.3 Bayesian analysis

To produce a comprehensive analysis of the effects of each variable (valence, content style, and verification badge) on purchase intention, we conducted a Bayesian analysis (for details of its application in marketing, see Rossi and Allenby [28]). A Bayesian approach allows for direct inferences concerning the probability of success (i.e., a purchase) given a condition (e.g., positive valence). The final probabilities, namely the posterior probabilities, incorporate the data obtained from the experimental condition as well as prior beliefs on the distribution of the data. When there is previous knowledge about the potential effects of a variable on an outcome, the prior beliefs should consider this information, thus resulting in an informative prior.

We first used a Bayesian approach to make inferences about the proportions within each IV of a positive PI (i.e., a "yes" on the binary PI variable). For the tablet, a total of 187 (out of 462) participants would purchase the product, and for the trip, 250 (out of 457) would purchase the trip package. The control group (CG) comprised the conditions that promote higher PI identified in the literature: positive valence, specific content, and presence of the badge. The treatment group (TG) comprised the conditions that promote lower PI identified in the literature: negative valence, general content, and absence of the badge. This analysis only considers the number of purchases in order to determine if the conditions for the TG are indeed less effective than the CG in terms of PI.

The plausible probability models took into account that conditions of the TG presumably lead to a lower PI than the conditions of the CG. Due to the lack of information on the exact extent of the effect, the prior probabilities were distributed equally within probabilities greater than 50% and within probabilities less than 50%, but the lower probabilities had a larger weighting (p = 10%: .175, p = 20%: .175, p = 30%: .175, p = 40%: .175, p = 50%: .100, p = 60%: .050, p = 70%: .050, p = 80%: .050, p = 90%: .050). The posterior probabilities were derived from the prior probabilities and the likelihood probabilities were derived from the data.

The posterior probability results for the tablet and trip reveal that a purchase is less likely to occur in the TG for the variable valence (tablet: model 20% = 90.9%; trip: model 30% = 96.3%) and is slightly less or equally likely to occur for the variable content (tablet: model 40% = 73.1% and model 50% = 26.9%; trip: model 50% = 98.7%). The probability that a purchase is equally likely to occur in the absence of a badge is 90.1% for the tablet and 98.6% for the trip (model 50%). Moreover, the probability that the TG is less effective than the CG in encouraging purchases (i.e., the sum of the posterior probabilities of the models p = 10–40%) is as follows: (i) valence: 100% (tablet and trip), (ii) content: 73.1% (tablet) and 0.3% (trip), (iii) badge: 9.5% (tablet) and 1.0% (trip). Therefore, the data demonstrate that a negative review is ineffective in driving purchase behavior for both products. Regarding the content, the results shows that a review with general comments has a 73% probability of being less effective than a review that includes specific comments for the search product. This probability is only 0.3% for the experiential product. For the badge, there is a strong indication a purchase is equally likely to occur either in the presence or absence of a badge for both types of products.

The next step assesses the posterior distributions and credible intervals (CIs) within each condition for each product to calculate the probability of a purchase occurring given the assigned condition. The posterior distribution is a conditional probability on the data and prior beliefs, the latter being represented by a prior distribution. The family of the distribution is chosen based on the type of data. As our study used binomial data, we used a beta-binomial, Be(α,β), as the conjugate-type for the prior and posterior distributions. The shape of the beta distribution is defined by the parameters α and β. A likelihood function specifies how the data and variables are related. The final distribution (i.e., the posterior) incorporates the prior beliefs and the likelihood function. As before, we chose the prior beta (i.e., α and β parameters) for the CG conditions reflecting higher PI, and the prior beta for the TG conditions reflects lower PI. From the posterior beta, 95% CIs and point-mass probability were calculated (Table 5). The latter is a direct output from the formula α/(α+β) (posterior α and β) and represents the center of the final distribution. The former indicates there is a 95% probability that the true PI probability is in the given interval between the lower and upper bounds.

Table 5 Results of the Bayesian analysis per condition for each product.

Search Product (Tablet)								
Variable	**Condition**	**Prior alpha**	**Prior beta**	**Posterior alpha**	**Posterior beta**	**Point mass**	**Lower-bound (95% CI)**	**Upper-bound (95% CI)**
Valence	Negative	2	4	32	206	13.34%	9.42%	18.05%
	Positive	4	2	161	75	68.27%	62.15%	73.99%
Content	General	2	4	85	147	36.60%	30.57%	42.97%
	Specific	4	2	108	134	44.61%	38.42%	50.91%
Badge	Absence	2	4	93	142	39.54%	33.42%	45.89%
	Presence	4	2	100	139	41.82%	35.67%	48.14%
Experiential Product (Trip)								
Variable	**Condition**	**Prior alpha**	**Prior beta**	**Posterior alpha**	**Posterior beta**	**Point mass**	**Lower-bound (95% CI)**	**Upper-bound (95% CI)**
Valence	Negative	2	4	70	158	30.64%	24.89%	36.83%
	Positive	4	2	186	55	77.25%	71.68%	82.24%
Content	General	2	4	130	103	55.81%	49.39%	62.10%
	Specific	4	2	126	110	53.40%	47.01%	59.71%
Badge	Absence	2	4	127	104	54.99%	48.54%	61.33%
	Presence	4	2	129	109	54.21%	47.86%	60.48%

Our observation of the point-mass probabilities is in line with and related to the previous analysis. The purchase probability with a specific comment present is slightly higher than if a general comment is shown for the search product but not for the experiential product. The presence of a badge leads to greater purchase levels for the search product. However, this effect is small, and it is null for the experiential product. The strongest effect was found in the valence of the OCR. A negative valence review powerfully impacts PI. The purchase probability with negative reviews present is only 13.3% for the tablet and 30.6% for the trip (a noteworthy difference). This indicates that people are less willing to take the risk of purchasing search products than experiential products. Additionally, the reviews for the search products are perceived as more credible than those for the experiential products, thereby impacting the consumers' decision-making processes (Jiménez & Mendoza, 2013). As expected, positive valence reviews have a strong effect on PI. Sixty-eight percent of the participants reported an intention to buy the tablet and 77% reported an intention to buy the trip package under this condition. Moreover, different from the negative condition, the positive condition only had a 9% difference between product types.

6. Conclusion and implications

Our study explored how three OCR extrinsic cues (valence, content style, and verification badge) interact with two intrinsic cues (search and experience product categories) and influence consumers' purchase intentions (see Figure 2). Although there was no main effect of content style or verification badge on PI, there was an observable main effect of OCR valence on PI across both product categories. Interestingly, the interaction of review valence with content style and verification badge had a significant influence on subsequent PI for both search and experience products. When the OCR valence was positive, specific content style and presence of a verification badge led to higher PI for both product categories. Conversely, for negative OCR valence, general content style and absence of a verification badge led to higher PI for both product categories. Theoretical and managerial implications are discussed based on these findings in the next sub-sections.

6.1 Theoretical implications

With the exponential rise in e-commerce, online information cues that influence purchase decisions have received great attention. Although the current study explores various previous findings, prior research neglects the joint effects caused by the linguistic component of product reviews and the presence or absence of VPs on consumers' PI even though consumers are continuously exposed to these cues. Thus, the findings of this study extend our understanding regarding the effect intrinsic and extrinsic OCR cues have on consumers for different product types. We extend the marketing research on eWOM by adopting the cue utilization theory to examine how PI is influenced by intrinsic cues (search and experiential products) and extrinsic cues (OCR cues). To the best of our knowledge, the present study is the first to examine the unique interplay between content style, purchase verification, and valence. Although search versus experiential product categories have received considerable attention across domains, research on the interactions among eWOM cues is sparse. In their work, Choi et al. [31] examined the effects of intrinsic cues (company reputation, newness, and retro features) and extrinsic cues (review valence, product popularity, price, and user engagement) on digital video game sales using signaling theory. They reported that the intrinsic cues of newness and retro features and the extrinsic cues of review valence, popularity, and price had a positive impact on sales, while company reputation had an insignificant effect. However, their findings were limited to a single product type. By contrast, we used two distinct product categories. The findings of this behavioral study, based on frequentist and Bayesian statistical analysis approaches, demonstrate that the effect of OCR valence of search and experiential products supersedes the effect of other review cues on PI. Positive valence increases PI and vice versa, as has been found in previous studies (Tata et al., 2020). Yet, our main contribution lies in the interaction between the review cues. The key findings of this study are summarized as follows. Firstly, the valence-content style interaction effect increases PI when the reviews are specific and positive and decreases PI when the reviews are general and positive for both product categories. Secondly, in terms of the valence-verification badge interaction, a positive review with a badge yields higher PI, and a positive review without a badge yields lower PI for the search products, with a weak tendency seen for the experiential products. Thirdly, when the valence of a review is negative, general content increases PI and specific content decreases PI. Fourthly, when a badge is present in a negative review, PI decreases, and the absence of a badge in a negative review increases PI. This last effect is noticeable for both experiential and search products. Fifthly, we do not find a significant effect of VPs on PI. A conceivable explanation is that the badge does not influence a review's helpfulness. In this sense, He et al. (J. He et al., 2020) analyze 14,605 reviews for tablets from different brands and find that VP and non-VP reviews are perceived to be almost equally helpful. In summary, the content style and presence of VP badges are not important alone, especially for experiential products. These findings contribute to the debate on the influence of verified versus nonverified content, as discussed in the Literature Review. Moreover, content style and VP badges impact PI differently according to the valence of the review. Lastly, the findings of the study show no asymmetric effect of review cues on the PI for search and experiential products. We believe this is because e-commerce blurs the distinction between search and experiential products (Klein, 1998), which motivates consumers to use analogous strategies when purchasing them online, such as spending similar amounts of time online collecting information for both product types (P. Huang et al., 2009).

6.2 Managerial implications

Our findings offer several implications for e-commerce managers and designers. Specifically, this study highlights five key OCR-related factors: review valence, linguistic expression in reviews' content (i.e., specific or general content style), verification of the review (i.e., the presence of a VP badge), interactions of the cues, and their different impacts on consumers' PI of search and experiential products. The impact of valence combined with content style and the verification of the reviews on product purchasing behavior has strategic implications for digital businesses. Because our study reveals the asymmetrical impact of the variables under consideration, information system designers should categorize and structure the features and presentation of OCRs for different product categories based on the type of extrinsic cue (see Liu et al. (Y. Liu et al., 2013) on extracting OCR features from a designer's point of view). This will also simplify the evaluation process for consumers and assist them in information processing (Babić Rosario et al., 2020). Firstly, e-commerce managers should focus on highlighting positive reviews on their platforms. For example, as a strategy for increasing sales, managers can display reviews in ascending order. In other words, instead of putting recent reviews first, reviews can be serialized according to valence. Also, managers can encourage consumers to leave specific comments about their products when they write positive evaluations. If reviews are negative, then general comments should be displayed. Secondly, digital commerce platforms can adopt the use of VP badges to indicate that a purchase is genuine. In doing so, the platform also endorses the reviewer by including a VP badge in their reviews, which can simultaneously create trustworthiness and positively impact sales (J. He et al., 2020). Additionally, VP badges can be immediately applicable to e-commerce websites (Bigné et al., 2020). Highlighting high-quality reviews benefits consumers, sellers, and platforms (Z. Zhang et al., 2021). Considering the current highly competitive business environment, “review fraud” is a usual occurrence that borders ethical infringement in eWOM communication (Luca & Zervas, 2016). Therefore, the indication of VPs could dilute the effects of fraudulent reviews.

6.3 Limitations and future directions

The present study has a few limitations that encourage new research prospects. Firstly, to control the number of words in each comment for the participants and measure their purchase intentions, this study presented modified versions of the actual reviews; however, the participants might not have considered the reviews thoroughly. Future researchers can use an incentive-compatible task and conduct field studies to gauge actual purchase behavior (Morales et al., 2017) or incorporate visual attention through eye-tracking studies (Bigne et al., 2020). Secondly, we sought to address search versus experiential product categories, but each category was represented by only one product. Hence, the use of caution is necessary when generalizing the findings, and future researchers should consider using more than one product. Thirdly, the stimulus presented was a simplified version of an online review. Actual reviews contain additional cues (e.g., average star ratings and the names of the reviewers) and have different formats (e.g., visual content). Fourthly, since neutral valence product reviews contain both the positive and negative aspects of the product, we did not include them in our study in order to clearly demonstrate the effects of review polarity (five-star versus one-star reviews) (Bigne, Ruiz, et al., 2021), thereby avoiding the diminishing of the diagnostic element of reviews (S. Park & Nicolau, 2015). Future studies can improve the framework by examining the effect of neutral valence (three-star ratings) on review credibility and subsequent consumer purchase behavior. Finally, future research can employ the cue utilization framework on various moderators of OCRs, such as cultural background, review platforms, consumers’ knowledge, review length, product popularity, and so on, and measure their influence on PIs.

CHAPTER 3

HEART RATE VARIABILITY IN MARKETING RESEARCH: A SYSTEMATIC REVIEW AND METHODOLOGICAL PERSPECTIVE

This is the second out of three complied publications. The aim of the paper was to develop systematic literature review on the use of heart rate variability in marketing research. The study provides methodological guidelines and research directions for future research. It has been accepted and published online at Psychology & Marketing (Wiley):Kakaria, S., Bigné, E., Catrambone, V., & Valenza, G. (2023). Heart rate variability in marketing research: A systematic review and methodological perspectives. *Psychology & Marketing,* 40. https://doi.org/10.1002/mar.21734

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Heart rate variability in marketing research: A systematic review and methodological perspectives

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Abstract

Heart rate variability is a promising physiological measurement that accesses psychophysiological variations in response to a marketing stimulus. While its application spans diverse fields, there is a limited understanding of the usability and interpretation of heart rate variability in marketing research. Therefore, this hybrid literature review provides an overview of the emerging use of heart rate variability in marketing research, along with essential methodological considerations. In this context, we blend marketing mix framework with stimulus-organism-response theory, segregating the use of heart rate variability in various marketing research contexts. We follow the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework to reflect on 33 records obtained from six databases. Our findings suggest that 42% of studies used heart rate variability to investigate promotion-related topics. Overall, heart rate variability is mostly used in combination with Galvanic skin response (48%). Further, 39% of studies used non-portable systems for data collection. Last, using the theory characteristics methodology (TCM) framework, we identified six research avenues: (1) affective, cognitive, and sensorial constructs; (2) personality, thinking style, and demographics; (3) product experience; (4) advertising and branding; (5) correlation with immersive technologies; and (6) triangulation with other neurophysiological tools.

KEYWORDS
bibliometric analysis, biometric, consumer neuroscience, heart rate variability, marketing research, systematic review

1 | INTRODUCTION

Advances in consumer neuroscience research in the last two decades have allowed marketing researchers to effectively utilize psychophysiological tools to quantify the affective and cognitive processes of consumers that are triggered by marketing stimuli (Bell et al., 2018; Casado-Aranda & Sanchez-Fernandez, 2022; Mcaleer et al., 2022). Consumer neuroscience research applies neuroscience and psychological methods to processes that underpin consumer buying behavior (Karmarkar & Plassmann, 2019; Lee et al., 2018). Alvino et al. (2020) proposed a framework that classifies consumer neuroscience tools into three categories based on how responses to marketing stimuli are measured: (a) behavioral tools that record conscious reactions (e.g., selfreports, reaction time); (b) physiological tools that measure voluntary or involuntary physiological changes (e.g., Galvanic skin response, heart rate variability);

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1. Introduction

Advances in consumer neuroscience research in the last two decades have allowed marketing researchers to effectively utilize psychophysiological tools to quantify the affective and cognitive processes of consumers that are triggered by marketing stimuli (L. Bell et al., 2018; L.-A. Casado-Aranda & Sanchez-Fernandez, 2022; Royo-Vela & Varga, 2022). Consumer neuroscience research applies neuroscience and psychological methods to processes that underpin consumer buying behavior (Karmarkar & Plassmann, 2019; N. Lee et al., 2018). Alvino et al. (2020) proposed a framework that classifies consumer neuroscience tools into three categories based on how responses to marketing stimuli are measured: a) behavioral tools that record conscious reactions (e.g., self-reports, reaction time); b) physiological tools that measure voluntary or involuntary physiological changes (e.g., Galvanic skin response, heart rate variability); and c) neurophysiological tools that assess brain activations (e.g., electroencephalogram, functional magnetic resonance imaging). In this context, heart rate variability series, defined as the instantaneous variation of time intervals between adjacent heartbeats, is a promising tool for identifying and evaluating consumer psychophysiological responses to marketing stimuli, given its cost-effectiveness and easy-to-acquire data capabilities. Additionally, advancements in wearable and portable electrocardiogram (ECG) devices (e.g., fitness monitors, Apple watches) provide continuous (temporally precise over seconds, minutes, and hours), ecological (real-world conditions), and scalable collections of cardiac activity data in different contexts (B. W. Nelson et al., 2020), broadening opportunities for marketing researchers to improve real-time consumer experiences (Orazi & Nyilasy, 2019).

Although there is debate about the precise definition of emotion, Kleinginna and Kleinginna (1981) posited that emotion can be divided into three components: subjective experience, expressive response, and physiological arousal. Because emotional states and physiological arousal are inextricably related (Herman et al., 2018), the employment of physiological, non-invasive measurements has become prevalent in marketing research (L.-A. Casado-Aranda & Sanchez-Fernandez, 2022). In this sense, cardiac activity is not restricted to physiological arousal but is also linked to cognitive and affective processes (Candia-Rivera et al., 2022; Massaro & Pecchia, 2019; Poels & Dewitte, 2006; Verhulst et al., 2019). The use of heart rate variability recordings can improve two major constraints of traditional marketing methodologies by providing: (1) ease of continuous measurement for unconscious level processing of stimuli in a naturalistic setting; and (2) quantitative and robust physiological measurements related to consumers' affective and cognitive responses to triangulate with self-reports (L. Bell et al., 2018); however, there is a lack of standardization in marketing research design and the data pipeline.

With this in mind, this systematic literature review aims to achieve the following research goals: (1) to promote the use of heart variability tools in marketing research by providing methodological guidelines, and (2) to draw out major strands of potential research. We also highlight two major research questions: (RQ1) What are the emerging marketing research topics investigated using heart rate variability? and (RQ2) What heart rate variability measures are commonly used in marketing research? As a result, and based on the Theory Characteristics Methodology (TCM) Framework, this study identifies six research avenues for marketing research using heart rate variability. Likewise, this study provides guidelines for conducting heart rate variability studies.

In section 2, we outline the theoretical basis for heart rate variability and provide background on the marketing mix and stimulus-organism-response (SOR) framework. In section 3, we use the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework to identify relevant articles. In section 4, we present the findings and discuss potential developments in marketing research. This study adapts a hybrid review methodology (see Paul and Criado (2020) for the classification of systematic review articles), wherein we follow a descriptive and bibliometric oriented analysis of the records and follow the TCM approach to present future research avenues. Section 5 provides guidelines for planning heart rate variability-based study for marketing research. Section 6 summarizes the study and highlights the limitations.

2. Theoretical background

First, it is important to distinguish between "heart rate" and "heart rate variability" measurements. Heart rate variability is a time series, also referred to as R-R interval series or interbeat interval series, drawn from the timing between successive heartbeats, identified through R-peaks in the ECG. Heart rate refers to the number of heartbeats in a specific time interval and is a feature that can be derived from heart rate variability series analysis.

2.1 Fundamentals of heart rate variability

Heart rate variability series is the time resolved signal that reflects changes in cardiovascular activity caused by the synergistic action of its two constitutive branches: the sympathetic nervous system and the parasympathetic nervous system (Acharya et al., 2006; Shaffer & Ginsberg, 2017). While sympathetic nervous system plays a dominant role in the body's fight-or-flight response, which may increase heart rate, the parasympathetic system activity is associated with a rest-and-digest state and may decrease heart rate (see Figure 1). Their joint activity maintains a balanced state in the body (Pham et al., 2021) and contributes to the regulation of heart rate over time, thus defining heart rate variability at each moment in time. Sympathetic nervous system may exhibit physiological arousal through increased heart rate and blood pressure, while the parasympathetic one may decrease physiological arousal, i.e., heart rate deceleration via the vagus nerve. Importantly, concurrent sympathetic and parasympathetic nervous system heartbeat regulation activity may result in nonlinear dynamics (Sunagawa et al., 1998). The parasympathetically (vagally) mediated heart rate has faster beat-to-beat variations than the sympathetically mediated heart rate, which has slower changes in beat-to-beat variations.

The autonomic nervous system continuously interacts with the central nervous system via bottom-up or top-down communications (Candia-Rivera et al., 2022; Owens et al., 2017). Specific brain regions, such as the prefrontal cortex, amygdala, and medulla oblongata, considered part of the central-autonomic network (Silvani et al., 2016; Valenza et al., 2019), are involved in decision-making, threat response, and emotional processing. In this context, the heart rate variability series may be considered as a proxy measurement of brain–heart interplay (Candia-Rivera et al., 2022).

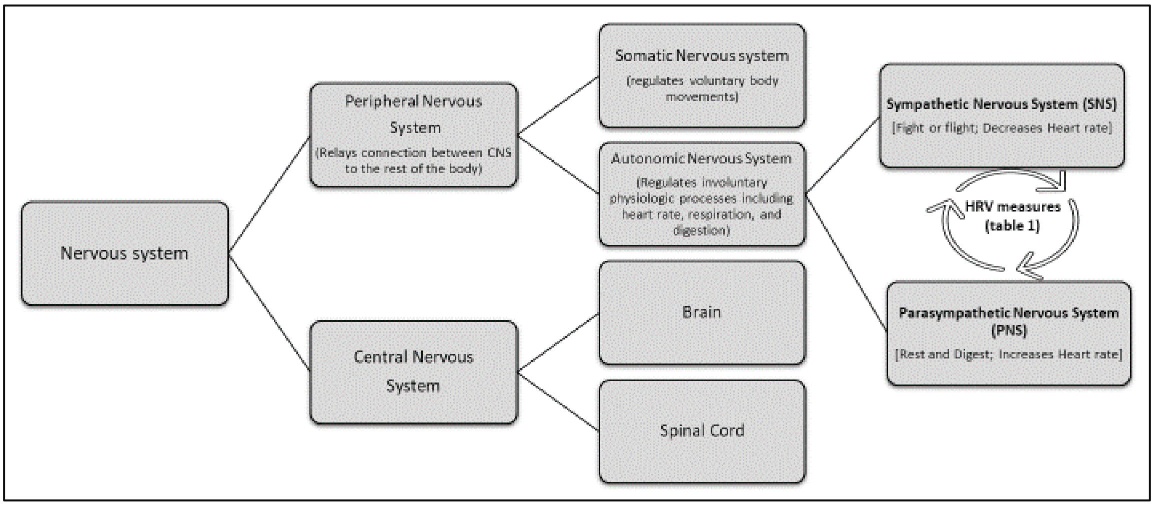

Figure 1. Schematic and exemplificative diagram of the nervous system and its relation to the sympathetic and parasympathetic branches. Source: Author's own elaboration.

2.1.1 Data collection

ECGs are the gold standard for retrieving heart rate variability series; alternatively, pulse rate variability may be used as a heart rate variability surrogate series. An ECG captures rhythmic changes in the heart via electrical impulses, while the pulse represents volumetric change in blood profusion (B. W. Nelson et al., 2020). An ECG system acquires electric potentials generated by the rhythmic movement of the heart due to depolarization, captured via electrodes placed on the chest. Pulse rate variability obtains heart rate variability information from pulse wave signals (time variations in pulse-to-pulse cycles) and is usually obtained through photoplethysmograms (i.e., an optical technique) from various locations on the body, such as the fingers, arms, or wrists (Ishaque et al., 2021). Photoplethysmography is a low-cost, noninvasive tool for capturing changes in autonomic activity. The higher portability, lower cost, and noninvasive qualities of pulse rate variability make it easier to implement in marketing studies, but at the cost of a sensible decrease in signal quality.

Heart rate variability is a highly nonstationary, complex signal that expresses temporal variation in adjacent heartbeat intervals (Acharya et al., 2006; Catrambone et al., 2019). To ensure signal robustness, the data analysis pipeline requires preprocessing (Bulagang et al., 2020) to account for missing data detection, segmentation of intervals of interest, artefacts (missing beats and arrhythmias), and noise rejection. Preprocessing includes filtering, which deletes inapplicable frequency components, thereby increasing the defined signal-to-noise ratio. To obtain the heart rate variability series, the amount of time between heartbeats (i.e., R-peaks) (Peltola, 2012) should be measured in the ECG, which allows for the RR intervals (heart rate) to be estimated and, therefore, the heart rate variability series. The R-peak usually has the highest value in the ECG series. It is recommended that at least 15 minutes of resting state be recorded before beginning an experiment to normalize the initial internal state of the subject (Catai et al., 2020), although such timing is subjective and contingent upon experimental conditions.

2.1.2 Analysis and measures

One of the most widely used algorithms to identify R-peaks is from Pan and Tompkins (1985). There is a diverse amount of software providing similar outputs available for analyzing the heart rate variability (see Singh & Bharti 2015). Data analysis quality is heavily dependent on data acquisition procedures (see detailed checklists by Catai et al., 2020).

Heart rate variability analysis can be performed in different domains, including time, frequency, and nonlinear, as reported in table 1. Time domain metrics capture periods of various lengths, with difference-based indices that are indicative of robust, short-term variations (Pham et al., 2021), while other metrics, mainly those influenced by PNS activity, are better suited for short-term analysis (Shaffer & Ginsberg, 2017). Frequency domain metrics are derived from spectral analysis, whereby the heart rate variability series is decomposed from fundamental oscillations into three main components: very low frequency (VLF), low frequency (LF), and high frequency (HF). Based on recent autonomic dynamics evidence, the LF power band is considered a marker of sympathovagal activity (Shaffer & Ginsberg, 2017), and HF power a marker of vagal activity, as long as the respiratory frequency is in the same frequencies (Thomas et al., 2019). It has been argued that the ratio between LF and HF power (LF/HF) is indicative of sympathovagal balance; however, the scientific community has only debated the specificity of these bands separately. Employing several derived features is recommended to ensure the robustness of the analysis. Since frequencies are dependent on the length of the recording window, it is advisable to report LF and HF power in both normalized and absolute forms. Nonlinear indices quantify the predictability underlying cardiovascular regulation (Ishaque et al., 2021). Entropy-based indices measure the predictability (or regularity) of a signal to discern randomness and complexity. Lower entropy (lower irregularity) indicates more predictable cardiac variability dynamics (Peltola, 2012). The correlational dimension (CD) calculates the regression line from the log-log representation; the higher the CD, the greater the heart rate variability complexity (Ishaque et al., 2021).

Heart rate variability indices	**Unit of analysis**	**Functional description**
Time domain (linear domain)		
Heart rate (HR)	Beats per minute (bpm)	Number of R-peaks per minute. The variability in the HR provides information about the functioning of nervous control on heart activity and the heart's ability to respond.
Standard deviation of RR intervals (SDRR)	Milliseconds	Mean square difference between each RR interval and their mean, normalized by the number of RR intervals in the given time window. Mediated by cardiac vagal activity. Alternatively, the standard deviation of NN intervals (SDNN) can also be used.
Square root of the mean squared differences between successive RR intervals (RMSSD)	Milliseconds	Reflects beat-to-beat variance in heart periods. Correlated with HF power and pNN50. Mediated by cardiac vagal activity.
Percentage of adjacent RR intervals with a difference of more than 50 milliseconds (pNN50)	Percentage (%)	Usually correlated with the RMSSD and HF power. Mediated by cardiac vagal activity.
Triangular index		Total number of RR intervals divided by the number of RR intervals in its modal bin in the density distribution histogram. Highly correlated with SDRR. Obtained as a graphical representation (histogram, scatter plot) of N-N intervals.
Frequency domain (linear domain)		

Total power	ms^2	Spectral power in the <0·4 Hz band. Modulated by sympathetic, vagal, and baroreceptor activity.
Low frequency (LF) peak	Hz	Frequency associated with the magnitude peak in the LF band (0.04Hz-0.14Hz). Modulated by sympathetic, vagal, and baroreceptor activity.
Very low frequency (VLF) band	ms^2	Absolute power of the VLF band (0.003–0.04 Hz). A not-specific measure of autonomic activity and health condition.
Low frequency (LF) band	ms^2	Absolute power calculated in the LF band (0.04Hz-0.14Hz). Modulated by sympathetic, vagal, and baroreceptor activity.
High frequency (HF) band	ms^2	Absolute power calculated in the HF band (0.14Hz-0.4Hz). Modulated by cardiac vagal activity if the respiratory frequency is within 0.14-0.4Hz.
High frequency (HF) peak	Hz	Frequency associated with the magnitude peak in the HF band. Modulated by cardiac vagal activity if the respiratory frequency is within 0.14-0.4Hz.
LF/HF		Ratio between LF and HF band powers. Modulated by sympathetic, vagal, and baroreceptor activity.
Nonlinear domain		
Approximate entropy (ApEN); **Sample entropy (SampEn);** **Shannon entropy (ShEN)**		Quantification of heartbeat dynamics regularity and predictability. The lower the entropy value, the more predictable and regular the signal. Likely to be modulated by cardiac vagal activity.
Correlational dimension (CD)		Measure of fractal dimension. Proportional to the probability that two arbitrary points on the orbit are closer together than r. Likely to be modulated by cardiac vagal activity. As CD values increases, the

	cardiac system reflects better adaptive responses to external stimuli.

Table 1. Summary of common heart rate variability measures and their functional descriptions. Adapted from Pham et al. (2021) and Shaffer & Ginsberg (2017).

2.2 Heart rate variability and marketing research

Marketing actions elicit neural and physiological responses. For our review, we integrated the marketing mix framework with the SOR framework. Our conceptual framework (Figure 2) clearly illustrates marketing mix as antecedental to consumer psychophysiological processing, which results in behavioral output. Prior studies have utilized the classic 4Ps framework (Waterschoot & Bulte, 1992), which includes four dimensions—product, price, promotion, and place—successfully highlighting the contribution of physiological and neurophysiological tools in consumer marketing (see Bazzani et al. [2020] for a review). These dimensions help managers craft products and campaigns that suit consumer needs. Previous literature reviews have utilized the SOR framework to examine underlying consumer physiological mechanisms (Xiong & Zuo, 2020). Mehrabian and Russell's (1974) SOR framework highlights the stimulus component as an external (environmental) factor, while the organism component reflects the consumer's affective or cognitive intermediate processes as a consequence of being exposed to stimulus. The response component reflects approach or avoidance behavior, i.e., shopping behavior outcomes in response to the stimulus (Mehrabian & Russell, 1974). This unique framework will help navigate the literature and facilitate an understanding of the influence of marketing stimuli on consumer responses through heart rate variability metrics.

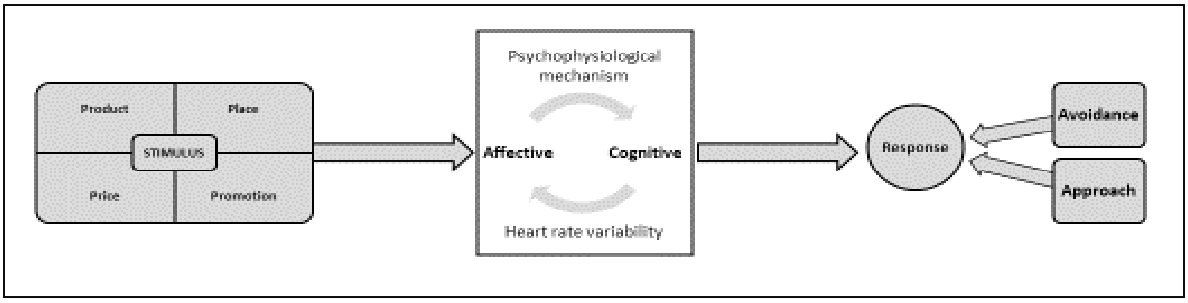

Figure 2. Conceptual framework formed by blending marketing mix and SOR theories.

3. Methods

To analyze how heart rate variability has been used in marketing research, we adapted the guidelines as specified in PRISMA (see Page et al. [2021]). Figure 3 shows a PRISMA flowchart summarizing the review process.

3.1. Search strategy

Our primary source for this study was Scopus, since it has the broadest range of indexed academic journals and has been used in previous marketing studies to develop review articles (Mariani et al., 2022). Our secondary electronic databases included Web of Science (WOS), Frontiers, PubMed, PLoS ONE, and a quick crosscheck with Google Scholar. We then ran a query ("heart AND rate" OR "electrocardiogra*" OR "HRV" OR "heart AND rate AND variability") in our primary database with search fields related to "article title," "abstract," and "keywords." We considered work that was published up until May 05, 2022. The inclusion and exclusion criteria were set before proceeding to further stages.

3.2 Screening procedures

For the exclusion criteria, articles outside of the areas of business, management, and accounting were removed. Articles other than those in journals, that predated 2000–2022, or were published in any language other than English were also excluded. Among the inclusion criteria, documents categorized as articles were retained, and only the source titles that corresponded with the Scopus database for marketing journals within the business, management, and accounting sections (Appendix A). Source titles and corresponding articles that were removed at this stage can be viewed in Appendix C. After a manual, in-depth screening of the remaining articles, only those that passed our relevance criteria were included in the results. The relevance criteria indicate a) studies that measure consumer affective- or cognitive-relevant constructs, and b) studies that report one or more empirical results using heart rate variability series, either as a core or complementary measure. Documents that didn't pass this stage can be viewed in Appendix C. To reduce the probability of bias in developing the final corpus, these criteria were individually checked by two authors. The primary author established the inclusion and exclusion criteria for extracting appropriate records, while the secondary author established the relevance criteria. The final list of records was developed after both authors independently scanned each record for their suitability and resolved doubts.

3.3 Secondary databases

In conjunction with the primary database, a similar search resulted in 15 articles from WOS (n = 7) (see Appendix F), Frontiers (n = 2), PubMed (n = 0), PLoS ONE (n = 3), and the crosscheck with Google Scholar (n = 3). The results obtained from WOS were already part of the Scopus dataset and were excluded to avoid duplication. We read the abstracts of the remaining eight articles and found two ineligible for inclusion in the final corpus.

3.4 Record selection

The Scopus database yielded 27 articles, and the secondary databases yielded six additional papers; the final corpus included 33 articles. Next, we retrieved the dataset, which included article titles, author information, countries and regions, publication details (i.e., total number of publications, total and average citations), all keywords, and journal sources. Table 2 presents the articles.

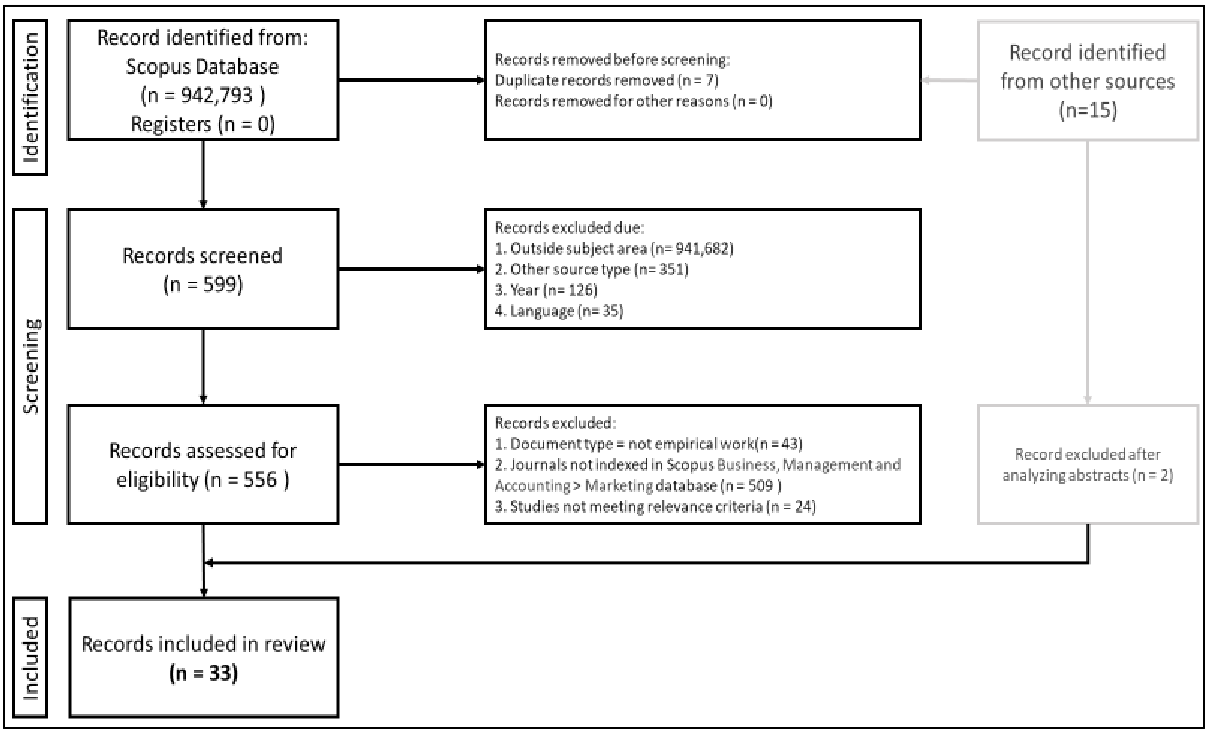

Figure 3: PRISMA flow chart indicating each step for identifying articles.

4. Results and discussions

This section presents the key findings through descriptive analyses of the records, followed by a bibliometric analysis. This is followed by commentary on prospective research lines and general considerations for executing studies that use heart rate variability.

4.1 Descriptive analysis

In addition to the key records findings using our framework, we also provide details about the underlying theories, the research design, the various types of devices to record heart rate variability and commonly used consumer neuroscience tools with heart rate variability.

4.1.1 Marketing mix

Table 2 divides the articles based on four marketing mix themes and provides an overview of sample demographics, heart rate variability measures used, and the key findings of each article relevant to RQ1 and RQ2. Heart rate variability has been used the most for studying promotion- and product-related aspects of the marketing mix (43% and 27%, respectively). Aspects related to place (15%) and price (3%) were not of interest.

Article	Sampling	Design	Measure	Findings
PROMOTION				
Rodero & Potter (2021)	52 (29 females) Age (19–32)	Within subject	Heart rate	Messages in commercials with moderate emphasis (vs. no emphasis) improved consumer cognitive processing.
Martinez-Levy et al. (2022)	72 (36 males) Age (M = 37.5; SD = 10.8)	Between subject	Heart rate	Lower emotional reaction observed in the closing section of second version of the spot compared to the first version.
Breuer et al. (2021)	11 (9 males) Age (18–32)	Within subject	Heart rate	Sport spectator arousal decreases when outcome uncertainty is lowered; arousal increases when a winning game is close to ending.
So et al. (2021)	21 (12 females)	Between subject	HF band, LF band, VLF band,	Heart rate variability dependent on the genre. High or low arousal content

	Age (16–59; M = 38.09, SD = 14.02)		LF/HF ratio	derived from previous heart rate variability is more engaging.
Sung et al. (2021)	125 (70 females) Age (M = 21.26, SD = 3.96)	Between subject	Heart rate	Greater arousal and engagement for non-luxury vs. luxury brand stories. Heart rate significantly decelerated in non-luxury vs. luxury conditions.
Bellman et al. (2019)	1,040 (530 females) Age (18–83)	Within subject	Heart rate	Heart rate was significantly negatively correlated with fixation duration (attention).
Clark et al. (2018)	144 (72 females) Age (M = 32.44, SD = 11.48)	Between subject	RMSSD	Nonsignificant results between in-stream autoplay and click-to-play conditions.
Guixeres et al. (2017)	35 (20 males) Age (M = 25, SD = 5)	Within subject	Heart rate, RMSSD, pNN50, LF peak, LF band, HF band, HF peak, LF: HF ratio, total power, ApEN, SampEn, ShEN	SD2 Poincare index significantly different in ad recall vs. no ad recall conditions. Similarly, LF band was significantly different for ad preference vs. ad non-preference groups.
Sung et al. (2016)	40 (20 males) Age (M = 20.12, SD = 3.14)	Within subject	Heart rate	Cardiac deceleration evoked by advertisements with novel cues, in contrast to original advertisements of identical products.

Christoforou et al. (2015)	16 (11 females) Age (M = 22)	Within subject	RMSSD	Moderate negative relationship between RMSSD and divergence of eye gaze patterns while watching narrative-based video.
Venkatraman et al. (2015)	29 (11 females) Age (M = 33; SD = 10)	Within subject	LF band, HF band	Cardiac deceleration correlated with ad preference, ad recognition, and change in purchase intent.
Ha-Brookshire & Bhaduri (2014)	67 (47 females) Age (M = 34.36)	Within subject	Heart rate,	Heart rate deceleration is greater when messages are framed as malevolent vs. benevolent.
Bellman et al. (2013)	64 (33 males) Age (19–75)	Mixed subject	Heart rate	Web browsing ad relevance received more attention for low-involvement product commercials compared to high-involvement product commercials.
Bos et al. (2013)	35 (12 males) Age (18–25; M= 20.6)	Within subject	Heart rate	No significant differences observed in HR between negative, neutral, and erotic film clips.
PRODUCT				
Küster et al. (2021)	100 (54 females) Age (M = 21.49, SD = 2.46)	Between subject	Heart rate	RR interval (HR) significantly differs based on product choice.

Simmonds et al. (2020)	133 Age (M = 46)	Mixed subject	Interbeat interval	Multisensory (audiovisual) cues elicit heart rate acceleration.
Mas et al. (2020)	49 (36 females) Age (M = 19.14, SD = 1.9)	Within subject	Heart rate	Heart rate decreases when long sonic logos are slow-paced.
Noseworthy et al. (2014)	290 (163 males) Age (M = 25.2)	Between subject	Heart rate	Fluctuating arousal varies the severity of negative (anxiety) or positive (curiosity) emotion, which alters product evaluations.
Maxian et al. (2013)	52 (37 females) Age (M = 21)	Within subject	Heart rate	Viewing more loved brands led to cardiac deceleration.
Gangadharbatla et al. (2013)	60 (44 females) Age (M = 20.2)	Between subject	Heart rate	Insignificant support for billboard recognition altering heart rate.
Mehta et al. (2012)	95 (60 females)	Between subject	Heart rate	A moderate level of noise (70dB) increases processing fluency and construal processing, enhancing performance on creative tasks.
Walla et al. (2011)	21 (14 females) Age (M = 28.14, SD = 6.29)	Between subject	Heart rate	Significant reduction in heart rate when liked (vs. disliked) brand names are shown.
Hernandez & Minor (2011)	30 (17 female)	Within subject	Heart rate	Arousal (HR) levels inversely related to brand recall

	Age (M = 34.17)			scores but not recognition scores.
PLACE				
Luangrath et al. (2022)	144 (94 males)	Within subject	Heart rate	Vicarious haptic effect enabled ownership and product evaluation for individuals reporting an elevation in heart rate in virtual reality retail store.
Hariharan et al. (2016)	37 (27 male)	Within subject	Heart rate	Auction dynamics moderated relationship between emotional arousal (HR) and bid deviation.
Adam et al. (2015)	240 (182 males) Age (M = 22.09)	Within subject	Heart rate (study 1)	Time pressure and social competition significantly and positively influenced arousal levels (HR).
Pettigrew (2011)	2	Within subject	Heart rate	Experiencing a Disney theme park did not elicit changes in HR compared to other theme parks.
PRICE				
Alexander et al. (2015)	90 Age (M = 24.8, SD = 9.6)	Between subjects	HF band	Decrease in HR for consumers who received coupons vs. those who didn’t receive coupons.
OTHER				
Cahlíková et al. (2020)	190 (95 females)	Between subject	Heart rate	Stronger physiological stress response leads to lower competition willingness.

Hattke et al. (2020)	136 (83 males) Age (M = 23.37; SD = 3.31)	Between subject	Heart rate	Bureaucratic red tape induces negative emotional reaction.
Falk et al. (2018)	80 (All male)	Between subject	Heart rate	Significant negative relationship between unfair payment on HR variability.
Adam et al. (2012)	96 (79 males) Age (M = 22.64)	Between subject	Heart rate	Excitement (HR) is higher in fast vs. slow Dutch auctions. High level of excitement leads to lower bids.
Carter (2008)	12	Within subject	Heart rate	Binaural beats did not affect heart rate.

Table 2. Records categorized according to the 4P marketing mix scheme.

4.1.2 Common theoretical lens

Since the literature on the use of heart rate variability in marketing research is assorted, the records were divided based on two broad theoretical lenses—cognitive and affect-based (see Appendix D). Affect-based theories were used as underlying mechanisms in 51% of studies, and only 27% used a cognitive-based theory. The limited capacity model of motivated mediated message processing (LC4MP) was a commonly used theory in 12% of the articles. LC4MP assumes that consumers have limited cognitive processing capacity to encode, store, and retrieve. This theory proposes that cognitive resources can process media messages automatically (from the environment) or through a controlled processing mechanism (conscious effort) (Lang, 2000).

4.1.3. Research designs

Out of 33 empirical research articles, 52% used a within-subject design when using heart rate variability as a physiological tool (see Table 2). A between-subject design was used by 42%, and only 6% of studies used a mixed-subject design. Among these designs, between-subject provides easier setup and less risk of biasing the participants; within-subject requires lower sample sizes and offers a greater chance of capturing true differences in conditions;

and mixed-subject provides greater statistical power in marketing research (Viglia et al., 2021).

4.1.4 Common heart rate measurements

Out of the 33 articles, approximately 85% of the articles have used heart rate (or heart rate range) as the measurement (see Table 2). While heart rate is the most basic and commonly used metric in marketing research, several studies have used alternative and complementary metrics (e.g., RMSSD) derived from the heart rate variability studies. Interestingly, most studies employed time-domain measurements, which does not require understanding of spectral decomposition technique (see section 2.1). Even so, certain time-domain and frequency-domain indices may share similar physiological correlates (see also Table 1).

4.1.5 Hardware setup

Traditional devices, i.e., non-portable ECG devices used to extract heart rate variability data using specialized software in limited laboratory settings, are being replaced with portable wearable devices that are cheaper and can be used in real-world settings (Dobbs et al., 2019). Although there is debate about the accuracy of traditional versus wearable devices, growing research has found wearable devices to be a good alternative to traditional devices (B. W. Nelson et al., 2020). As per our analysis, 11 records did not clearly mention devices in the methodology or procedure sections. Of the remaining records, 59% of studies used non-portable devices and 41% used portable devices. Table 3 lists the studies and associated devices. Records show that the most common non-portable device was the Biopac MP150 system (18%), whereas the most common portable device was from Shimmer systems (14%).

Reference (n =22)	**Devices**	**Portability**
Luangrath et al. (2022); **Ha-Brookshire & Bhaduri (2014)**	Biopac MP36	Non-portable
Küster et al. (2021)	PowerLab/16SP	Non-portable
Rodero & Potter (2021); Mas et al. (2020); Alexander et al. (2015); Venkatraman et al. (2015)	Biopac MP150 system	Non-portable
Martinez-Levy et al. (2022);	Shimmer Systems	Portable

Breuer et al. (2021); Clark et al. (2018)		
So et al. (2021)	Upmood PPG	Portable
Sung et al. (2021)	Empatica E4 wristband	Portable
Simmonds et al. (2020)	PsychLab Peripheral Pulse Amplifier	Non-portable
Falk et al. (2018)	Polar F810i	Portable
Hariharan et al. (2016)	Bioplux sensor system	Portable
Noseworthy et al. (2014)	iWorx PT-104	Non-portable
Maxian et al. (2013); Gangadharbatla et al. (2013)	Coulbourn Instruments bioamplifier	Non-portable
Walla et al. (2011)	Nexus-10-BVP sensor	Non-portable
Pettigrew (2011)	Polar infrared	Portable
Hernandez & Minor (2011)	Burdik EKG10	Non-portable
Carter (2008)	WrisTech HL-168	Portable

Table 3. List of devices used to capture the heart rate variability series.

4.1.6 Complementary tools

In conjunction with heart rate variability devices, our analysis found that studies frequently used electrodermal activity series (48%) and eye tracking (21%) tools. Interestingly, both of these tools are autonomic nervous system based. Electroencephalogram-based studies (18%) capture central nervous system activity (brain signals). Appendix E highlights complementary tools used across different studies. A detailed review of these tools can be found in Alvino et al. (2020) and Casado-Aranda and Sanchez-Fernandez (2022).

4.2 Bibliometric analysis

In order to quantitively analyze our corpus using bibliometric methodology, we followed the guidelines and best practices suggested in Donthu et al. (2021). These can be classified into two broad categories: (a) a performance analysis of publications (i.e., descriptive contribution of articles and journals); and (b) science mapping (i.e., exploring relationships between different research constituents) (Mukherjee et al., 2022).

4.2.1 Performance analysis

Using performance analysis, marketing journals were ranked based on their productivity, i.e., the total number (Figure 4) and most cited articles using heart rate variability tool (Table 4). Psychology & Marketing with four articles (12%), and PLoS ONE with three articles (9%), were the journals with comparatively more publications out of the 23 journals analyzed. The most cited publications were Venkatraman et al. (2015) with 25.3% of the total citations and Mehta et al. (2012) with 12.9%. Interestingly, while Venkatraman et al. (2015) utilizes other consumer neuroscience tools, Mehta et al. (2012) only used heart rate variability to reflect consumer arousal.

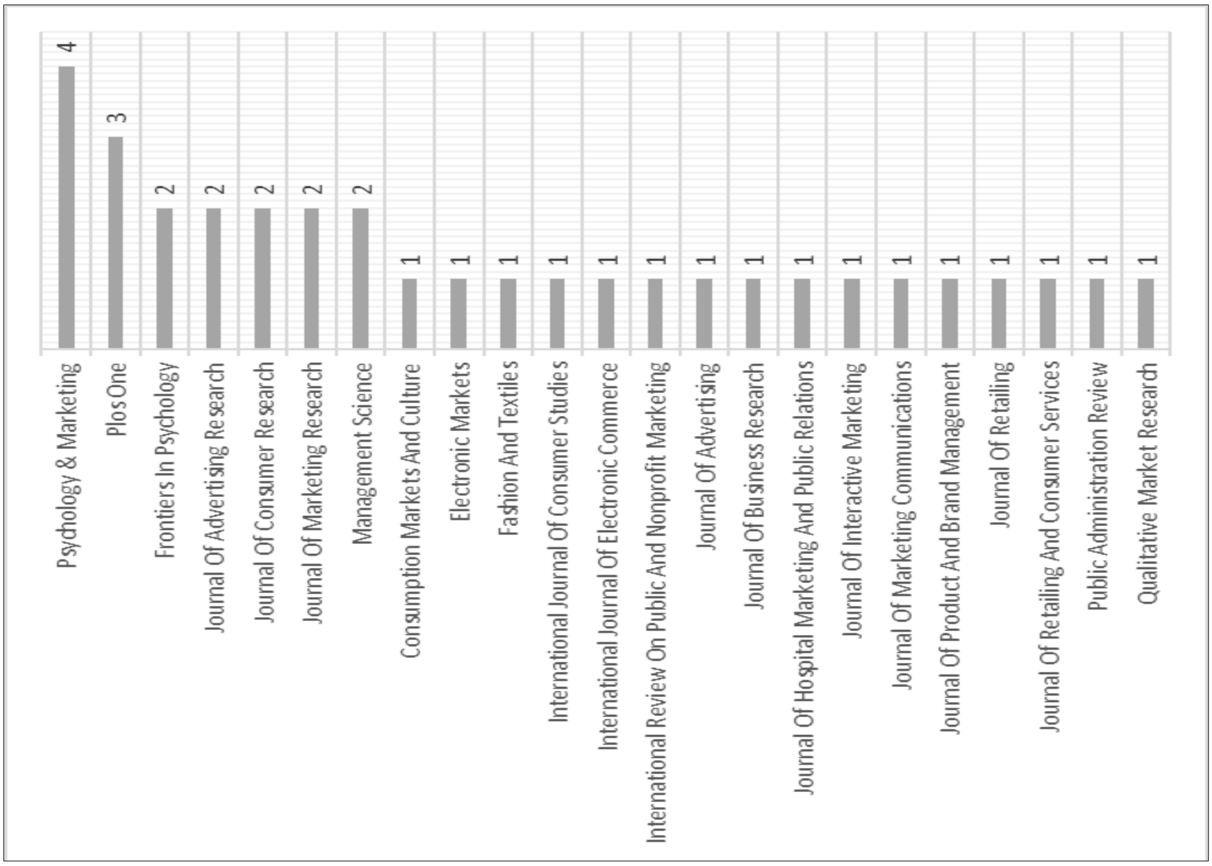

Figure 4. Marketing journals with articles that used heart rate variability.

Articles (Year)	Source title (n = 9)	Total citations (n = 960)
Predicting Advertising Success Beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling (2015)	Journal of Marketing Research	243

Is Noise Always Bad? Exploring the Effects of Ambient Noise on Creative Cognition (2012)	Journal of Consumer Research	124
The Role of Arousal in Congruity-based Product Evaluation (2014)	Journal of Consumer Research	63
Objective Measures of Emotion Related to Brand Attitude: A New Way to Quantify Emotion-related Aspects Relevant to Marketing (2011)	PLoS ONE	59
Auction Fever! How Time Pressure and Social Competition Affect Bidders' Arousal and Bids in Retail Auctions (2015)	Journal of Retailing	48
Consumer Neuroscience-based Metrics Predict Recall, Liking and Viewing Rates in Online Advertising (2017)	Frontiers in Psychology	46
Brand Love is in the Heart: Physiological Responding to Advertised Brands (2013)	Psychology & Marketing	44
Excitement up! Price down! Measuring emotions in Dutch auctions (2012)	International Journal of Electronic Commerce	44
Psychophysiological Response Patterns to Affective Film Stimuli (2013)	PLoS ONE	36
Emotional Responses to Bureaucratic Red Tape (2020)	Public Administration Review	35

Table 4. List of top 10 featured articles by citations using heart rate variability.

4.2.2 Science mapping

For science mapping, we conducted an author co-citation analysis (i.e., analyzing relationships among the authors of cited publications) and a co-occurrence analysis (i.e., examining existing interactions between articles based on keywords) (Donthu, Kumar, Mukherjee, et al., 2021).

Out of 114 authors involved in 33 articles, only one author was part of 3 articles—Steven Bellman at the University of South Australia. For the co-citation analysis, we kept the minimum number of citations per author to five. This reduced the number of authors from 3,006 to 94. The results are presented in four clusters (red, green, blue, and yellow) in Figure 5. Based on these clusters, Table 5 shows the five most co-cited authors in our corpus. Our analysis shows that out of 33 records, 20 documents cited 22 works of Annie Lang 41 times; 15 documents cited 26 works of Peter Lang 38 times; 14 documents cited works of Maragret Bradely 32 times; 13 documents cited 15 works of Robert Potter 26 times; and 8 documents cited 15 works of Michel Wedel 19 times.

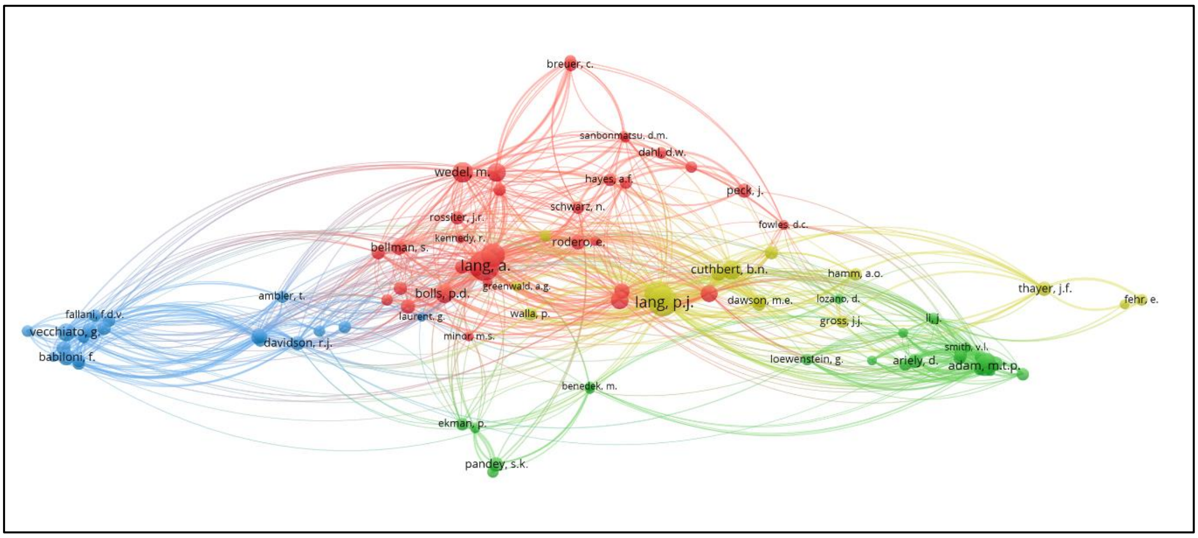

Figure 5. Co-citation analysis of most cited authors using VOSviewer (Van Eck & Waltman, 2010).

Citations	Author	University	Most referred work	Cluster
41	Annie Lang	Indiana University Bloomington	The Limited Capacity Model of Mediated Message Processing (2000)	Red
38	Peter Lang	University of Florida	Emotion and Motivation I: Defensive and Appetitive Reactions in Picture Processing (2001)	Yellow
32	Margaret Bradley	University of Florida	Emotion and Motivation I: Defensive and Appetitive Reactions in Picture Processing (2001)	Yellow

26	Robert Potter	University of Alabama	Psychophysiological Measurement and Meaning (2012)	Red
19	Michel Wedel	University of Maryland	A Review of Eye-tracking Research in Marketing (2008)	Red

Table 5. List of co-cited authors with the most citations and their most influential work.

For the co-occurrence analysis of keywords, we adapted steps from Veloutsou and Mafe (2020). First, keywords were obtained only from 24 records, since the other nine records did not give the authors' or an index of keywords. Second, all keywords with the same meaning were edited or replaced. Specifically, terms such as "brain wave," "galvanic skin response," and "branding" were changed to "electroencephalography," "skin conductance," and "brand." Third, we eliminated keywords that were generic, broad, and unsuitable to the study context. Fourth, in the final set, only 104 out of 117 keywords were found to be interconnected. Figure 6 illustrates the three main clusters derived from the co-occurrence analysis. Cluster 1 represents the consumer neuroscience tools used, along with heart rate variability. Major keywords in this cluster include "electroencephalography," "skin conductance," and "eye tracking." This cluster complements the knowledge presented in Table 5. Cluster 2 indicates the use of heart rate in promotion-related studies. Major keywords here include "heart rate," "advertisement," and "brand." As seen in Table 2, most records fall under the promotion theme of the marketing mix, and cluster 2 verifies this. Cluster 3 highlights emotional appraisal of the organism that forms the experience. Major keywords here are "emotion," "arousal," and "facial expression."

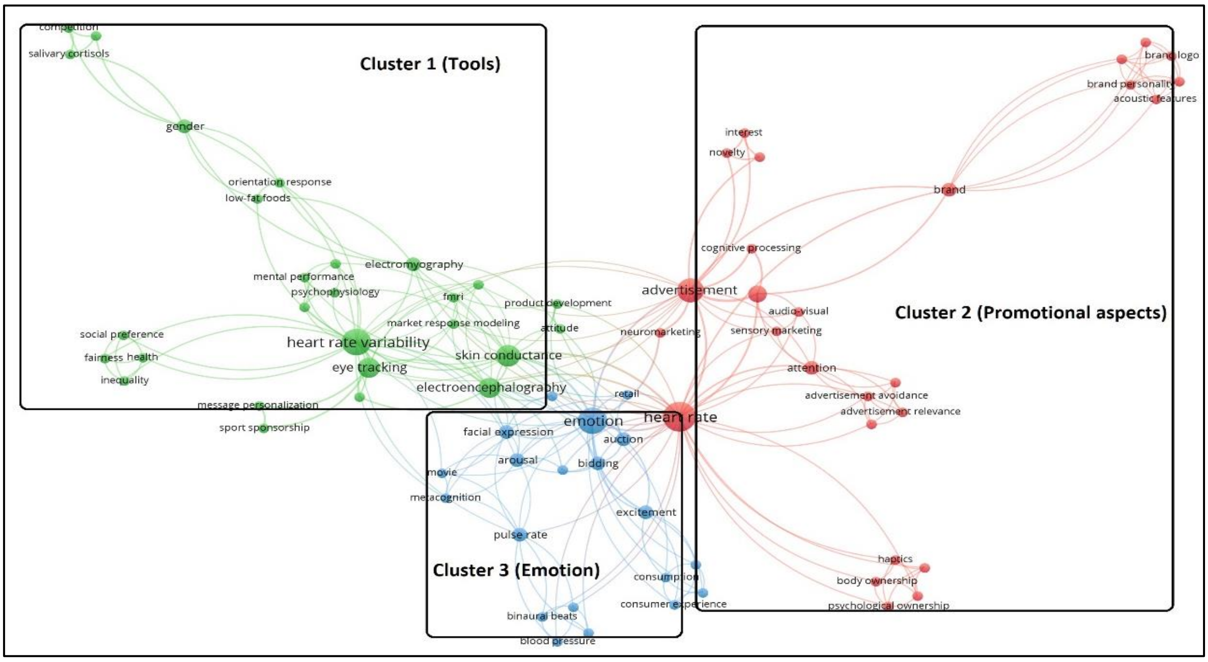

Figure 6. Keyword co-occurrence analysis using VOSviewer (Van Eck & Waltman, 2010).

4.3 Research avenues

Based on our analysis and expertise in marketing and psychophysiological signal processing, we propose six research avenues blending consumer centric SOR theory and traditional 4P marketing mix for potential marketing research. Following Loureiro et al. (2020) for future research directions, we divided our proposals in three distinct, but related, aspects of theory, characteristics, and methodology. Subsequently, Table 6 provides research questions for future studies.

4.3.1 Theory: New research directions

Most of the papers addressed isolated topics without any theoretical integration with marketing or consumer decision-making. The first avenue embraces consumer decision-making elicited by any 4P marketing mix through affective, cognitive, and sensorial constructs**.** Marketing researchers and practitioners stand to gain from understanding the physiological effects of emotions, as they play a vital role in consumer decision-making (Gaur et al., 2014). Emotional influence on consumer decision-making is categorized as integral (induced by advertisements, events, etc.) and incidental (brand choice, risk taking, etc.) (Achar et al., 2016). Valenza et al. (2014) used a probabilistic approach to analyze heartbeat dynamics, categorizing four emotional states based on the circumplex model of affect and using heart rate variability-derived features. The basic emotion approach classifies emotions into discrete categories (surprise, anger, joy, fear, etc.) evoked by marketing mix stimuli (Laros & Steenkamp, 2005). Additionally, the research has shown heart rate variability to be a physiological correlate of different cognitive domains, such as memory, attention, executive functions, and visuospatial skills (Forte et al., 2019), as well as cognitive load (Solhjoo et al., 2019). Research has also demonstrated the relationship between flow state and heart rate variability (Tozman et al., 2015).

4.3.2 Characteristics: New research directions

The second avenue considers personality, thinking style, and demographics. This set of variables can be considered as consumer profiles for decision-making. Zohar et al. (2013) highlighted significant associations between distinctive participant personality traits and heart rate variability metrics. Novel constructs, such as aggression (Kristofferson et al., 2017), can be correlated with heart rate variability indices (Zohar et al., 2013), thereby providing a refined understanding of consumer behavior

The third avenue addresses product experience at the point of sale and during consumption and usage. Alvino et al. (2020) highlighted the use of consumer neuroscience tools to study product experiences in retail stores. The LF/HF ratio as an heart rate variability metric may be useful for identifying the stress levels of individuals in controlled environments (Dulleck et al., 2011). The relationship between heart rate variability metrics and positive experiences should be further explored, as they may impact behavioral intentions, such as willingness to pay, patronage, and real purchase behavior. Customer experience involving the space–time dimensions of physical retail stores, including digital settings and virtual reality, can be informed via heart rate variability metrics. The space dimension of retail store can influence product allocations, store ambience (color, lights, or music), store crowdedness, and stimuli information (size, price tags, displays, packaging, or branding). The crowd level in retail stores may influence the psychological stress state due to limited space (Stokols, 1972). The time dimension refers to the saliency of stimuli over time, and heart rate variability could contribute to the measurement of arousal and excitement during a shopping trip to a retail store.

The fourth avenue focuses on advertising and branding. Almost 25% of heart rate variability studies examined the impact of several types of advertisement (e.g., television, trailers, YouTube videos, video games) on emotions (valence and arousal), cognitive processes (attention, engagement, memory, etc.), and consumer behavior (preferences, satisfaction). Continuous response remains a challenge when delivering message content (e.g., subsequent exposure to an ad, affect to arousal). In advertising research, it is useful to delineate the influence of frames, objects and subjects, and layout. A/B testing, or more sophisticated testing, represents an excellent opportunity to measure continuous emotional reaction to advertising content or formats and variations. Additionally, continuous measurements of time stimuli, such as video ads or online search, might provide variations over time indicating consumer responses to specific elements of each stimulus, such as size, colors, logos, and claims.

4.3.3 Methodology: new research directions

The fifth and sixth avenues address the correlation between heart rate variability and immersive and neurophysiological tools. In recent years, heart rate variability has been increasingly used in many fields to complement mixed reality systems (Halbig & Latoschik, 2021). Virtual reality enables consumer researchers to depict a variety of real-world situations with a suitable level of details, contextual elements, and sensory information, which allows for high ecological validity during experimentation. Carefully chosen stimuli relevant to marketing applications can evoke a range of experiences, such as stress, presence, enjoyment, or anxiety, which can be precisely correlated with physiological data. Studies published in the last decade in consumer research journals show that heart rate variability measurements are often used in conjunction with other neuroscientific tools, such as eye tracking and electroencephalography (see Appendix E). Furthermore, machine-learning algorithms may be applied to identify consumers' emotional experiences by utilizing features extracted from heart rate variability series. Random forest, k-nearest neighbor, and support vector machine are classifiers commonly used by researchers (see Bulagang et al. (2020) for a review).

Research directions	**Research avenues**	**Research questions**
Theory	Consumer decision-making involving affective, cognitive, and	Can heart rate variability dissociate rational and impulse buying of different product types such as hedonic and functional?

	sensorial constructs	Can heart rate variability series be used to predict the influence of product attributes or retail features on purchase behavior? How do various sensory touch points (e.g., scent, music, light, touch, and taste) influence heart rate variability and lead to purchase decisions? As consumers' emotional and cognitive factors are associated with brand experience (Plassmann et al., 2012), what insights into their underlying physiology can be inferred from the use of heart rate variability?
Characteristics	Personality, thinking style, and demographics	How do heart rate variability metrics differ based on personality traits, thinking styles, and demographics (e.g., gender and age)? How do these consumer responses evolve over time, framed by social interactions and environmental conditions (e.g., time and multitasking)?
	Product experience	How can continuous recording of heart rate variability detect consumers' experience and engagement with the products or services? How can heart rate variability infer a dissociative effect of space and time dimensions of the physical and virtual retail store on consumers' purchase behavior?
	Promotional aspects (advertising and branding)	How can portable heart rate variability devices be used to pretest or profile consumers for personalized and effective advertisements? Can heart rate variability assist in improving behavioral targeting of advertisements? How can heart rate variability analysis complement other biometric tools to improve detection of

		discrete consumer emotional responses (e.g., joy, fear, and sadness) to advertising content? How can heart rate variability captured through portable devices be improved to track consumers' affective states throughout the day? What insights can be derived from heart rate variability into consumers' attention and arousal towards advertising content?
Methodology	Correlation with immersive technologies	How can heart rate variability devices integrate with augmented and virtual technologies for capturing consumers' experiences in the metaverse environment?
	Triangulation with neurophysiological tools	How can heart rate variability series data be corroborated with other consumer neuroscience tools to accurately forecast behavior? Can the use of machine-learning algorithms and artificial intelligence improve heart rate variability analysis to detect consumer emotions better?

Table 6. Overview of research questions involving the use of heart rate variability

5. Guidelines and implications for planning heart rate variability studies in marketing

In this section, we outline general instructions for the new researchers or non-expert readers.

(i) Designing an empirical study with heart rate variability: (a) At the initial stage, the researcher should choose the stimulus type (interactive, multisensorial, or static) as categorized by the themes in Table 2; (b) the study context (natural vs. artificial environment) should be selected; (c) the type of device used to capture heart rate variability should be chosen (see Table 3); and (d) the sample size of the study should be based on research design and sample criteria (see section 4.1.3). It is recommended that sample size is estimated using power analysis (e.g., GPower 3.1) based on the study design, as sample size can significantly influence the outcomes of statistical tests; and (e) the choice of analysis and suitable measurement are dependent upon the study's objectives and the researcher's expertise.

(ii) Recommendation for choosing measurements: From a methodological viewpoint, it is quite difficult to perform a comparison analysis between heart rate variability measurements defined in time, frequency, and nonlinear domains. These measurements, in fact, may be redundant with respect to their physiological correlates (e.g., cardiac parasympathetic activity may be linked to RMSSD in the time domain and HF power in the frequency domain), while they may show different statistical power in a given task discerning marketing behaviors. We recommend the use of time domain measurements especially in case of short-term recordings (i.e., less than one minute), and the use of frequency domain measurements in recordings of length between 2 and 5 minutes. Beyond the spectral paradigm, effective measurements with specific physiological correlate should be used, maybe in a time-resolved fashion (Valenza et al., 2018). In case of longer recordings, analysis in the frequency domain should be performed through time-resolved methods (e.g, time-varying spectral analysis). Nonlinear analysis may be performed in series longer than 5 minutes. Of note, nonlinear analysis is more sensitive to fast changes and spikes in the series than time and frequency analyses.

(iii) Participants' characteristics: Various combinations of exogenous and endogenous factors can contribute to confounding in heart rate variability analysis. It is important that researchers pay detailed attention to participants' age, lifestyle (smoking, alcohol consumption, drug use, coffee intake, etc.), pathological conditions, and fitness levels for accurate measurement comparisons (Acharya et al., 2006).

(iv) Data triangulation**:** This process involves data correlation attained via multiple methods (quantitative or qualitative) or techniques (behavioral, physiological, or neurophysiological) to make behavioral predictions. Researchers should acknowledge that heart rate variability can be correlated with consumer arousal levels and their emotional valence (positive or negative). This provides an incentive to validate heart rate variability measures with other consumer neuroscience tools (see Appendix E) and rigorously validated self-reports, to provide a robust picture of consumer emotions (Royo-Vela & Varga, 2022). In their recent work, Baldo et al. (2022) concurrently used heart rate variability, electrodermal activity, electroencephalography, and self-report responses to examine the effect of stimulus type (images, videos, and TV advertisements) on consumer decision-making. The results revealed that heart rate variability correlates with self-report valence and predicts advertisement and brand recognition. Across the stimulus type, heart rate variability reliably recognized differences between positive and negative valence, whereas electrodermal activity consistently correlated with self-report arousal. While heart rate variability was not a significant predictor of the purchase intention, frontal alpha asymmetry obtained from electroencephalograms significantly predicted purchase intent. Taken together, the complementary nature of the techniques provides various sources of data to help forecast attitude and subsequent behavior.

(v) Statistical factors: Checking the normality of physiological data is essential. The heart rate variability series may not be normally distributed, requiring non-parametric approaches or bootstrapping methods for inferential analysis (Massaro & Pecchia, 2019). Non-parametric approaches, such as fast Fourier transform, are simpler to employ with high processing speed compared to parametric approaches (Malik et al., 1996).

6. Conclusion

Heart rate variability is emerging as a reliable, accurate, and valuable noninvasive tool for capturing consumer physiological and emotional responses. Despite gaining prominence in varied research domains, heart rate variability methodology is a daunting task for marketing researchers. The present study is the first to conduct a comprehensive literature review on the use of heart rate variability in marketing research. Previous research has scarcely utilized its full potential and has often been used as a complementary tool. To overcome this limitation, this literature review provides twofold contributions: (1) develops a conceptual framework that provides a structured overview of the evolution of heart rate variability tools over the past two decades and prominent topics covered in marketing research; and (2) provides research avenues and guidelines for theoretical and practical exploration in the marketing domain. Our review offers perspectives to both practitioners and researchers alike, making it a worthwhile contribution.

Our literature review attempts to assist future marketing researchers with the use of heart rate variability. To achieve this aim, we interspersed the production-oriented marketing mix (Constantinides, 2010) with the consumer-centric SOR framework. Regarding the most frequent topics investigated through heart rate variability, promotional aspects dominate previous marketing research, followed by product aspects of the marketing mix. Regarding measurements, heart rate is used most frequently. Further, the time-domain measurements are the most common. Regarding data collection, ECG devices are being replaced by portable or wearable devices placed on fingers or wrists.

A deeper analysis of the topics addressed in previous papers was performed through a co-occurrence analysis of keywords, showing three cluster topics: (1) consumer neuroscience tools used, along with heart rate variability; (2) heart rate in promotional issues; (3) highlighting emotional appraisal of the organism that forms the experience. These results indicate the complementary nature of heart rate variability with other neurophysiological tools, its focus on promotional issues, and its suitability for measuring emotions.

Based on our analysis, we suggest six main research avenues. First, the consumer decision-making elicited by any of the 4Ps with a special focus on emotional effects. Second, as heart rate variability relates to the subject's nervous system, we advocate for new research that goes deeper regarding personality, thinking style, and demographics and their relationship with heart rate variability. Third, consumer experience at the point of sale and during consumption or usage might be a fruitful research area for heart rate variability. Fourth, as advertising stimuli trigger emotional effects, continuous heart responses to such stimuli become a useful research area. Fifth, integrating heart rate variability with immersive technologies can provide an opportunity for capturing novel affective and cognitive constructs with high ecological validity. Sixth, using heart rate variability with other neurophysiological tools provides immense potential for predicting consumer behavior.

Additionally, we emphasize that future research should consider the two key ethical dimensions with respect to its use for marketing research. First, the protection of participant confidentiality, privacy, and informed consent should be an unwavering commitment of the researcher. Second, the reporting of the analysis and subsequent findings should be rigorously valid, interpretable, and transparent.

6.1 Limitations and directions for future research

This research comes with two drawbacks that may provide opportunities for future researchers. From the methodological perspective, our database held only journal articles and no conference papers. The latter may point to emerging research relevant for understanding heart rate variability in the marketing context. The exclusion of marketing-allied subject areas (e.g., tourism and hospitality) limits deeper contributions of the heart rate variability tool.

CHAPTER 4

COGNITIVE LOAD DURING PLANNED AND UNPLANNED VIRTUAL SHOPPING: EVIDENCE FROM A NEUROPHYSIOLOGICAL PERSPECTIVE

This is the third out of three complied publications. The study examined differences in cognitive load while making a planned and unplanned purchase in a virtual-reality based supermarket. The study also examined the effect of flow experience and impulsivity on behavioral outcomes such as the desire to stay and unplanned expenditure. It is accepted and published online in the International Journal of Information Management: Kakaria, S., Saffari, F., Ramsøy, T. Z., & Bigné, E. (2023). Cognitive load during planned and unplanned virtual shopping: Evidence from a neurophysiological perspective. *International Journal of Information Management,* 72. https://doi.org/10.1016/j.ijinfomgt.2023.102667

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Research article

Cognitive load during planned and unplanned virtual shopping: Evidence from a neurophysiological perspective

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A B S T R A C T

Rapid adoption of virtual-reality-assisted retail applications is inadvertently reshaping consumer buying patterns, making it crucial for businesses to enhance their shopping experience. This new scenario challenges marketers with unique hurdles in both the commercialization of products and in managing information cues derived via VR retailing. Therefore, this study examined consumers' impulsive behavior and unplanned purchases in a virtual retail store, using self-reports and electroencephalography. Borrowing assorted perspectives from retailing, virtual reality, and neuromarketing literature, we extended the stimulus-organism-response framework to evaluate how unplanned behavior evolves through conscious and unconscious measures. We found that consumers' impulsiveness was significantly associated with their unplanned expenditure and the number of unplanned purchases. Using mediation analysis, we observed that flow experience during shopping partially mediated the relationship between the sense of presence and the desire to stay longer in a virtual shopping store. Desire to stay in the virtual store positively influenced store satisfaction, basket-size deviation, and budget deviation. Additionally, cognitive workload obtained via electroencephalogram revealed significant differences during both planned and unplanned purchases. These findings provide fresh opportunities for retailers to leverage the disruptive potential of immersive and interactive virtual technology to transform consumer shopping experiences.

1. Introduction

Over the past decade, the landscape of consumer retail experience has rapidly evolved, including the expediting of consumer rates of adopting extended reality technologies, due to continuous improvements in retailing solutions and artificial intelligence ecosystems (i.e., hardware, software, and applications) (Dwivedi et al., 2022; Grewal et al., 2017; Koohang et al., 2023). Recent reports estimate that the global market for the metaverse will reach $678 billion in U.S. dollars by 2030 (Alsop, 2022), with more than 25% of consumers worldwide anticipated to spend time regularly in the metaverse by 2026 (Alsop, 2022). In contrast to augmented-reality (AR) environments, users wear head-mounted display (HMD) glasses and experience virtual reality (VR) as a replacement for the local physical environment, ranging from low-level to high-level degrees of telepresence (Rauschnabel et al., 2022). Utilizing VR technology to partake in retailing activities, under the ambit of metaverse retailing i.e., retail-related activities in virtual spaces, is an emerging distribution channel that offers a unique setting for marketing research (Dwivedi et al., 2022). The challenge therein lies in businesses capturing, analyzing, and inferring consumer spending patterns in VR-based shopping environments, to enable crafting management-level strategies (Blasco-Arcas et al., 2023; Giang Barrera & Shah, 2023).

Unplanned shopping poses challenges for retailers because it affects overall cart value at the point of purchase, management of assortments, and sale of new products (Kato & Hoshino, 2021; Nigam et al., 2022). A recent report on social media consumers suggests that a staggering 63% of purchases are unplanned, 23% are impulsive, and only 14% are planned (Chevalier, 2021). Arguably, encouraging unplanned purchases may be of greater significance to retailers in ascertaining higher profit margins. However, retailers need a better understanding of unplanned purchases, one that embraces consumers' explicit opinions and implicit

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1. Introduction

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Consumer research defines unplanned purchases as those undetermined at the brand or category level prior to the store visit (Abratt & Goodey, 1990; Inman et al., 2009; Streicher et al., 2021), whereas impulse purchases occur due to the spontaneous urge to buy a product (Rook & Fisher, 1995). Consumer decision-making for impulsive and unplanned purchases can differ depending on whether the consumer uses a deliberative or an implementing mindset

(Sohn & Ko, 2021). Notwithstanding the differences between these two approaches, prior works have used appropriate insights from impulse-buying literature to explain unplanned buying behavior. In this sense, multiple reviews and meta-analyses of impulsive buying (see Iyer et al., 2020; Mandolfo & Lamberti, 2021) constitute a reference for our research. Regarding the outcome of unplanned buying, the literature is prone to focus on sales as a key variable (Hui, Huang et al., 2013). However, three intermediate variables may contribute to explaining sales volume: the number of products or the number of units per product bought, the desire to stay at the store, and the amount of time spent in the store (C. W. Park et al., 1989). Desire to stay and time spent are of chief interest, as they can explain purchase behavior and provide intrinsic value in cases where consumers do not buy. Moreover, the interaction between price levels and the available shopping budget shapes final purchase decisions.

Although knowledge of explicit unplanned buying behavior is valuable, scant literature addresses the neural mechanisms that influence such behavior. From a methodological perspective, most of the published research on impulse buying and unplanned purchases has utilized questionnaires and experimental designs (Mandolfo & Lamberti, 2021). In contrast to such research, we use an electroencephalogram (EEG) to complement the survey data, as it provides a superior temporal sequence in the context of dynamic consumer decision-making (Lin et al., 2018). Further, electroencephalography serves as a unique, non-invasive physiological index for continuously measuring cognitive workload (Antonenko et al., 2010) during planned versus unplanned purchases within a consumer shopping journey. Therefore, this study integrates in-store observational variables and unconscious responses, to provide an integrative explanation of their influence on purchase decisions.

Developing VR technology can help businesses to better understand consumers' in-store shopping patterns and to explore its potential as a major distribution channel (Barrera & Shah, 2023). In this study, we present consumers with a shopping task in a simulated virtual environment whose resemblance to a physical supermarket has three benefits for our research. First, it increases the study's ecological validity because it provides a realistic depiction of product assortment, store layout, and shopping experience (hedonic and utilitarian values) (Alcañiz et al., 2019), as well as comparable information-seeking (C. Xu et al., 2021) and choice behavior (Fang et al., 2021), and holistic means of capturing cognitive workload (Xi et al., 2022). Second, observing and monitoring subjects in such a scenario helps to test variables that are difficult to observe in physical environments (Schnack et al., 2020; Wang et al., 2021). Third, recent developments in VR complement the use of neurophysiological tools (e.g., EEG) in examining accurate measures of brain responses when shopping, allowing for better experimental control of variables and, thereby, better internal validity (Wajid et al., 2021; Wedel et al., 2020).

Understanding the reasons behind consumers' unplanned buying is fundamental to outlining theoretical implications and managerial insights for businesses. Thus, we aim to contribute to the existing literature, first by integrating dispersed elements of unplanned buying that pivot on consumer traits (e.g., impulsivity), store experience (e.g., desire to stay and flow experience), and available consumption resources (e.g., budget and time) in unplanned purchases. Next, we measure implicit brain responses (e.g., cognitive workload) via EEG, so this study expands on the current knowledge of the internal mechanisms that differentiate between planned and unplanned buying at a neural level. Finally, we consider the influence of VR characteristics (i.e., sense of presence) and psychological mechanisms (e.g., impulsivity and flow experience) on planned and unplanned shopping behavior in a stimulus-organism-response (SOR) framework. Such an integrative approach will lead to a better understanding of the dimensions that influence unplanned buying and contribute to the development of virtual commerce as a distribution channel. Finally, this study addresses the call for further research that Hilken et al. (2022) and Dwivedi et al. (2022) outline, to investigate consumer behavior vis-à-vis VR marketplaces. From a managerial point of view, marketers can benefit from this approach by identifying information signals (i.e., behavioral cues at the store) that produce insights about unplanned purchases at the point of sale, which may ultimately lead to better assortment configuration and product disposition.

The remainder of the article will unpack the following topics. Section 2 outlines the prior research on impulsive, planned, and unplanned shopping behavior. In addition, the section discusses cognitive load during shopping and introduces the SOR framework. Section 3 provides theoretical support for the hypotheses. Section 4 details the study methodology and provides a sample profile. Section 5 reports the data analysis results of the experiment. Section 6 discusses theoretical and practical implications, limitations of the study, and the scope of future research. We conclude the study with key takeaways in Section 7.

2. Literature review

2.1 Impulsive, planned, and unplanned shopping behavior

In the past, researchers have distinguished between impulsive, planned, and unplanned purchases. This distinction between planned and unplanned purchases has been studied in a retail context (Abratt & Goodey, 1990). Planned purchases are those for which consumers deliberate and make a list of products they want, prior to reaching the point of purchase, whereas in unplanned purchases occur when consumers stroll past the point of purchase and recognize that they need or desire the product they see. Piron (1993) studied variations in shoppers' emotional reactions to unplanned, planned, and impulsive shopping. Compared to planned shoppers, impulsive shoppers experienced a greater desire to purchase and a greater feeling of helplessness, whereas unplanned shoppers felt significant differences in desire to purchase, but also feelings of guilt (Piron, 1993). Verplanken and Sato (2011) reason that "purchases may be unplanned but not impulsive, such as habitual purchases, purchases that unexpectedly solve an existing problem, or purchases that are simply too unimportant to plan or think about." Therefore, unplanned purchasing is not a necessary condition of impulsive buying (Rook & Hoch, 1985). According to regulatory focus theory, promotion-oriented consumers engage in more unplanned buying; prevention-oriented consumers avoid impulse purchases (Kato & Hoshino, 2021). Shoppers engage in unplanned buying when they see the product and recognize the need for it (Bellini et al., 2017), whereas impulse purchases occur with no established need for it (Amos et al., 2014). Factors that drive unplanned buying behavior include the overall shopping-trip goal, store-specific goals, promotions, time spent shopping, and convenience (D. R. Bell et al., 2011). As a result, unplanned purchase behavior is triggered at subconscious level (Ozkara & Bagozzi, 2021; Saffari et al., 2023).

2.2 Cognitive load during shopping

Examining the role of cognitive load on consumers is critical for information science and management research (Eberhard, 2021). It is a multidimensional construct that reflects the cost (i.e., mental, physical, temporal demand) that the focal task imposes on working memory (Hart, 2016; Sweller, 2011). Individuals have only limited workload capacity to expend. With an increase in task complexity, performance can suffer if it exceeds the individual's workload capacity (Xi et al., 2022). Concurrently, excessive or complex information can overwhelm individuals and lead to information overload, especially in the case of sensory information (Malhotra, 1984; Malhotra et al., 1982). Presumably, different situations and tasks require varied working-memory resources and can be intrinsic or extraneous in a shopping context (Schmutz et al., 2009). According to Plass and Kalyuga (2019), if search processes are not at least minimally guided or explicit instructions are not provided during the task, a significant effect on working-memory load occurs, hindering meaningful (or optimal) learning. Borrowing perspectives from cognitive load and information overload theories, exerting greater mental efforts will yield a suboptimal shopping experience, leading to less time spent in the environment, dissatisfaction with the product or service, shopping cart abandonment (Mirhoseini et al., 2021; Schmutz et al., 2009), social media fatigue (Guo et al., 2020), affecting working memory's usability during consumption, the "feature fatigue effect" (Thompson et al., 2005). Huang (2000) identifies complexity and novelty as two dimensions of information overload applicable to online shopping behavior. While information complexity reduces consumer desire to visit a shopping site, information novelty increases customer intent to visit it (Huang, 2000). Additional consequences include risk-averse behavior and impatience with money (Deck & Jahedi, 2015), decision quality (H. Zhang et al., 2018), and decision difficulty (Hu & Krishen, 2019). Consumers exploring the VR version of a physical shopping environment with which they are familiar are likely to experience low cognitive load and positive impacts on their attitude toward shopping in VR (Luna-Nevarez & McGovern, 2021). While studies on cognitive load have relied more on subjective self-reports than using objective physiological techniques (Krell et al., 2022), EEG is a direct and valid method for capturing cognitive load, unhindered by the individual's biases resulting from cognitive limitations or preferences (Schapkin et al., 2020). Using EEG, cognitive load can be predicted by analyzing the change in relationship between power spectrums (Antonenko et al., 2010; Schapkin et al., 2020). Prior studies in marketing (see Table 1) have utilized neurophysiological tools (i.e., EEG) to measure cognitive load, while others have estimated cognitive load via EEG in VR (Tremmel et al., 2019) and multimedia learning environments (Murtazina & Avdeenko, 2020).

Table 1. Summary of prior empirical works using cognitive load and information load theories in consumer research.

Study	Objective	Use of immersive technology / Context.	Implicit measures to record cognitive load.	Design(*)	Theoretical (or framework) support	Key findings
Lee & Sergueeva (2017) ~ Study 3	To examine the association between chewing gum and consumer thought - engagement.	No. Airport retail elements.	No. Questionnaire.	BS	Chewing effect; Cognitive load theory	When cognitive load is high, the chewing effect is mitigated.
Zhang et al. (2018)	To analyze the relationship between quality (enablers and inhibitors) of online product recommendations and online product brokering efficiency and loyalty.	No. E-commerce shopping.	No. Questionnaire.	WS	Information overload theory; Cognitive load theory	Information overload was found to be positively associated with product screening cost and product evaluation cost, and negatively associated with decision-making quality.
Huang & Zhou (2019)	To investigate impact of personalized product recommendations on consumer decision quality.	No. Online shopping.	No. Questionnaire.	BS	Information overload theory	Personalized product recommendations can reduce information load effect on (perceived) information overload.
Aydınoğlu &	To analyze the impact of verbal	No.	No.	BS	Imagery theory	Cognitive load disrupts

Krishna (2019) ~ Study 4	communication of retail store deals on consumer's consumption imagery.	Retail-store deals.	Questionnaire.			consumption imagery effectiveness of retail store deals.
Fan et al. (2020)	To analyze the influence of AR adoption in online retail on consumer product attitudes.	Yes. Augmented reality. Product category.	No. Questionnaire.	BS	Cognitive load theory; cognitive theory of multimedia learning; Situated cognition theory; and cognitive fluency theory	Cognitive load is lowered by environmental embedding and simulated physical control.
Mirhoseini et al. (2021)	To investigate the influence of product type and arithmetic task complexity on consumer's perceived satisfaction and mental effort.	No. Online grocery.	No. Questionnaire.	WS	Cognitive absorption theory	Experience product types exert higher perceived mental effort than search products, and arithmetic complexity is positively associated with perceived mental effort.

Bigne et al. (2021)~ Study 1	To examine online advertising effectiveness on social media.	No. Online advertisement.	Yes. EEG	WS	Cognitive load theory	Viewing user-generated content when the advertisement is embedded in social media did not increase the cognitive load.
Arghashi (2022)	To examine influence of AR attributes (positive and negative) on consumer purchase intention	Yes. Augmented reality.	No. Questionnaires.	BS	SOR framework; Information overload theory; Wow-effect	Contrasted with non-AR apps, AR apps lessen information overload, and information overload positively influences perceived distraction of the consumers.
Xi et al. (2022)	To examine the distinct effects of immersive technologies on workload.	Yes. Virtual reality and Augmented reality. Record shop.	No. Questionnaire.	BS	Cognitive load theory	VR had no significant effect on subdimensions of workload but AR significantly related to overall workload.
Kim (2022) ~ Study 4	To analyze the effect of cognitive load on product evaluations when primed.	No. Product evaluation	No. Questionnaire.	BS	Priming effect; Cognitive load theory	Inducing cognitive load can mitigate the effects of happiness primes on

						product evaluation.
This Study	To examine differences between cognitive load during planned and unplanned shopping.	Yes. Virtual reality. Supermarket.	Yes. EEG	WS	SOR framework ; Cognitive load theory	Cognitive load was higher during planned purchases as compared to unplanned purchases.

(*) WS: within-subjects; BS: between-subjects

2.3 Applying the SOR framework in VR-based shopping.

Previous research has utilized virtual environments to understand the influence of product types (e.g., food and beverage, wine, electronics), types of stores (e.g., supermarket, dressing room), and intrinsic and extrinsic cues (e.g., product attributes and in-store promotions) on shopper behavior in retail (Xi & Hamari, 2021; C. Xu et al., 2021). However, the use of the SOR framework in VR has been limited and scattered. Mehrabian and Russell (1974) introduced the seminal SOR framework, widely employed to examine consumer behavior in information science, virtual reality, neuroscience, and retailing contexts (Daisy et al., 2022; Suh & Prophet, 2018; Vieira, 2013; Xiong & Zuo, 2020). It comprises three interrelated components. The first, stimulus (S), is the consumers' shopping environment (i.e., a conventional physical store, an online store, or a fully immersive virtual store). These environments contain a range of cues acting as antecedents, affecting an individual's internal state (Jacoby, 2002). Environmental stimulus in a retail context includes a mix of store atmosphere, technical features, and situational cues (Buckley, 1991; Daisy et al., 2022). Previous studies in VR have used technological (e.g., visual display, movement tracking, interactivity) and content-based (e.g., virtual journey, gaming) stimuli to prompt psychological and behavioral responses (Suh & Prophet, 2018). In our study, we use sense of presence as a core aspect of stimulus components, for two interlinked reasons. First, it is considered to be the primary aim of virtual experiences that seek to engage users to interact and simulate in the environment (Grassini & Laumann, 2020). Second, it influences elements of an individual's internal processing of the VR shopping environment, such as flow experience, as well as organism's response, such as purchase intention (Shen et al., 2021). Taken together, sense of presence appears to be a critical variable for the VR shopping experience. Sense of presence refers to a feeling of "being there" in an artificial environment that can imitate certain qualities of reality, offering individuals a sense of being in a different place where they actually are (Grassini & Laumann, 2020; Scarfe & Glennerster, 2019).

The next element comprises the individual's internal state, including emotional and cognitive processing vis-à-vis the environmental stimuli, known as the organism (O) (Vieira, 2013). In a VR context, Kim et al. (2020) used cognitive and affective (enjoyment, emotional involvement, and flow state) responses; Jin et al. (2021) used arousal and pleasure; Chen et al., (2022) used telepresence, perceived diagnosticity, and playfulness as organism components. In our framework, we use consumers' impulsiveness and flow experience as elements of organism components**.** Consumer's impulsive behavior involves the complex interplay of personal and in-store factors (Redine et al., 2023), making it critical for investigation during a virtual shopping scenario (Suh & Prophet, 2018). Previous studies in VR have examined the role of the impulsivity trait in the urge to buy impulsively (J. V. Chen et al., 2022) and of shopper personality traits in impulse purchases (Schnack et al., 2021)**.** However, research has scarcely pursued associating consumers' impulsiveness and unplanned purchases in a VR context. With this perspective, our framework allows validating the role of impulsivity during virtual shopping, extending previous research by Schnack et al. (2020) and Vrechopoulos et al. (2010). Next, a VR shopping experience elicits a flow experience (Cowan & Ketron, 2019), immersing a person in the activity in which they are participating (Nakamura & Csikszentmihalyi, 2009), intrinsically an enjoyable state (Hoffman & Novak, 1996) with a positive relationship with behavioral intention to use VR technology for shopping (Han et al., 2020). To analyze the organism component of the SOR framework and consequently optimize the customer experience requires examining the consumer flow experience in a VR environment and its subsequent influence on behavioral intentions (Kim et al., 2020)._VR environments provide greater perceptual and cognitive benefits compared to real environments (Xi et al., 2022) and promote a sustainable method of shopping (Laukkanen et al., 2022). In this regard, sense of presence and flow experience emerge as two critical factors associated with technological and psychological mechanisms that explore consumer behavior when engaging with immersive technology (Suh & Prophet, 2018; Wedel et al., 2020).

The third element is the individual's response (R) to the combination of stimulus and organism components (Vieira, 2013). VR studies have used store attractiveness (Jin et al., 2021), urge to buy (J. V. Chen et al., 2022), and behavioral intentions (Loureiro et al., 2021) as response elements in a retail context. The SOR framework has served mainly to produce behavioral and observational outcomes in VR, such as shopping time and amount spent (Schnack et al., 2021), but unconscious outcomes have rarely been used as response measures. While the VR environment is suitable for directly capturing consumers' experience, studies have rarely evaluated consumers' desire to stay in a virtual store in conjunction with explicit and implicit shopping outcomes. Data obtained from EEG provide objective interpretations of consumers' subjective evaluation of multisensory stimuli (Bazzani et al., 2020). In this regard, using EEG-derived cognitive load as a proxy for the shopping experience provides novel implicit measures by which to expand the SOR framework. Given these gaps, our conceptual framework (Figure 1) uses sense of presence in the virtual store as stimulus, consumers' dispositional trait of impulsivity and their flow experience as organism, and implicit (cognitive load during planned and unplanned shopping) and explicit (unplanned shopping expense, number of unplanned purchases, time spent in purchasing planned and unplanned products, budget deviation, basket-size deviation, desire to stay, and store satisfaction) metrics as response in the shopping journey.

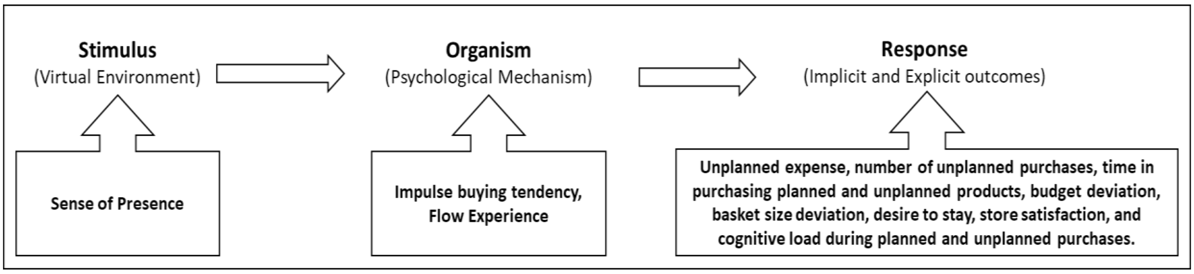


Figure 1. Conceptual framework

3. Theoretical background and hypotheses development

3.1 Consumer impulse buying during shopping.

Consumers' impulsiveness is often described as their disposition to purchase on an urge, with little reflection. Rook and Hoch (1985) identified five elements of impulsive behavior to distinguish it from non-impulsive behavior: (1) sudden desire to act, (2) urge to buy, (3) possible psychological conflict, (4) reduced cognitive evaluation of product attributes, and (5) no consideration of the consequences. Consumers' impulse buying can qualify as a complex mixture of their conative, visceral, and cognitive factors (see Mandolfo & Lamberti, 2021). Previous literature has also identified the factors that influence impulse buying behavior, including individual characteristics, demographics, and personality traits; economic resources, such as available budget (Iyer et al., 2020); product category variables; situational factors of the store; and marketing-driven actions (Bellini et al., 2017; Iyer et al., 2020). Previous studies have shown an association between the consumer's impulsivity and unplanned purchase behavior (Streicher et al., 2021). The urge to buy impulsively often leads to a consumer's unplanned purchases during shopping (Bellini et al., 2017). In their work, Paul et al. (2022) highlighted significant antecedents to the urge to buy, including perceived enjoyment, perceived usefulness, hedonic and utilitarian values, positive and negative affect, scarcity, and impulsive buying tendency. In the context of virtual-reality-based shopping, previous studies have found that telepresence, perceived diagnosticity, and playfulness positively influence an urge to buy impulsively (J. V. Chen et al., 2022). Consequently, higher impulsivity leads to more unplanned purchases (Santini et al., 2019) and sometimes unplanned purchases act as an indicator for quantifying consumers' impulse buying (Mandolfo & Lamberti, 2021). While the association between consumers' impulsive and unplanned behavior has scarcely been studied in a virtual commerce context, we posit that consumers will reflect purchase patterns analogous to e-commerce (Chan et al., 2017) and physical store environments (Amos et al., 2014), as follows:

H1. Consumers' impulsivity positively influences their (a) number of unplanned product purchases and (b) unplanned purchase expenses.

3.2 Cognitive load during planned and unplanned purchases

Planned purchases are the result of a previously recognized problem or a buying intention formed prior to entering the store (Piron, 1993). During a planned-purchase scenario, consumers carry shopping lists that act as a physical cue for products and brands they desire to purchase (Suher et al., 2019). Unplanned purchases occur due to the lack of a purchase decision before the shopping trip. This means that during a shopping trip, consideration of unplanned purchases tends to occur later than planned purchases (Hui, Huang et al., 2013). Unplanned purchases are of high economic value (i.e., revenue) and are also the flagship for retailers in managing the store products portfolio. Previous studies have concurred that information load during shopping is inextricably linked to the length of time spent (Jacoby et al., 1976). Additionally, from a subconscious perspective, goal-directed (top-down attention) vs. stimulus-driven (bottom-up attention) behavior interacts with cognitive load and temporal boundaries during decision-making (Orquin & Mueller Loose, 2013), and previous research has shown that shopper's use of shopping lists is a goal-directed behavior (Ahmed & Ting, 2018). From our study's perspective, goal- vs. stimulus-oriented behavior can be analogous to predefined planned vs. non-specific unplanned shopping tasks (Bialkova et al., 2020; Huddleston et al., 2018). In contrast to unplanned purchases, where consumers do not have predetermined specific subgoals, consumers undertaking planned purchases have multiple smaller goals that they achieve by adding items present on the shopping list to the basket (Suher et al., 2019). Consumers with a higher-level motivation to fulfill their goal pursuits (i.e., products on the shopping list) are faster at finishing their in-store shopping (Suher et al., 2019). Both perspectives affirm that cognitive load during unplanned and planned purchasing will be significantly associated with the time spent in each phase. Therefore, our hypothesis is as follows:

H2a. Cognitive load during planned and unplanned purchase phases will positively influence the duration of time spent in planned and unplanned purchases, respectively.

Because the amount of time available for shopping regulates shoppers' information processing of items and related in-store cues (Bettman, 1979), we anticipate that once planned purchases are completed, consumers may experience less cognitive load when shopping for unplanned items. Previous research has shown that individual involved in a task with high motivation can temporarily increase cognitive load (Mutlu-Bayraktar et al., 2019), such as for a goal-oriented planned task. Saffari et al. (2023) found a significant association between higher cognitive load and a low frontal asymmetry score during planned decisions, whereas a higher frontal asymmetry score and lower cognitive load occur during unplanned decisions. We posit that cognitive load during unplanned purchases will vary from that during planned purchases, due to the lack of goal specificity (Sweller, 2011). Consequently, our hypothesis is as follows:

H2b. Cognitive load during unplanned purchases will significantly differ from that during planned purchases.

3.3 Presence and flow experience as aspects of VR shopping

Sense of presence is an innate part of the virtual experience and serves as a quality assessment of the virtual shopping experience (Alcañiz et al., 2019; Xi & Hamari, 2021). Immersion, engagement, and sensory fidelity are chief determinants of presence, whereas emotional responses and behavioral intentions are consequences of presence in virtual experiences (Yung et al., 2021). Pizzi et al. (2020) reported that compared to traditional store environments, subjects perceived a stronger sense of presence in VR retail environments, but the effect was not dependent on the technological self-efficacy of the individual subjects. Additionally, individuals in virtual environments report greater feelings of immersion and perceived naturalness compared to a desktop shopping experience, leading to enhanced telepresence (Schnack et al., 2019). We expect that due to the immersive nature of VR enhancing the psychological feeling of engagement with the environment (Wang et al., 2021) and the amount of involvement a task in a virtual environment requires (Witmer & Singer, 1998), shoppers will desire to stay longer in the virtual environment.

Previous research has shown flow experience as a critical diagnostic cue in virtual experience because it significantly elevates satisfaction from VR spectatorship (Kim & Ko, 2019). Flow experience is described as a holistic sensation from which an individual feels absorbed, with complete involvement in an activity (Csikszentmihalyi & LeFevre, 1989). Accordingly, when immersed in VR, the user exhibits concentration on the task, with a feeling of positive gratification (Suh & Prophet, 2018). Furthermore, flow experience is a crucial mediator for consumers' continued intent to utilize an information system (Dincelli & Yayla, 2022; Yan et al., 2021). Antecedents to flow experience include easiness, usefulness, and enjoyment, which consequentially influence subjective well-being and the continued intention to use VR technology (Kim & Hall, 2019). Flow experience is positively associated with exploratory shopping behavior and positive affect (Novak et al., 2000), purchase intention and loyalty to an online supermarket (Morales-Solana et al., 2021), psychological ownership (Yuan et al., 2021), and consumer enjoyment of a retail store (Wang & Hsiao, 2012) during shopping activities. We believe that will positively influence consumers' desire to stay longer in the virtual shopping environment. Presence and flow experience are distinct but interconnected constructs involving immersion, such that the presence has been showcased as an antecedent to flow experience (Bachen et al., 2016). We argue that flow experience will mediate the association between sense of presence and the desire to stay to shop in a virtual environment (Figure 2). Therefore, we state our hypothesis as follows:

H3. Flow experience will mediate the relationship between sense of presence and the desire to stay in the virtual shopping environment.

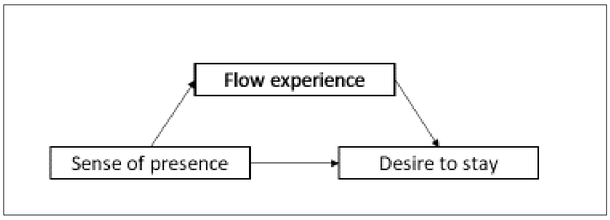


Figure 2. Proposed mediating effect of the flow experience.

3.4 Influence of consumers' desire to stay and the impact of time on shopping behavior.

We examine desire to stay as a response variable and a component of consumers' approach behavior, linked with behavioral intentions (Wakefield & Baker, 1998). From the perspective of SOR theory, consumers' affective responses in traditional retail stores influence approach behavior, which, in turn, might strongly influence unplanned shopping behavior (Donovan et al., 1994). Previous studies have examined the influence of time spent on a shopping trip on consumers' budget deviations, which is defined as the amount spent from the total budget during a shopping trip (Stilley et al., 2010). Due to depletion of the self-regulatory process during in-store shopping, consumers can have less inclination to stay within a predetermined budget as the length of the shopping trip increases (Stilley et al., 2010). We define basket-size deviation as the quantity of unplanned products in excess of planned product purchases during a shopping trip (i.e., basket-size deviation = total products bought – planned products bought).

In the online retail context, Kim et al. (2007) found that a high level of image interactive technology (i.e., 3D virtual model) positively influenced the desire to stay on the retail website, which, in turn, strongly influences patronage intentions. Satisfaction is a central concept in retailing literature, and is described as a multidimensional experience influenced by the quality of the store and the merchandise available (Oliver, 2014). From roots in expectancy disconfirmation theory, Bloemer and Ruyter (1998) conceptualized store satisfaction as the "outcome of the subjective evaluation that the chosen alternative (the store) meets or exceeds expectations." Using the SOR framework, Elmashhara and Soares

(2022) linked consumers' desire to stay with shopper satisfaction in a retail atmosphere. Therefore, we hypothesize the following:

H4. Consumers' desire to stay in a virtual store will positively influence (a) budget deviation, b) basket-size deviation, and (c) satisfaction with the store.

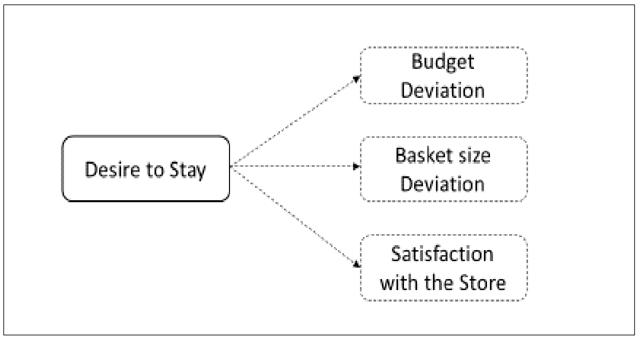


Figure 3. Schematic representation of the effect of desire to stay on budget deviation, basket size deviation, and satisfaction with the virtual retail store.

Availability of time is a critical factor that affects unplanned shopping behavior and sales in a retail context (Davydenko & Peetz, 2020). Time considerations can result in negative effects, such as failure to purchase intended products, brand switching, and purchase-volume deliberations (C. W. Park et al., 1989), and positive effects such as in-store explorations of different product categories (Hui et al., 2009), accelerated information acquisition (Pieters & Warlop, 1999), and brand choice (Bigné et al., 2016). Under limited time constraints, shoppers can only process limited information available to them (Bettman, 1979), and thus, they rely on internal memory more than externally available cues (C. W. Park et al., 1989). Alternatively, shoppers encouraged to choose products without time constraints can explore more aisles (Granbois, 1968), which incentivizes unplanned buying (D. R. Bell et al., 2011). Therefore, we concur that the quantity of unplanned items bought positively correlates with the duration of time spent during an unplanned shopping phase without time pressure or constraints. Therefore, we hypothesize the following:

H5: The length of time spent during unplanned shopping is positively associated with the number of unplanned products bought.

4 Methodology

4.1 Research design and study context

In a typical shopping trip, consumers purchase a mixture of planned and unplanned items. Therefore, this study found within-subject design to be suitable for exposing all participants to the same shopping scenario, i.e., planned and unplanned shopping phases. Within-subject designs provide repeated measures per participant; therefore, researchers commonly use them for capturing consumers' brain activity continuously during decision-making, using EEG (Ozkara & Bagozzi, 2021; Saffari et al., 2023). Furthermore, compared to between-subject designs that require a larger sample size for adequate statistical power and are sensitive to interindividual differences, within-subject designs provide greater statistical power and increase the probability of capturing true differences between experimental conditions (Viglia et al., 2021; Viglia & Dolnicar, 2020). Given the focus of our study—i.e., to examine the differences between (sub)conscious planned and unplanned shopping measures—a within-subject design is preferable to a between-subjects design.

4.1.1 Conceptualization and implementation of VR shopping experience

We focused on consumer shopping behavior in a virtual supermarket. For this, a three-dimensional VR supermarket (see Appendix A.1) consisting of more than 20 product categories was developed using UnrealEngine software V4.1 (Epic Games, United States) and run on a Windows 10 desktop using Steam (Valve Corporation, United States). We used the HTC Vive 5 (HTC Corporation) HMD, and two hand controllers for interaction and instant teleporting (see Appendix A.2) as the indirect walking technique (Prithul et al., 2021). Layout of the supermarket, appearance of virtual items, and their digital prices closely resembled local Danish supermarkets. Like physical stores, participants could stand facing the shelves and reach out to specific products by extending their arms or bending down to retrieve items placed on upper and lower shelves. The items listed on the planned list were strategically placed, to force the participants to move around the entire store. To complete the shopping trip, participants had to step on the indicated red circle (see Appendix A.4), at which point the duration of the shopping trip stopped recording. Participants received basic training before the beginning of the main experiment. An example of participant shopping in a virtual retail store can be seen here: https://imgur.com/a/f1tcZGr.

4.1.2 Experimental routine

Participants were informed that they had to purchase a prescribed list of products before purchasing other products they desired, with a budget of 260 Danish kroner (approx. 35 euros). Planned product expenses were roughly one-third of the overall budget provided to the participant. This order of purchase sequence mimics natural shopping behavior (Hui, Huang et al., 2013). The experimental routine was divided into three phases, as Figure 4 shows. In the first phase, the participants signed the consent form clarifying the purpose of the study and approving the usage of their demographic data. They were then asked to complete an impulsivity questionnaire, after which an EEG cap was applied while they read the task instructions (Appendix B). A 30-second baseline (or resting state) EEG was recorded. In the second phase, participants were set up with an HMD and provided with basic training and familiarization with the environment before the start of the experiment, to mitigate the influence of having used VR on subsequent tasks. The researchers emphasized to the participants that they should behave as though they were spending their own money. The EEG instrumentation continuously recorded each participant's cognitive load throughout the entire shopping trip. To indicate the desired product for purchase, participants had to extend their arm toward the product until it turned green (see Appendix A.3). Meanwhile, the researchers manually entered the indicated product as purchased and the virtual amount left for shopping. In the third phase, participants filled out a self-report survey, before they received a gift voucher for 250 Danish kroner (approx. 35 euros) via email, as compensation.

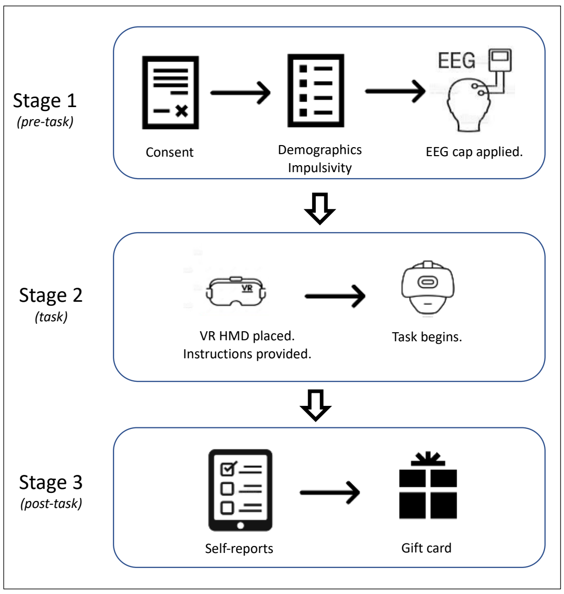


Figure 4. Schematic representation of the three experimental phases.

4.2 Measurement of variables

Response measurements were obtained from three complementary data sources. The first consisted of self-report measures (see Appendix C) that included a 9-item impulsiveness scale from Rook and Fisher (1995), a 3-item flow experience scale adapted from Kim et al. (2020), a 2-item desire-to-stay scale from Elmashhara and Soares (2022), a 1-item store satisfaction scale adapted from Pizzi et al. (2019), an 11-item sense of presence scale from Herpen et al. (2016), and demographic details for each participant. The second source of data comprised common observational measures derived from the virtual shopping trip, used to capture shopping behavior (Schnack et al., 2020). These included overall time spent, time spent during planned purchases and unplanned purchases, respectively, overall expense, unplanned purchase expense, and number of unplanned purchases. The third source of data was derived from electrophysiological recording (EEG), which measures brainwave activity and has been recognized as a reliable tool for obtaining insights into the underlying unconscious mechanisms of consumer decision-making during shopping (Golnar-Nik et al., 2019; Lin et al., 2018). We captured cognitive workload for both planned and unplanned purchases by placing electrodes on the scalp. We adapted a reference for simultaneous development of explicit and implicit data collection from Wang et al. (2021).

4.2.1 Cognitive load via EEG

The EEG signals were continuously recorded from the scalp using the portable 32-channel wireless Brain products LiveAmp (Brain Products©) device with standard 10–20 electrode placement. The online reference is located at prefrontal (Fpz site), and we used common average referencing for the offline analysis. Further technical details appear in Appendix D. The initial phase in the analysis of EEG signals is the pre-processing stage, wherein the acquired signals are cleaned in order to remove artifacts before transforming time series into the frequency domain for spectral analysis (Lin et al., 2018). For this, we used a Python library called MNE (version 0.23.1). The EEG signals were filtered with a bandpass of .1–100 Hz and a sampling rate of 500 Hz. Meanwhile, we used event-related desynchronization and synchronization (ERD/ERS index) (Murtazina & Avdeenko, 2020) with frontal and parietal locations, to assess cognitive load during planned and unplanned purchase phases. This popular method calculates the percentage change in frequency band power during tasks relative to the baseline state (Antonenko et al., 2010). The number of trials for the planned phase was the same for each participant (M= 6) but differed for unplanned purchases (M= 5.8, SD= 2.9). Participants who did not purchase (n=3) in unplanned conditions were removed from the EEG analysis.

4.3 Data gathering and sample profile

From November to December 2021, we recruited 32 participants (M_{age}= 31.5 years, S.D. = 6.5) through advertising on social media and convenience sampling techniques. Convenience sampling allowed us to recruit healthy participants with no clinical neuropsychological preconditions for recording EEG, in addition to a balanced gender ratio and representation of students to non-students in our study. Forty-seven percent of participants were employed, 53% were male, 44% were students, 75% had a university degree, and 91% visited the supermarket frequently. Participants with no previous VR shopping experience represented 72% of the sample. A recent systematic review of the usability of EEG in marketing research reported that previous studies have used an average sample size in the range of 16–42 (Bazzani et al., 2020, pp. 10–11). Moreover, recent studies using VR to capture shopper behavior have used sample sizes similar to this study's, such as Zhao et al. (2017) (n= 24, within-subject design), and Schnack et al. (2020) (study 2, n = 46, between-subject design). Moreover, using regular shoppers as participants improves the experiment's external validity (Xi & Hamari, 2021). Additionally, the use of VR reduces non-representative sampling bias (Cowan & Ketron, 2019) and hypothetical bias (Fang et al., 2021), providing a realistic decision-making context for capturing cognitive workload during shopping (Xi et al., 2022).

5. Results

All shopper-related measures indicated acceptable reliability scores (Table 2). Cronbach's alpha (α) is a measure of reliability of a scale, evaluated using the mean of bivariate correlations between the items, with adjustment for the number of items, to determine if the items assess the same construct (Cronbach, 1951). It ranges from 0 to 1, and values greater than 0.7 are considered satisfactory (Mazzocchi, 2011, p. 10). The score for one participant was omitted for sense of presence and store satisfaction, due to a technical error. Out of 32 participants, 3 did not make any unplanned purchases, finishing the shopping trip after only purchasing the items on the list.

Table 2. Reliability and descriptive analysis of scales used in the study.

Scales	# Items	α	N	Mean	S.D
Impulsiveness (Rook & Fisher, 1995)	9	.74	32	3.36	0.7
Flow experience (Kim et al., 2020)	3	.77	32	4.66	1.1
Desire to stay (Elmashhara & Soares, 2022)	2	.80	32	4.50	1.4
Sense of presence (Herpen et al., 2016)	11	.80	31	5.04	0.8
Store satisfaction (Pizzi et al., 2019)	1	-	31	2.65	0.9

Descriptive analysis of time spent and expenses incurred during planned and unplanned phases, across gender and previous shopping experience, appear in Figures 5a and 5b. Average length of time spent shopping was 501.5 seconds, the average amount spent was 207.03 Danish kroner (approx. 27.8 euros), the number of unplanned items bought outside the planned list averaged six per individual, and the average time spent purchasing planned and unplanned items were 37.12 and 38.9 seconds, respectively. There were no significant gender differences in overall time spent ($t(30)= 1.943$, $p = .061$) and overall expenses ($t(30) = .384$, $p = .704$). Furthermore, impulsiveness scores did not vary significantly across genders ($t(30) = .972$, $p = 0.339$). Finally, previous virtual shopping experience had no significant impact on overall time spent ($t(30) = .469$, $p = .643$) and overall expenses ($t(30) = .580$, $p = .566$).

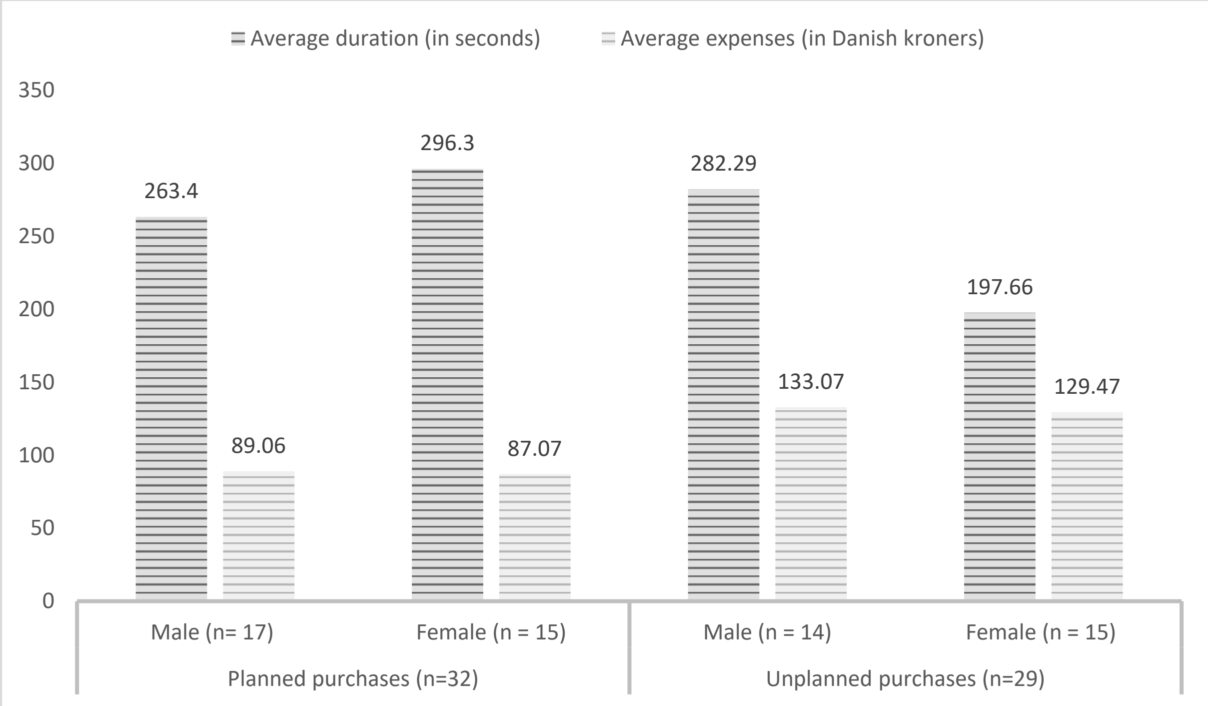


Figure 5a. Differences in average time spent and expenses during planned and unplanned phases across genders.

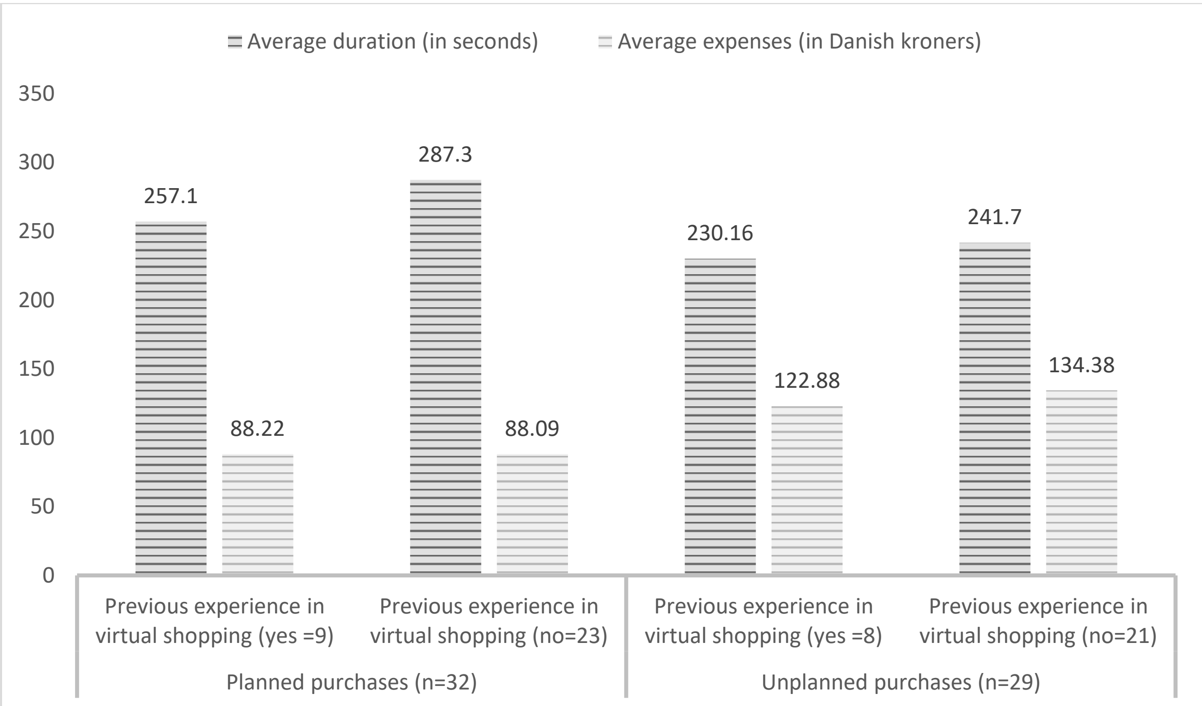


Figure 5b. Differences in average time spent and expenses during planned and unplanned phases, based on previous virtual shopping experience.

Table 3 provides a summary of hypotheses tested using linear regression, a common predictive analytical technique to evaluate a bivariate relationship between the continuous predictor (independent) variable and continuous outcome (dependent) variable (Mazzocchi, 2011, p. 179). Results of linear regression analysis showed that impulsivity scores significantly predicted the number of unplanned purchases (F (1, 30) = 7.446, p = .011, R^2= .199) and unplanned purchase expenses (F (1, 30) = 5.191, p = .030, R^2=.148). Thus, $H1_{a,b}$ is supported. This result shows that consumer impulsiveness explains 19.9% of unplanned purchases and 14.8% of unplanned expenses. Previous studies have documented similar inferences, positively associating higher impulsivity with unplanned spending behavior in retail (Hui, Inman et al., 2013). To examine H2, we used only 29 participants, as 3 participants did not purchase in the unplanned condition, effectively excluding them from statistical tests. Results of a 5000-sample bootstrapped regression indicated partial support for H2a, confirming the significant effect of cognitive load during unplanned purchases on time spent during unplanned purchases (F (1,27) = 9.583, p=.031, R^2= .262), whereas only marginal effect was observed for the influence of cognitive load during planned purchases on time spent during planned purchases (F(1,27) = 6.409, p= .062, R^2= .192). These findings exhibit that 26.2% and 19.2% of time spent during unplanned and planned purchase phases are due to cognitive load experienced during each phase of shopping. Bootstrapping is a resampling technique using replacement required for making robust statistical inferences when the data does not reliably showcase distributional assumptions of parametric models (Lavrakas, 2012, p. 65). A Wilcoxon Signed-Ranks test indicated statistically significant differences between cognitive load during planned purchases and unplanned purchases (Z= 109, p< .019), supporting H2b. The results showed differences in cognitive load during unplanned purchases (Mdn = -24.24) were lower than in planned purchases (Mdn = -18.46). We also ran a Wilcoxon Signed-Ranks test to examine differences between time spent during planned purchases (Mdn = 257.43 seconds) compared to unplanned purchases (Mdn = 206.93 seconds), and the results indicated significant differences (Z= 141, p< .021). A Wilcoxon Signed Ranks test is a non-parametric hypothesis-testing technique (Nussbaum, 2014, p. 190), used when the test of normality and homogeneity of equal variance is not held, in the case of paired observations, i.e., data has been collected from the same set of participants across all conditions. As in our study, participants performed both planned and unplanned shopping tasks. Figures 6A and 6B present topographic brain maps for planned and unplanned purchases obtained from parietal and central regions. Figure 6C highlights the differences obtained for cognitive load in planned and unplanned conditions, indicating higher cognitive load values for planned purchases. Planned purchases demand an executional task that requires brain activation to accomplish it, whereas unplanned purchases include an explorative search, and only at peak times is there a brain cognitive load activation when any item is attracting consumer attention.

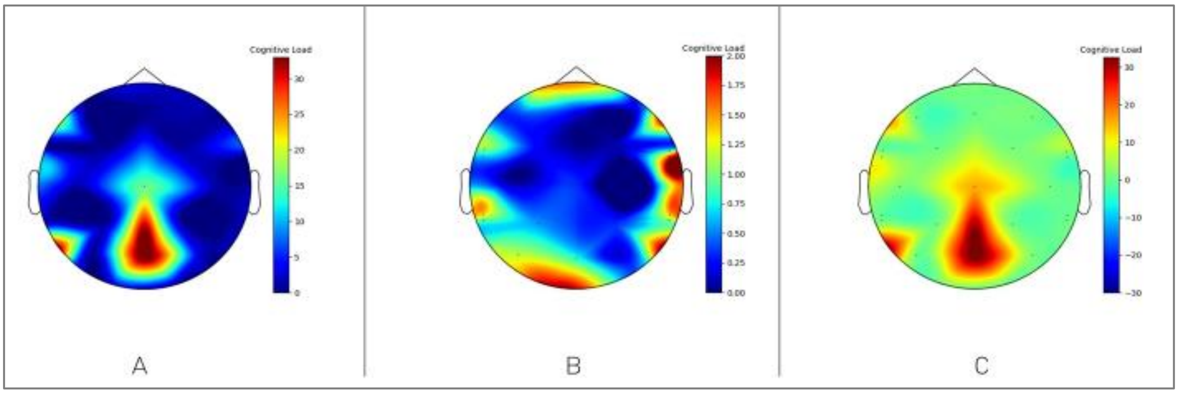


Figure 6. Topographic scalp distributions for cognitive load during (A) planned purchases, (B) unplanned purchases, and (C) their differences.

Table 3. Summary of hypothesis testing using linear regression. (*p<.05)

	Predictor	Outcome	R^2	F-statistic	p-value
H1	Impulsivity score	a. Number of unplanned purchases	.199	F(1,30) = 7.449	p= .011*
		b. Unplanned purchases expense	.148	F(1,30) = 5.191	p= .030*
H2a	Cognitive Load (planned shopping)	Duration of time spent during planned purchases	.192	F(1,27) = 6.409	p = .06
	Cognitive Load (unplanned shopping)	Duration of time spent during unplanned purchases	.262	F(1,27) = 9.583	p = .03*
H4	Desire to stay	a. Budget deviation	.361	F(1,30) = 16.915	P < .00*
		b. Basket-size deviation	.284	F(1,30) = 11.898	p < .00*
		c. Satisfaction with the store	.086	F(1,29) = 2.745	p = .01*
H5	Length of time spent	Number of unplanned purchases	.453	F(1,30) = 24.8	p < .00*

Further, our study examined the mediating role of flow experience on the relationship between sense of presence and the desire to stay in the virtual store. To test H3, we used SPSS PROCESS model 4 (Igartua & Hayes, 2021). The results showed a significant indirect effect of sense of presence on the desire to stay (b = 0.376, t = 2.636). Further, the direct effect of sense of presence on desire to stay in the presence of flow experience was also found significant (b = .7008, p < .01). Thus, flow experience partially mediates the relationship between sense of presence and the desire to stay. Table 4 presents a summary of the mediational analysis. Our results corroborate previous results showing the effect of sense of presence on flow experience (Shen et al., 2021). This finding attests to previous research recognizing the role of studies that have attested to flow experience as a mediator (Daisy et al., 2022).

Table 4 Mediation analysis

Relationship	Total effect	Direct effect	Indirect effect	Confidence interval		t-statistics	Conclusion
				Lower bound	Upper bound		
Sense of presence -> Flow experience -> Desire to stay	1.077 (p< .00)	.7008 (p< .01)	.3765	.0636	.8744	2.636	Partial Mediation

Consumers' desire to stay significantly predicted budget deviation ($F(1, 30) = 16.915$, $p < .000$, $R^2 = .361$), supporting H4a. We also found a significant effect of consumers' desire to stay on basket-size deviation ($F(1, 30) = 11.898$, $p = .002$, $R^2 = .284$), supporting H4b. Evidently, the more consumers desired to stay in the virtual environment for shopping, the more money was spent, and the more products were purchased. To examine H4c, we ran a 5000-sample bootstrap regression to examine the influence of desire to stay on store satisfaction and found a significant positive relationship between them ($F(1,29) = 2.745$, $p = .010$, $R^2 = .086$). These results show that consumers' desire to stay in a virtual shopping store can explain their budget deviation of 36.1%, basket-size deviation of 28.4%, and store satisfaction of 8.6%. The results also showed significant support for H5, revealing a positive effect between the time spent during the unplanned shopping phase and the number of unplanned items purchased ($F(1, 30) = 24.8$, $p < .001$, $R^2 = .453$). Of unplanned purchases, 45.3% were due to the effect of time spent in the unplanned phase. Consequently, the amount spent purchasing the unplanned products significantly correlated with the number of unplanned items purchased ($r(32) = .864$, $p < .001$). The greater the time duration in the store after purchasing planned products, the greater was the expenditure in purchasing unplanned products.

6. Discussion

In this section, we outline the key findings that have emerged from our analysis, highlight theoretical and managerial implications, and recommend future research prospects by underscoring a number of this study's limitations. We conclude by summarizing three key takeaways, derived from our empirical study, for designers, retailers, and researchers.

Our results furthered the classical Stimulus-Organism-Response (SOR) framework (Mehrabian & Russell, 1974) by assessing the relationship between environmental and psychological factors that influence shopping behavior in a virtual retailing context. The study's virtual supermarket closely resembled local supermarkets; therefore, the findings of the study align with prior literature on shopper behavior and provide fresh insights for retailers. At the outset, our findings showed that consumer impulsiveness significantly impacts unplanned purchase behavior. This finding substantiates previous research that suggests comparing non-impulsive shoppers with shoppers who have a stronger disposition to buy on impulse, which results in more unplanned purchases and expense (Mandolfo & Lamberti, 2021). Such a comparison extends the previous literature on the influence of consumers' impulsive behavior in virtual shopping environments (J. V. Chen et al., 2022) and impulse buying on unplanned shopping (Chan et al., 2017). Prior studies on consumers' unplanned purchases in comparison with planned purchases explored the willingness to pay (Sohn & Ko, 2021), behavioral differences (using in-store video tracking) (Hui, Huang, et al., 2013), purchase of new products (Kato & Hoshino, 2021), and effects of attentional breadth during in-store shopping (Streicher et al., 2021). Our study sought to examine neurophysiological correlations of consumer decision-making during planned and unplanned purchases. To differentiate between them, we used EEG measurements to capture cognitive load at the neural level. Cognitive load hampers individual task performance when information processing exceeds working memory capacity (Sweller, 2011). We found significant differences in cognitive workload between consumers purchasing products on the shopping list and those shopping outside the list. Interestingly, our results also reveal that the cognitive load that shoppers experience during each phase of shopping positively impacts the time they spend on it. This finding extends the previous consumer research (see Table 1) and information systems research (Brachten et al., 2020; Dincelli & Yayla, 2022) on the effect of cognitive load. Next, our study revealed flow experience as an organism component that partially mediated the relationship (see Table 4) between the stimulus component (i.e., sense of presence) and behavioral component (i.e., desire to stay). Figure 1 highlights the sense of presence, an individual's sense of "being there" in an immersive environment, as a stimulus component of the framework. Pertinent to virtual environments (Grassini & Laumann, 2020; Skarbez et al., 2017), it is a critical metric that boosts consumer involvement with the shopping experience (Pizzi et al., 2020). A low R-value indicates that desire to stay emerges as a good predictor at the store level. While our study furthers the crucial role of the consumer flow experience during virtual shopping, our results align with previous studies measuring flow experience in immersive environments (Kautish & Khare, 2022) and establishing its positive association with behavioral outcomes, such as store-visit intention (Kim et al., 2022), satisfaction (Lee, 2020), and psychological ownership (Yuan et al., 2021). Retailers should recognize the role of designers and developers of virtual environments in providing shoppers with high levels of presence, by exploring sensorial aspects as well as promoting their interaction with the products in the virtual shop, to heighten flow experience. Next, consumers' desire to stay in-store yielded significant budget deviation (i.e., the amount spent from the total budget during a shopping trip), basket-size deviation (i.e., total products bought, excluding planned products bought), and store satisfaction. Previous studies have shown that shopping atmospherics, enjoyment, and involvement positively enhanced consumers' desire to stay, which positively impacted consumer satisfaction, word-of-mouth, and patronage intentions (Elmashhara & Soares, 2022; Kim et al., 2007). Finally, the longer the time the shopper spent in the environment; the more unplanned purchasing occurred. Taken together, our study extracted three types of shopper data—i.e., observational metrics from virtual reality, self-reports, and neurophysiological measures—to triangulate consumer decision-making in a shopping context, useful for developing theories as well as retail strategies (Wang et al., 2021; Wedel et al., 2020). As part of the response component that has only received limited examination in virtual reality (VR) retailing, we included both implicit (i.e., cognitive load during planned and unplanned purchases) and explicit (i.e., unplanned shopping expense, number of unplanned purchases, time spent in purchasing planned and unplanned products, budget deviation, basket-size deviation, desire to stay, and store satisfaction) measures (Xi & Hamari, 2021).

6.1 Theoretical contributions

This research contributes to marketing and information systems literature in several ways. The study uses the SOR framework to highlight the interaction between technical aspects of the environment and consumers' (sub)conscious behavioral responses in a retail environment. First, we extend the framework to validate the role of impulse buying and unplanned purchases in a virtual-reality-based shopping context, previously limited to online impulse buying research (Chan et al., 2017). Our study showed a significant association between impulse buying and unplanned purchases. This finding may not come as a surprise since previous studies have established the same relationship (Mandolfo & Lamberti, 2021). However, noting that the replication of impulsive behavior extends its influence to virtual retailing as well is interesting. This finding corroborates that of Chen et al. (2022), wherein consumers' impulsivity trait affects their urge to buy impulsively during virtual shopping. Next, we further broadened the SOR framework to incorporate the role of consumers' cognitive load in making planned and unplanned purchases, highlighting the aspects of information processing in the virtual shopping context. In our study, we recorded cognitive load using EEG and found it at a higher level for planned purchases than for unplanned purchases. As such, this finding is significant for two reasons. First, it further substantiates the differences between goal-oriented (planned) shopping behavior, which, at times, requires greater mental effort to process the stimulus than stimulus-driven (unplanned) shopping behavior (Orquin & Mueller Loose, 2013). Second, earlier research indicated that shoppers who have shopping lists spend relatively less time and money and purchase fewer products than shoppers without the list (Davydenko & Peetz, 2020). Our results imply that consumers exert a relatively smaller amount of mental effort when shopping without a list than with a list, increasing their inclination to spend more money and acquire more items. Next, the study extends the research on the positive impacts of flow experience in an immersive shopping environment. As a positively affective psychological state, flow experience prompts the individual to exhibit curiosity and heightened focus on the task and; at times, a lack of awareness of self and physical surroundings complements that state (Suh & Prophet, 2018). It emerged as an important mediator between the sense of presence the virtual system creates and consumers' desire to spend more time shopping in the environment. Consequently, it led to greater virtual consumption, such as budget and basket-size deviations indicate. Therefore, as shoppers feel it, flow experience is an appropriate addition to the "organism" element of the SOR framework. Previous research highlighted such factors as sense of presence, interactivity, skills, and intrinsic and extrinsic motivations contributing to flow experience. In turn, flow experience contributes to developing consumer brand attitude, making it a critical construct for virtual experience (Shen et al., 2021). Last, previous studies using the SOR framework used only explicit measures (Loureiro et al., 2021). By leveraging the VR system, our study incorporated implicit measures, to expand the framework. Xiong and Zuo (2020) have applied the SOR framework to highlight the benefits of using neuroscientific tools to explore users' cognitive and affective processes informing their behavioral responses (e.g., task performance, information handling). Thus, analyzing how unconscious information processing influences planned and unplanned purchase patterns serves practitioners and researchers equally (Ozkara & Bagozzi, 2021). Our study squarely contributes to the development of the NeuroIS (i.e., the blend of information systems and neuroscience methodologies) domain (Kirwan et al., 2023). Moreover, we respond to the need for broader behavioral science perspectives on emerging metaverse retailing (Dwivedi, Hughes, Wang, et al., 2022), applying a SOR framework with roots in environmental psychology (Mehrabian & Russell, 1974) to explain virtual consumption (Shen et al., 2021).

6.2 Practical implications

Notably, the components (stimulus, organism, and response) of the framework support the phases of the customer shopping journey (J. V. Chen et al., 2022) at various consumer touchpoints (Yoo et al., 2023). The study findings present multiple critical perspectives that can assist managers and information system designers in better understanding consumers' spending patterns inside a VR-enabled supermarket.

First, we extend our previous understanding of consumer impulsivity and how it impacts behavioral outcomes, such as the amount of money spent and the duration of the shopping trip. Our results show the importance of marketers noting that consumers' impulsive tendency leads to greater unplanned purchase quantity and expenditure. Retailers may nudge consumers, triggering unplanned purchases by using distinct types of incentives, such as sensory stimuli, displays, shelf design, price promotions, and technical-device salient interactions (Thaler, 2018). However, retailers must adopt incentives compatible with consumer satisfaction in stores. Previously, Hui et al. (2013) highlighted the complexity in establishing an association between length of in-store shopping trips and unplanned spending, due to methodological difficulty in measuring the in-store path accurately. However, by leveraging the potential of the VR-assisted retail environment, we found incremental differences in the consumers' desire to stay in the store, which leads to higher budget and basket-size deviations. Second, previous studies have highlighted the implications of using neuroscientific methodologies in marketing (Alvino et al., 2020), information science (Xiong & Zuo, 2020), and virtual reality research (Wedel et al., 2020) and how it can assist businesses in making informed decisions. In our study, we used EEG, which objectively assess affective decision-making and could complement self-report measures (Wajid et al., 2021). Using EEG, we determined the differences between planned and unplanned purchases. We observed lower cognitive load when consumers engaged in unplanned purchases than when they purchased products on the list. This should encourage retailers to customize the environment to increase consumer exploration and strategize product assortment in a way that reduces consumers' cognitive workload. Unplanned purchases seem to be associated with less cognitive effort, which may relate to a pleasant in-store experience. Numerous nudges toward stores may distract a consumer from the shopping list and, ultimately, lead to regret over forgetting the main goal of the shopping visit (i.e., treating the shopping list as a main driver to visit the store). Indeed, Baymard's (2020) study of online shopping points out that an abandonment rate of almost 70% occurs during online shopping (Baymard, 2020), whose cause may be the feeling of guilt resulting from an increase in unplanned purchases (Nigam et al., 2022). Prior research found that a shopping list serves as an external memory aid to help a shopper navigate the trip with the least amount of information in working memory (Block & Morwitz, 1999), reducing extra expense and time (Davydenko & Peetz, 2020). However, according to our research, shoppers' cognitive load—a proxy for mental efforts exerted in information processing—is significantly less when they shop without a list. Therefore, contrary to the conventional understanding that advises businesses to provide shoppers with more information, our research suggests that managers should give them a balanced amount of information instead of risking cognitive overload by subjecting shoppers to information processing that is not strictly necessary. Third, since our findings show that satisfaction and longer stay at the supermarket result in more unplanned purchases, retailers should deliver memorable in-store experiences—as the experience economy model (Pine & Gilmore, 2011) suggests—by delivering greater utilitarian and hedonic value that ultimately leads to more unplanned purchases. Therefore managers and designers should seek synergetic work through a design-science paradigm (Hevner et al., 2004). Here, the design considerations and business goals combine to craft the shopping experience in VR-based shopping environments (Dincelli & Yayla, 2022, p. 15). In this regard, the four-phase 3DR3CO design framework (i.e., observe navigation, engage consumer interaction, behavioral data analysis, and VR shop design) that Elboudali et al. (2020, p. 9) propose, can promote retailers and designers working in synergy for continuously tracking shopper's interaction inside a virtual environment, to develop a personalized shopping experience. Last, our study found a partial mediating effect of flow experience between the sense of presence and the desire to stay, resulting in more unplanned purchases. Designers can increase positive store-related emotions by improving flow experience, in turn affecting behavioral intention, store attractiveness, and retail choice (Jin et al., 2021) while customized implementation of virtual commerce improves customer engagement (Lim et al., 2022).

6.3 Limitations and future research directions

Despite being a unique study of its kind that incorporates neurophysiological measures of cognitive load to differentiate consumer shopping patterns in a virtual reality-based supermarket context, some caution should apply to interpreting its findings. Nonetheless, in turn, its limitations provide a basis for widening the scope of future research. First, the current study assumed that unplanned buying takes place after a shopper purchases a list of planned products. Although this is realistic, some consumers may actually combine planned with unplanned purchases by category. We did not counterbalance the planned and unplanned tasks, choosing instead to follow Hui et al. (2013) by asserting that unplanned purchases tend to take place after planned purchases. Second, the present study showcases the potential use of VR technology as the venue for in-store purchase behavior, which can include designing and testing store layouts, modification of store atmosphere, and interaction with products. The virtual environment this study used only caters to one of the senses, i.e., sight. However, other modalities, such as haptics, olfactory, and auditory sensation, are major components influencing emotions and attitudes toward retail stores that the virtual shopping experience can incorporate (Biswas, 2019; Loureiro et al., 2019). In this vein, a promising line of inquiry could be to incorporate a multisensorial approach along with various atmospheric cues, such as product-related scents, that can influence human senses in VR stores (Roschk et al., 2017). Whether different types of atmospheric cues can further increase or decrease consumers' cognitive workload is of immense importance from academic and managerial perspectives, especially for the low-involvement product category (Mirhoseini et al., 2021). As such, self-report measurements (e.g., NASA Task Load Index) can complement the use of EEG to index cognitive workload and further explore various cognitive workload dimensions in virtual commerce (Xi et al., 2022). Third, although earlier studies used similar sample sizes in EEG consumer research (Bazzani et al., 2020), we acknowledge the effect that a limited number of samples can have on the generalizability of our findings. Our results, however, seem to corroborate previous studies (i.e., Saffari et al., 2023). Fourth, our study did not control for the influence of product type nor the role of involvement. The environment we used had more than 250 products, making it impossible for the researchers and developers to expend more resources on tracking movements and interactions with each product. Fifth, while contrasting the immersive shopping experience with traditional and e-commerce shopping has been a consistent research focus in marketing over the last decade (Xi & Hamari, 2021), comparing shopping experiences beyond grocery product categories (e.g., apparel, home décor) requires further research for a comprehensive understanding of unique behavioral outcomes.

7. Conclusion

Most behavioral research focuses on opposing deliberate thinking to intuitive or unconscious decision-making (Kahneman, 2011), mainly for discrete choices. A shopping trip consists of multiple continuous choices where each path can support some decisions, and another can support others. Both slow and fast paths in a single shopping trip underlie this study, namely, purchases based on prior goal-oriented tasks (e.g., a shopping list) and unplanned purchases. The findings may be valuable for transforming virtual retail environments that seek to enhance the consumer shopping experience, thereby maximizing behavioral responses. Thus, our study explored consumers' impulsivity, flow experience, and the influence of virtual reality attributes on consumers and how these positively translate into unplanned shopping behavior in a VR environment, through such measures as duration and money spent while shopping. The key takeaways of the study are multifaceted. First, the sense of presence that the flow experience mediates effectively increases consumers' desire to stay in the virtual environment. Thus, designers should develop environments with minimal distractions (e.g., pop-ups) and encourage seamless interaction with the environment. Second, cognitive load is greater when consumers are purchasing products on the list and is less during purchases made without a list. This should encourage managers to carefully develop strategies to highlight selective sales promotion advertisements. Besides, minimizing consumers' cognitive load can encourage them to explore the environment further, leading to improving the shopping experience and purchasing behavior. Finally, for business-to-consumer organizations planning to introduce immersive systems as distribution channels, understanding the consumer's dynamic purchase decisions necessitates insight into their unconscious and conscious metrics. This triad of data sources will draw the focus of NeuroIS scholars as they work in tandem to develop conceptual and methodological understandings of consumer shopping behavior (Kirwan et al., 2023).

APPENDICES

Appendix A. VR Images

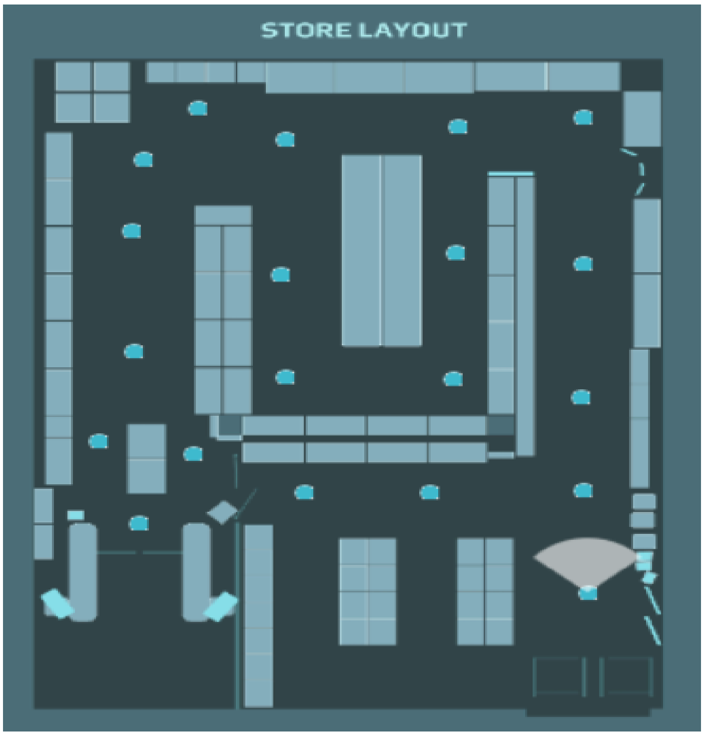
1. Image indicating the product display in the store.

2. The blue arrow indicates instant teleporting for individuals to reach close to the desired product or section.

3. To purchase the product, participants must indicate ‘grab’ when the focal product turns green.

4. Prior to exiting the store, the participants must teleport to the red circle to indicate the end of the shopping trip.

5. A 2-dimensional layout of the virtual store.



Appendix B. Task instructions to the participants

Hi there,

Welcome to our virtual supermarket. For this shopping trip, we need you to imagine the following:

You reached home after work and found out that you needed to go grocery shopping. You go to the nearby supermarket, pick up the shopping cart and proceed with shopping. You must first purchase the indicated products on the shopping list. You have a budget of 260 DKK. With the remaining amount, you can purchase additional products if you need them. Just like in a real supermarket, feel free to explore the environment and add products to your cart that you would like to have after the shopping trip.

Have fun shopping!

Appendix C. Adapted scales from previous studies.

Scales	Range
Impulsivity (Rook & Fisher, 1995) (α =.74)	**1-7**
1. Sometimes I feel like buying things on the spur of the moment. 2. "Just do it" describes the way I buy things. 3. "I see it, I buy it" describes me. 4. Sometimes I am a bit reckless about what I buy. 5. I carefully plan most of my purchases. 6. I often buy things spontaneously. 7. I buy things according to how I feel at the moment. 8. "Buy now, think about it later" describes me. 9. I often buy things without thinking.	
Sense of presence (Herpen et al., 2016) (α =.80)	**1-7**
1. I was able to search the shopping area completely by looking around. 2. I was able to take full control of the events that occurred while shopping. 3. I felt involved in the shopping trip. 4. I had all my senses fully engaged in the shopping trip. 5. I was completely unaware of events that took place outside the shopping area. 6. There were moments when I felt completely focused on doing the shopping. 7. There were moments when I felt completely focused on the retail environment. 8. I felt I could walk around freely in the store. 9. I was able to examine the products closely. 10. I was able to concentrate on my purchase decisions. 11. I found it easy to move from shelf to shelf.	
Desire to stay (Elmashhara & Soares, 2022) (α =.80)	**1-7**
1. I like to stay at this store as long as possible. 2. I enjoy spending time at this store.	

Flow experience (Kim et al., 2020) (α =.77)	**1-7**
1. Do you think you experienced flow (moments when you are completely and totally absorbed in an activity) when using virtual reality for your shopping needs? 2. Most of the time I use virtual reality for shopping I feel that I am in flow (moments when you are completely and totally absorbed in an activity). 3. In general how frequently would you say you have experienced flow (moments when you are completely and totally absorbed in an activity) when you use virtual reality for shopping?	
Store satisfaction (Pizzi et al., 2019)	**1-5**
1. Are you satisfied with the store?	

Appendix D. EEG

All electrode impedances maintained below 15kΩ and a notch filter at 50 Hz were applied to remove powerline noise. The wireless EEG signal acquisition was sampled at 500 Hz, with low pass filter at 100Hz and high pass filter at 0.1Hz.

CHAPTER 5
CONCLUSION

In this section, conclusions drawn from the studies part of this thesis are discussed. Although Chapters 2, 3 and 4, have their own conclusions that includes limitations and insights on future research. First, we present the insights derived from each study are mentioned. Next, we highlight the limitations that are resulting either from theoretical or methodological aspects of each study. Lastly, we offer three strands of research for future researchers.

Discussion

The contribution of this thesis to marketing scholarship can be viewed through two interconnected perspectives – *expansion of classical theoretical framework(s) and novel methodological approaches* – both of which catered to understanding consumer behaviour.

Chapter 2 utilizes cue-utilization framework which is initially developed through the works of Szybillo & Jacoby (1974) and Burnkrant (1978), majorly focusing on perceived-quality judgements of physical products. Over the years several studies have extended their model to evaluate the interaction between intrinsic and extrinsic product cues. In our case, we examined the interactions between extrinsic attributes of product reviews (such as valence, verification, and content style) and their intrinsic attributes (such as search and experience nature of products). Thus, expanding the scope of the framework to trace the evolving and interrelated nature of cues in eWOM domain. For Chapter 3 and 4, Mehrabian & Russell (1974) Stimulus-Organism-Response framework provided the foundations. Initially the model was thought to be linear process, but studies over the time changed that conceptualization (e.g., Jacoby (2002)). Traditionally, organism and response components of the framework only observed explicit (self-reports) measurements, and implementation of the stimulus component was restricted to shopping environments. However, Chapter 3 and 4 of this thesis circumvents the traditional view of the model. In Chapter 3, the stimulus component incorporates the marketing mix (i.e., promotion, product, place, and price), as well as uses consumers' implicit measurement (i.e., heart rate variability) for the organism component to yield a behavioural response. Evidently, the study establishes a novel integrated framework of marketing mix and stimulus-organism-response model premised upon neurophysiological technique. Chapter 4 enriched the classical SOR framework with introduction of novel theoretical constructs, as well as corroboration of three varied sources of data (i.e., self-reports, VR-based observation, and EEG). Stimulus component included sense of presence as a technical aspect of a virtual supermarket environment, whereas the organism component included consumer's flow experience of virtual shopping and their impulsiveness. The response component used self-reports (store satisfaction, desire to stay), neurophysiological tools (Cognitive load via EEG), and observational metrics (time duration, expenses incurred, products bought, budget and basket-size deviations). Analysis of this study looked at how different components influenced each other. Taken together, the studies presented in this thesis expanded the traditional scope of marketing research.

Findings of the studies

Chapter 2 titled as *Interaction between extrinsic and intrinsic online review cues: perspectives from cue utilization theory (Kakaria, Simonetti, et al., 2023)* examined the interaction effects of linguistic style, verification of online reviews, and their valence on purchase intention for two distinct product categories (search and experiential products). The study used cue utilization framework to examine relationship between intrinsic cues (search and experiential goods) and extrinsic cues- content style (general versus specific), verified purchase badge (present versus absent), and valence (positive versus negative)—in a 2x2x2 mixed design. This survey-based behavioral study was conducted online using Clickworker with sample size of 500 participants based in USA. The results, using frequentist and Bayesian analyses, showed that the valence cue superseded other extrinsic cues for both product categories. Differences in the content style of the reviews and presence (or absence) of verified purchase badge have marginal effects on purchase intention for both products. Critically, the two interactions — valence-content style and valence-verified purchase badge — significantly affect purchase intention. Positive (vs. negative) reviews which have specific (vs. general) content style increase (decrease) purchase intention for search and experiential goods. Similarly, reviews that are positive (vs. negative) have presence (vs. absence) of verification badge contributed to higher (lower) purchase intentions for search than experiential products. Chapter 2 extended theoretical perspectives on eWOM literature, and for practitioners, the findings seem to suggest that e-commerce platforms should highlight positive reviews as default and that they can benefit from highlight verification badge for identification on genuine purchase which would gain credibility and trust from the consumers.

Chapter 3 titled as *Heart rate variability in marketing research: A systematic review and methodological perspectives (Kakaria, Bigné, et al., 2023)* presented a systematic literature review and bibliometric analysis on the use of heart rate variability in marketing research. The chapter schematically explains the emergence of heart rate variability measurements and provides conceptual framework that integrates marketing mix and stimulus-organism-response theories with heart rate variability. Using PRISMA framework study reviews 33 articles with the following descriptive findings: (i) 43% studies use it for promotion-related stimulus; (ii) most commonly used theory is the limited capacity model of motivated mediated message processing (LC4MP); (iii) 52% studies used within-subject designs; (iv) 85% studies uses heart rate (or heart rate range) metric; (v) almost 13 studies used traditional non-portable devices to capture heart rate variability signals; and (vi) electrodermal activity series was most commonly used with heart rate variability in 48% of the studies. Bibliometric analysis revealed three significant findings: (i) journal that most published the articles on heart rate variability in marketing research is Psychology & Marketing; (ii) most commonly cited article in heart rate variability research in marketing literature is *Predicting advertising success beyond traditional measures: new insights from neurophysiological methods and market response modeling;* and (iii) Annie Lang as the most citied author for their work on (LC4MP) theory. Using TCM (theory-characteristics-methodology) framework the study presented three critical research avenues for future scholars, such as consumer decision making involving affective, cognitive and sensorial constructs; product experience; and triangulation with neurophysiological tools. These research avenues offered 15+ research questions for future examination using heart rate variability. Lastly, another major contribution of the study was to provide guidelines for the use of heart rate variability to marketings scholars how to design an empirical study, recommendation on choosing metrics, participants characteristics, data triangulation, and statistical factors involved.

Chapter 4 titled as *Cognitive load during planned and unplanned virtual shopping: Evidence from a neurophysiological perspective*, expanded the classic stimulus-organism-response framework to examine the shopping behavior in virtual reality-based retail store. The study used sense of presence as part of stimulus component; consumer impulsiveness and consumer's flow experience in organism component; and used and explicit (unplanned shopping expense, number of unplanned purchases, time spent in purchasing planned and unplanned products, budget deviation, basket-size deviation, desire to stay, and store satisfaction) and implicit (cognitive load during planned and unplanned shopping, *captured through EEG*) variables under the ambit of response component. The study used within-subject design with 32 participants and provided schematic illustration of the three phases used to conduct the experiment. In the experiment, participants were provided budget to make purchases in sequence (planned -> unplanned) inside a virtual retail store which closely mimicked real-life supermarket. Responses for sense of presence, impulsiveness, flow experience, desire to stay, and store satisfaction were recorded via validated self-report questionnaires. Expenses, duration, and quantity of products were categorized as observational variable derived via VR. The results of the study were- (i) consumer impulsiveness significantly predicted unplanned purchases and unplanned expenses; (ii) cognitive load was higher in planned purchases as compared to unplanned purchases; (iii) flow experience partially mediated the relationship between sense of presence and the desire to stay in the virtual store; (iv) desire to stay in the virtual store significantly influenced budget deviation, basket-size deviation and satisfaction with the virtual store; and (v) the length of time spent in the virtual store significantly influenced the number of unplanned purchases. The findings of the study convey that consumers exert lower mental efforts when they are shopping without lists than having shopping list, which also increases their desire to stay longer in the virtual retail store and to spend more. For practitioners, the results of the study advise that virtual environment should not be overloaded with information that can cause distractions for the shopper leading to higher cognitive load which results in sub-optimized shopping experiences.

General limitations

The studies as part of this thesis contain three main limitations. First, Chapters 2 and 4 presented hypothetical scenarios to the participants which limit the ecological validity of the results to be generalized for all the consumers. In Chapter 2, the participant choices were limited to two categories of products unlike in real-world settings, and they were only exposed to only limited set of modified versions of user generated product review. In Chapter

4, the methodology did not permit counterbalancing the conditions of purchase- planned purchases always preceded the unplanned purchases, which might not be the case for each shopping trip to the supermarket. Although, the methodological underpinning of these studies is an extension of the previous studies in marketing research, these studies also inherent the problem ecological validity. Second, Chapter 3 provided a systematic literature review using PRISMA framework on the use of heart rate variability in marketing research. Due to the restrictive exclusion criteria, several relevant works published in conference proceedings and pre-prints were removed. Additionally, our inclusion criteria only used journal articles published in marketing research despite its usability in other domains such as tourism and hospitality research, virtual and augmented reality research. Third, both in Chapter 2 and 4, limited theoretical variables/metrics were examined which can limit the applicability of the studies in real-life contexts. In Chapter 2, despite using three critical variables (review valence, review verification, and review content style) for online consumer reviews, influence of other critical variables (e.g., review volume, review variance) were not examined. Similarly, Chapter 4 looked at differences between planned and unplanned purchases, whereas other types of purchases (e.g., reflective, and opportunistic) are not examined.

Future lines of research

This thesis presents a unique blend of explicit and implicit measurements in e-commerce and virtual reality-based retailing. While this thesis contributed to solving some of the existing issues in marketing research, it also presents three broad prospects for future research. First, additional frameworks to incorporate diverse set of online product reviews. Since cues present in the online consumer reviews can be static or dynamic, developing a framework to measure the continuous interaction between them and their impact on subsequent purchase behavior will be an interesting avenue of research.

Second, developing multi-method research practice to understand consumer's (neuro-) psychological and behavioral responses. Given the methodological development in marketing research in the last two decades, triangulation of datasets from conscious and subconscious consumer experiences is essential. An emerging question in this line of inquiry is to integrate multiple neurophysiological tools to forecast behavior.

Third, correlating neurophysiological tools with observational metrics obtained via consumers interaction with immersive technologies. With brands providing ever-improving immersive experiences to the consumers in terms of social engagements, product interactions, sensory touch points, and payment services, can neurophysiological tools help researchers and practitioners develop better insights into their underlying affective and cognitive responses. This will allow the researchers to develop and examine newer metrics for understanding consumer experiences. Extending this perspective, previous studies examining virtual shopping experiences can compare consumer experiences in various virtual stores for developing nuanced behavioral metrics rather than focusing on specific type of retail such as grocery store and home décor.

GENERAL OVERVIEW OF THE APPENDICE

This thesis contains three Appendices vital for the comprehensive understanding of the topic. In Appendix 1, titled as *How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach*, contains three studies using combination of various techniques- eye-tracking, electroencephalography, and survey- to examine congruent (vs. incongruent) advertisement and user-generated content on TripAdvisor. An important finding of the study is that even when participants viewed user-generated content on the TripAdvisor webpage in conjunction to the online advertisement, there was no significant increase in cognitive load. As part of the studies, I assisted in developing analysis and writing of the manuscript.

Appendix 2 and 3, titled as *Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket* and *The Role of Stimuli-Driven and Goal-Driven Attention in Shopping Decision-Making Behaviors—An EEG and VR Study*, with experimental backdrop parallel to Chapter 4, with more nuanced computational neuroscience approach. I was a core contributor to the conceptualization and methodological development of both these studies. Along with other researchers, I performed data collection for these studies and contributed to the development of manuscripts as well. In the former, the study examined asymmetrical activation in the frontal lobe of the brain which engages in decision-making and cognitive load obtained from frontal and parietal regions. The study a higher gamma asymmetry score during unplanned (vs. planned) purchases. Also, complementing the results of Chapter 4, this study found cognitive load to be higher during planned (vs. unplanned) purchases. In the latter, three EEG based computational features- Power Spectral Density, Connectivity, and Spectral Entropy – were used to differentiate goal-directed (analogous to planned purchases) and stimulus-driven (analogous to unplanned purchases) attention while shopping in a virtual retail store. Amongst the three features, spectral entropy yielded the highest discriminatory power. Results from power Spectral Density computational approach observed significant increase in theta band power over frontal, central, and temporal regions of the brain during planned purchases (vs. unplanned purchases), and alpha power band was observed to significantly lower over frontal and parietal regions during unplanned purchases. Functional connectivity analysis showed significant increase in frontoparietal activity during planned purchases (vs. unplanned purchases). On the contrary, during unplanned (vs. planned) purchases an increase in spectral entropy over frontoparietal region was observed.

APPENDIX 1

HOW ONLINE ADVERTISING COMPETES WITH USER-GENERATED CONTENT IN TRIPADVISOR.

A NEUROSCIENTIFIC APPROACH

Enrique Bigne, Aline Simonetti, Carla Ruiz, and Shobhit Kakaria

This is the first out of three published Appendices. The study uses multiple techniques such as online survey, eye-tracker, and electroencephalogram to examine how advertisements embedded in social media visual attention, cognitive load, and engagement. As part of this thesis, we are reproducing the online version of the study published in the Journal of Business Research. Bigne, E., Simonetti, A., Ruiz, C., & Kakaria, S. (2021). How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach. *Journal of Business Research,* 123. https://doi.org/ 10.1016/j.jbusres.2020.10.010

Appendix 1

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How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach

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TripAdvisor
Dual-processing theories
Advertising effectiveness
Eye-tracking

ABSTRACT

Drawing on cognitive load theory, congruence research, and dual processing models, the purpose of this study is to determine the effectiveness of online advertising in social media. To this end, three separate studies were conducted. First, using eye-tracking and electroencephalography, we examine the differences, based on whether or not an ad is embedded, in subjects' visual attention and engagement in a TripAdvisor webpage. Our findings showed that synergies between social media content and advertising content positively affect users' visual attention. A second study, using an online survey, assessed the impact of congruent/incongruent ads on ad recall. A third study, using eye-tracking, assessed the impact of congruent/incongruent ads on visual attention. Our findings suggest that consumers exposed to online ads for very limited time periods rely on less effortful, more heuristic, context-based processing strategies. Congruent ad-media contents can act as peripheral cues, activating knowledge structures and facilitating message processing.

1. Introduction

Social media has quickly become one of the most popular channels for disseminating information on brands (Bigne, Ruiz, & Curras-Perez, 2019). Online reviews have a significant impact in the travel industry (Chu, Lien, & Cao, 2019). Recent market research reveals that, in 2018, 65% of customers read online reviews for local restaurants and cafes before making purchase decisions (BrightLocal, , 2018).

Given the increasing competition in the hospitality industry, research into how the information cues in consumer-generated reviews affect the effectiveness of the advertising of tourism services is important. Dual-process theories provide comprehensive data on how individuals process information, establish their validity assessments and, later, make decisions. These theories posit that consumers process information through two routes, central/systematic processing and peripheral/heuristic processing.

When searching for advice on social media, consumers frequently encounter advertising content mixed in with user-generated content (UGC). While researchers have demonstrated the impact of online customer reviews on company sales, an uninvestigated issue is how the interaction of UGC and advertising content affects consumers' visual attention, ad recall, and engagement. Indeed, as stated recently by Babić-Rosario, de Valck, and Sotgiu (2020), a research gap exists in terms of how consumers create, spread, and evaluate electronic word of mouth (eWOM), and they called for research based on eye-tracking (ET) methodology. Thus, in consequence, the present study moves the research a step forward by using eye-tracking and electroencephalography (EEG) to measure consumers' visual attention and engagement with social media content and ads embedded in social media.

Although online ad effectiveness has been extensively analyzed through different measures, such as behavioral data (e.g. click-through rate) and self-reported measurements (e.g. attitudes and acceptance) (Belanche, Flavián, & Pérez-Rueda, 2017), scant attention has been devoted to analyzing online ads embedded in social media sites through unconscious measurements, such as neurophysiological tools. The literature review found few eye-tracking based studies that examined the impact of visual advertising stimuli and their effects on behavior related to online tourism services, and comparing the results with self-reported recall measurements (Muñoz-Leiva, Hernández-Méndez, & Gómez-Carmona, 2019). Attention has been recognized as the primary factor in advertising effectiveness since the appearance of the earliest models, such as AIDA (Strong Jr, 1925). Without attention, advertising cannot persuade the consumer. Visual attention has been taken to be a proxy of interest and preference, particularly measured through eye-tracking (for a review, see Wedel & Pieters, 2014), in different fields, including tourism research (for a review, see Scott, Zhang, Le, &

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Moyle, 2019). Research into advertising asymmetry has shown that higher consumer engagement with ads increases advertising recall and message involvement (Vecchiato et al., 2011).

Furthermore, a research question that remains under-investigated is whether ads embedded in social media have different effects depending on the media context in which they appear, that is, is ad-context congruence important to the consumer? For example, subtle forms of congruence, such as matching company advertisements and the third-party ads embedded alongside them, could have an impact on visual attention and ad recall. From a theoretical point of view, this issue is important to our understanding of advertising effectiveness on social media. This is important because previous empirical evidence regarding these ad-context effects is contradictory. Simola, Kivikangas, Kuisma, and Krause (2013) found that incongruence increases the visual attention paid to ads, whereas congruence improves ad recall. Kononova, Kim, Joo, and Lynch (2020) showed that brands advertised in context-irrelevant ads were more recognized than brands advertised in context-relevant ads.

The specific goals of this study are: (a) to identify which heuristic UGC information cues (e.g. star rating, volume of comments, consensus, ratings of the specific features of restaurants, other consumers' reviews, location) attract most consumer visual attention; (b) to analyze how online advertising embedded in social media competes with heuristic UGC cues to influence consumer visual attention patterns and engagement, and (c) to analyze the effects of online advertising of congruent/incongruent products on visual attention and ad recall. Specifically, we examine whether congruence between the advertisement and the ad has an impact on ad recognition (henceforth "recall"). Three studies were carried out to achieve these goals, measuring both self-reported and unconscious responses (eye-tracking and EEG). In Study 1, data was analyzed to assess if there was a difference in visual attention and engagement when ads were embedded, and were not embedded, with TripAdvisor content. A second study was carried out, through an online questionnaire, to assess the impact of congruence/incongruence on ad recall. Finally, Study 3 measured the visual attention paid to embedded ads through eye-tracking.

This study contributes to the existing body of literature as follows. First, it extends visual processing research by exploring consumers' viewing behavior, combining UGC and online advertising. Second, the study assesses the impact of different heuristic information cues on consumers' visual attention and engagement in social media. Third, the study analyses the effect of congruence on visual attention and ad recall and explores its possible interaction with UGC valence. Fourth, the paper complements previous studies by combining self-reported measures with unconscious responses, as suggested by Babić-Rosario et al. (2020). The literature review found few applications based on eye-tracking methodologies that examined the impact of visual advertising stimuli, and their effects on online tourism services-related behavior, and comparing the results with self-reported recall measurements (Muñoz-Leiva et al., 2019).

The remainder of this paper is organized as follows. First, the conceptual framework, based on consumers' information processing on social media content, specifically the congruence of ads embedded in social media, is discussed. Then, we describe three separate studies, one based on explicit measures (online study) and two on implicit measures (eye-tracking and electroencephalography/eye-tracking). The next sections discuss the results of the three studies and present the conclusions. Finally, some theoretical and managerial implications are provided.

2. Heuristic information processing, visual attention, and engagement

2.1. Consumer information processing on social media

Based on the dual-process literature on heuristic processing, the present study applies the heuristic-systematic model (HSM) (Chaiken, 1980). The HSM model puts forth a dual-process conceptualization in which individuals use systematic (examining all pieces of information) and/or heuristic (using informational cues, such as consensus, as simple decision-making rules) strategies when evaluating information on which to make a judgment.

A *star rating* is considered the simplest and most concise heuristic cue for consumers to process (Yoon, Kim, Kim, & Choi, 2019). Consumers immediately understand ratings and, therefore, expend more effort and time processing the textual information. Consumers' reviews may be affected by *consumer consensus*. The absence of support for an online review can create uncertainty in readers and cause the review to be rejected (Kim & Lee, 2015); consequently, opinions endorsed by other consumers (consensus) are more persuasive and trusted than individual reviews about the same product. Consensual information is a heuristic cue that has been successfully examined from the HSM perspective (Chaiken, 1980). The presence or absence of consensus with an overall rating may affect consumers' visual attention and engagement, as they may agree more with messages that other reviewers endorse, without fully absorbing the semantic content of the persuasive argumentation (Kim & Lee, 2015). Therefore, we pose RQ1:

RQ1: Which UGC heuristic information cues influence visual attention?

Consumers acquire visual information from ads in two ways: (i) actively, using their focal vision, looking directly at the ad; (ii) passively, even when they do not look at an ad, using their peripheral vision (Wedel & Pieters, 2014). Cognitive load theory (Sweller, 1988) describes the limitations of the working memory to process incoming information. Recent research (Pfiffelmann, Dens, & Soulez, 2020; Wiese, Martínez-Climent, & Botella-Carrubi, 2020) argued that ad intrusiveness negatively influences consumer attitudes toward ads embedded in social media. When consumers are evaluating information on TripAdvisor, the processing of advertising content is disrupted by the increase in cognitive demand generated by the evaluation task. Previous research has suggested that multitasking only has a negative impact on memory if the sum of the cognitive load imposed by processing the information in the ad and the evaluation task exceeds the consumer's cognitive capacity (e.g. Duff & Sar, 2015). Therefore, we pose RQ2:

RQ2: Does online advertising embedded in TripAdvisor affect (a) consumers' visual attention toward the ad, (b) consumer engagement?

The reduced impact of some informational cues might be explained because people pay less, or even no, attention to certain peripheral variables. On the other hand, cue-salience hypothesis explains that greater focus is put on some cues than on others (Markowitz, Shewcraft, Wong, & Pesaran, 2011). Therefore, we analyze how UGC and online advertising impact on consumers' attention and engagement when they are presented in the same setting. Accordingly, we pose RQ3;

RQ3: How do UGC and online advertising compete for the consumer's visual attention when (s)he is evaluating a tourist provider review?

To answer these research questions, the first study used a behavioral experimental approach with a within-subject design with ads embedded in the TripAdvisor websites of Italian restaurants. Spain was chosen as the study context. Spain accounts for 12.7% of the EU-27 total value added of the food and beverage service activities (FBSA) sector (Cabiedes-Miragaya, 2017). Spain has the greatest density of bars per person in the world (1/174).We chose TripAdvisor as it is the largest online community where consumers post reviews on restaurant service and food, and Italian restaurants due to their popularity. We used eye-tracking to measure visual attention and EEG to measure engagement.

2.2. Study 1: Eye-tracking and EEG study

2.2.1. Experimental design

As shown in Fig. 1, three slides of stimuli from TripAdvisor were used: two of them with an online advertisement ("Trip 1" and "Trip 2") and the third without the advertisement ("Trip 3"). For Trip 1 and Trip 2 each slide was divided into areas of interest (AOIs) based on the actual TripAdvisor layout: the overall restaurant score (AOI 1); number of

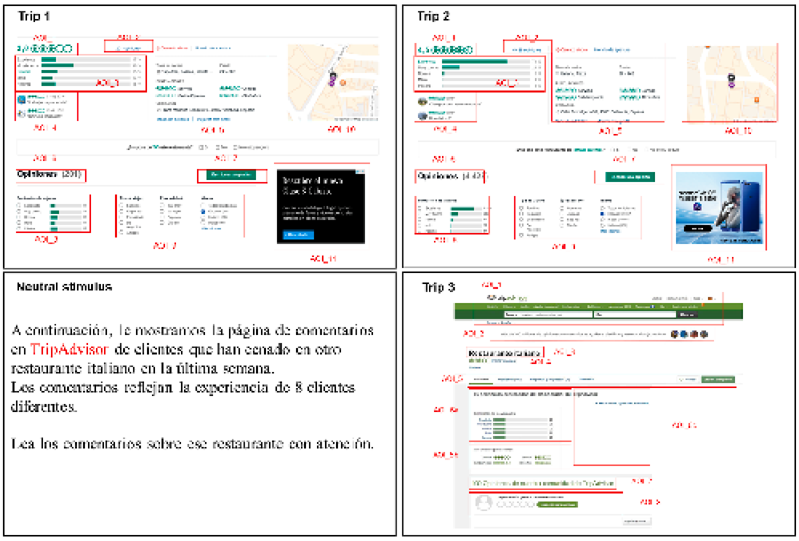

Fig. 1. Stimuli on a TripAdvisor page.

opinions (AOI 2 and AOI 6); consensus (breakdowns) of consumer reviews (AOI 3 and AOI 8); overall scores and headings of reviews of the restaurant (service and food) (AOI 4); scores of the attributes of the restaurant - service, value for money, food and atmosphere (AOI 5); client profile (AOI 9); calls to action to post reviews (AOI 7); and restaurant location (AOI 10). These two slides resulted in 11 AOIs. The slide without the advertisement had ten AOIs (Trip 3).

The participants viewed the stimuli through a 1920 × 1080-pixel monitor. The Tobii Pro TX300 device was used to monitor eye movements (eye-tracking), and iMotions software (iMotions 7.1.1.0, København V, Denmark) was used for the data recording. The ET device records at 300 Hz and has a built-in 23-inch monitor. We used the B-Alert X10 (Advanced Brain Monitoring, Inc) device to record the electroencephalogram (EEG) signals. The metrics for high engagement (HE), cognitive workload (WL), and frontal asymmetry (FA) were obtained through the ABM software built into the iMotions software.

2.2.2. *Data collection, sample, and procedure*

A company specializing in market research recruited the participants March-April 2018 from a sample of 104 Spanish TripAdvisor users (females 54.5%; 38.4% aged 25–30, 18.2% aged 31–40; 22.2% aged 41–50; and 21.2% aged 50–60; mean age: 37 years; 51.5% workers, 29.3% students, and 19.2% unemployed; 51.5% had used TripAdvisor more than three times in the previous three months).

The participants arrived in the laboratory and signed a consent form. Thereafter, the ET and EEG devices were calibrated and the participants received their instructions. The participants viewed the four screens depicted in Fig. 1. The "neutral stimulus" was presented before Trip 3. The presentation order of Trip 1 and Trip 2 was counterbalanced across participants, while the last two screens were presented in the same order for all participants. The participants went through the screens at their own pace; no questions were put to the participants during the visualization of the stimuli.

2.2.3. *Results*

2.2.3.1. Eye-tracking measurements. Due to some incorrect data being obtained from the eye-tracking, only 100 participant responses were retained as a valid sample. Continuous measures were used: time spent, time to first fixation (TTFF), and number of fixations. RQ1 addresses which UGC heuristic information cues influence visual attention in the stimuli that contain an ad (Trip 1 and Trip 2). The gaze-time metric revealed that each AOI received a different level of attention. The top central part of the TripAdvisor layout received more attention in both slides (around 27%). This was the biggest AOI, and the information contained in it might have been more relevant to the participants. A medium-sized area with the breakdown (consensus) of online ratings (AOI_3) was the second most significant area in terms of attention paid in both slides (Trip 1, 15.9%, and Trip 2, 18.30%). The gaze attention paid to this AOI was higher than other areas of similar size located at the bottom of the pages (AOI_8 and AOI_9), in the top right area (AOI_10), and in the top left area (AOI_1 and AOI_2). The AOIs paid least attention were the smallest; number of comments (AOI_2, and AOI_6) and "call to action to post a review" (AOI_7). The fixation-time metric offers additional support to previous findings, as it measured the time spent on each AOI as a percentage of total available time, based on fixation time. This showed that the participants spent almost the same time on each AOI. This interesting finding suggests that the subjects followed a common visualization pattern with the AOIs. This means that, when a tourist looks at TripAdvisor content, his/her visual attention pattern is the same for all pages.

Given the attention paid to online advertising of a product embedded in TripAdvisor pages (RQ2), we analyzed the gaze time spent on AOI_1. The attention given to the ad was 1.19 s for Trip 1 and 0.87 s for Trip 2. The percentage of attentional time was 6.3% and 5.78%, respectively. Overall, the attention given to the online ad was ranked fourth, behind the central area (online ratings of specific attributes) (AOI_5), the area with the consensus of online ratings (AOI_3), and the area with the online rating and heading of the comments given by two reviewers (AOI_4). The fixation time values were a bit lower than gaze time (Trip1: fixation (s) = 0.81, gaze (s) = 1.19; Trip 2: fixation (s) = 0.54, gaze (s) = 0.87), due to the different nature of the two metrics. The view pattern provided an important finding. The fixation times confirmed that the online ad embedded in TripAdvisor was ranked fourth in terms of attention paid to each area on the TripAdvisor page, partially supporting previous research. Hernández-Méndez and Muñoz-Leiva (2015) found that greater attention is paid to text featured on banners than to images. In restaurant menus, Yang (2012) found that the bottom areas attracted statistically significant fewer fixations than other areas. Our results showed that the ad stimulus located at the right-hand bottom of the page attracted attention, demonstrating that images are important for capturing attention. The area of least focal attention (i.e. the right-hand bottom area) attracted increased attention when an ad was located there. Thus, patterns of attention are probably driven by the nature of the stimuli.

RQ3 investigates whether the attention paid to the ad is at the expense of attention paid to other AOIs. The lower the TTFF, the higher is the attention paid to that AOI. The areas which attracted most gaze attention (AOI_5 and AOI_3) also had the lowest TTFF on both TripAdvisor pages (Trip1 = 2.9 and 2.8, and Trip2 = 2.9 and 2.6 s, respectively), followed by AOI_4 and AOI_10, and the area where the ad was located (AOI_11), with TTFFs of 10.3 and 8.5 s, respectively (values similar to those of area AOI_10, located in the top right-hand area). We conducted a comparative analysis of the time spent on the AOIs (in seconds and as a percentage of the total time) between the TripAdvisor pages containing the ad (Trip 1 and Trip 2) and the page without the ad (Trip 3). The results showed that more time was spent on the pages with the advertisement stimulus than on the page without the ad. The gaze time and the time spent, in percentage terms, on the two pages with the ad was 15.5 s for Trip 1 and 80.7%, and 11.6 s and 80.4% for Trip 2, and 9.3 s and 74.5% for the TripAdvisor page without the ad. Therefore, the percentages of attention paid to the ad was 6.2% for Trip 1 and 5.8% for Trip 2.

Overall, attention paid to the TripAdvisor pages is driven by three main issues, partially depicted in Fig. 2. The colored spots represent the areas fixated on by the participants. The scale goes from green to red, in which red represents the most time spent on the area, and green the least (red > orange > yellow > green). First, the top left-hand and top central areas are paid the most attention. Second, the attention paid to the online ad is not at the expense of the other stimuli on the TripAdvisor page. Moreover, the results showed a common view pattern on all pages.

2.2.3.2. *Brain response measurements.* EEG signals were recorded to assess if there was a difference in neural signals evoked across the three TripAdvisor pages (Trips 1, 2, and 3). The following metrics were used as dependent variables (DV): "mean high engagement (HE)", "mean workload (WL)", and "mean asymmetry (AM)". Valid EEG data were obtained from 83 participants for HE, 81 for WL, and 82 for AM (unused data for 18, 20, and 19 participants, respectively, and three extreme outliers, based on SPSS criteria, were eliminated). Separate within-subject ANOVAs were carried out for each EEG metric; these showed a statistically non-significant effect ($F_{HE}(2, 81) = 0.582$, $p = .586$; $F_{WL}(2, 79) = 1.834$, $p = .166$; $F_{AS}(2, 80) = 0.497$, $p = .610$), meaning that it is not possible to reject the null hypothesis that the metrics are the same across the groups. This result highlights that consumers do not expend high cognitive effort when processing social media content with embedded online ads.

3. Effects of ad congruence with social media content on ad recall and visual attention

3.1. *Congruence in advertising*

Congruence in advertising research describes the condition when an ad is consistent with the context in which it is placed (Wojdynski & Bang, 2016). This concept relates to the surroundings of ads, mainly in terms of content (thematic congruence). Congruence can establish stronger associative links and generate greater memory activation (Kim & Kim, 2020). This is important for advertisers as it is key for the decision on where to place ads. Moreover, strength of ad congruence varies based on the properties that match the ads to the context in which they are embedded (Dahlén, Rosengren, Törn, & Öhman, 2008). In the present study we understand congruence to be based on a measure of the relationship between the webpage content and the ad embedded on the site. A congruent TripAdvisor condition means that, for example, on a pizza restaurant's TripAdvisor website, embedded ads will promote the same type of food (pizzas/pizza restaurants). An incongruent condition exists when the food/restaurant types do not coincide.

Previous research has suggested that ads can have different effects on the consumer's visual attention and memory based on the media context in which they appear. The literature on the impact of congruence on advertising effectiveness provides contradictory results. Some research has shown that the fit between advertising messages and executional cues facilitates information processing (MacInnis & Park, 1991), while the existence of incongruent stimuli involves the viewer in greater information processing effort (Dahlén et al., 2008). Some related research has shown that thematic congruence between advertisements and

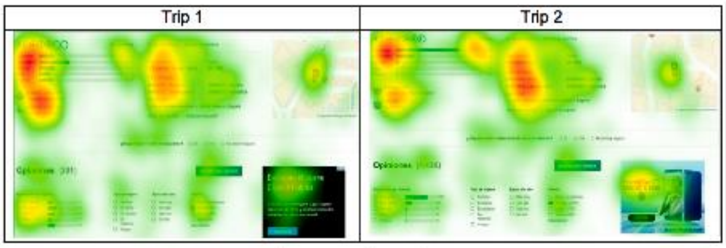

Fig. 2. Heatmap of Trip 1 and Trip 2.

magazines positively affects ad recall (Moorman, Neijens, & Smit, 2002). De Pelsmacker, Geuens, and Anckaert (2002) examined congruence between media context and advertisements. Their study confirmed the influence of context/ad similarity on brand recall in a TV context, but not in print advertising. Social media can be considered close to print, where the online posts are the context. However, Dahlén et al. (2008) showed that advertisements for brands that did not match with the magazine (i.e. thematic congruence) needed more processing. More recently, Rieger, Bartz, and Bente (2015) embedded congruent, partially-congruent and incongruent ads in news websites to investigate the effects of context congruence on both website and ad recall. These authors found that with unaided, as well as aided, recall measures, congruence led to higher recall ratings for both the website and the ad. In the context of YouTube skippable advertisements, Belanche et al. (2017) showed that in incongruent conditions, highly arousing ads demanded greater cognitive processing because of the associated greater distraction.

To complement the open discussion on the effects of congruence on ad recall, we pose the following RQ:

RQ4: Does ad-context congruence on social media increase ad recall?

Although behavioral data provides valid answers to many questions, it is not easy to measure accurately the reasons behind observed behaviors. Hence, in recent years, consumer research has incorporated the unconscious aspects of consumer choice through the observation of brain mechanisms (Bagdziunaite, Nassri, Clement, & Ramsøy, 2014). Neural activity can be measured in relation to marketing-relevant behaviors, such as attention, memory, affect, and choice, which are crucial for a better understanding of consumer behavior (Plassmann, Venkatraman, Huettel, & Yoon, 2015). Despite the increasing recognition of the value of employing neuro-techniques in marketing research, the service field still lacks research applying neuro-tools and "the time is ripe for service researchers to adopt neuro-tools" (Verhulst, De Keyser, Gustafsson, Shams, & Van Vaerenbergh, 2019).

As described in Study 1, eye-tracking has been extensively used to measure visual attention in advertising. This study uses eye-tracking to measure how the specific visual and textual features of positive- and negatively-valenced online reviews influence eye movement. Several eye-tracking measures are used in this study, such as time taken to first fixation, total duration of fixation, and number of revisits to certain areas of interest. These measures contribute to explaining the effectiveness of congruent/incongruent online ads embedded in social media.

The previous literature has demonstrated that semantic incongruency creates novelty and attracts attention (eye movements) toward semantically inconsistent objects (Underwood, Humphreys, & Cross, 2007). Simola et al. (2013) suggested that incongruence increases the visual attention paid to ads, whereas congruence improves ad recall.

Accordingly, we pose RQ5:

RQ5: Does ad-context congruence on social media increase the visual attention paid to the ad?

3.2. *Study 2: Online survey*

3.2.1. *Experimental design*

A within-subject design was used with TripAdvisor stimuli of four types of restaurants in Spain (pasta, pizza, paella, steak). We chose the restaurant types based on the number of restaurants on TripAdvisor Spain in each category, as a proxy for the overall preferences of Spanish people. Our stimuli used the same upper-page layout as TripAdvisor presents when displayed on a desktop. We decided not to include any comments on the basis that their subjective nature would be a confounder source in the analysis. We measured ad recall by comparing the percentage of correctly identified ads for each of the four conditions.

We conducted an online pre-test with 32 participants (mean age 27.7) to verify whether the ads chosen were perceived as congruent or incongruent. The participants rated pairs of images using a slider bar ranging from 0 to 100 (0 = not congruent at all, 50 = neutral, and 100 = very congruent). The image pairs were composed of a photograph of the advertised restaurant with either a congruent or an incongruent ad. Thus, each participant rated eight pairs in total (4 restaurants × 2 types of ad). The order of presentation was randomized across participants. A within-subjects ANOVA showed that the ad congruence manipulation was valid ($F(1, 31) = 297.726$, $p < .001$). The four ads chosen as congruent had a mean congruence of $M = 79.16$ ($SD = 17.05$), and the four ads chosen as incongruent had a mean congruence of $M = 18.05$ ($SD = 16.01$). We also looked at the congruence level means for each stimulus. The four congruent stimuli all had means above 0.50 (using a 95% C.I.), and the four incongruent stimuli all had means below 0.50 (95% C.I.).

In Study 2 we assessed the main effects of ad congruence and valence, and their possible interaction, on ad recall. We carried out a within-subjects (WS) 2 × 2 design with ad congruence (congruent × incongruent) and rating valence (positive: 4.5 stars × negative: 1.5 stars) as the independent variable (IV), type of restaurant as a covariate, and ad recall as the dependent variable (DV). Ad recall was measured through the subjects' recognition of the visual ads, following Moorman et al. (2002).

The four different restaurant types (pasta, pizza, paella, steak) used in the pre-test were again employed, with four stimuli: (1) positive valence and ad congruence (PVAC); (2) negative valence and ad congruence (NVAC); (3) positive valence and ad incongruence (PVAI); and (4) negative valence and ad incongruence (NVAI). Each participant viewed four stimuli (one for each condition, linked to one different restaurant per condition). Four groups of participants were used in order to cover all 16 stimuli (four types of restaurant × four conditions) (Table 1). The presentation order was randomized across participants.

3.2.2. *Data collection, sample, and procedure*

The data were collected in January 2020. The 295 participants, who all lived in Spain (57% female; age range: 18–67; mean age: 33.3; 62% employed; 27% students; and 11% unemployed; 93% use TripAdvisor to search for restaurants) answered a survey on the online platform Clickworker. The participants were paid a small amount of money for undertaking the experiment.

The participants viewed a screen displaying the first TripAdvisor stimulus (Fig. 3). The second, third, and fourth TripAdvisor stimuli were then presented. The participants were free to decide when to move on to the next stimulus. The order of presentation of the four stimuli was randomized across the participants. Then, three questions were asked (liking for the foods presented, frequency of eating in restaurants, frequency of using TripAdvisor to search for restaurants). Thereafter, a screen with pictures of the eight ads was displayed (however, the participants each saw only four of them while answering questions in the first part of the survey; their display positions were randomized across the participants.), and the participants had to identify the ads they had viewed during the experiment. Finally, they answered some demographic questions (e.g. gender, age) and a manipulation check question (i.e. a question asking about the purpose of the experiment).

3.2.3. *Results*

The participants viewed four TripAdvisor stimuli, each linked to one of four conditions (PVAC, NVAC, PVAI, NVAI). A within-subject binary logistic regression was carried out, using ad recall as the dependent variable (binary variable, 1: participant recalled the ad; 0: participant

Table 1
List of the four groups and conditions.

	Restaurant 1	Restaurant 2	Restaurant 3	Restaurant 4
Group 1	PVAC	NVAC	PVAI	NVAI
Group 2	NVAC	PVAC	NVAI	PVAI
Group 3	PVAI	NVAI	PVAC	NVAC
Group 4	NVAI	PVAI	NVAC	PVAC

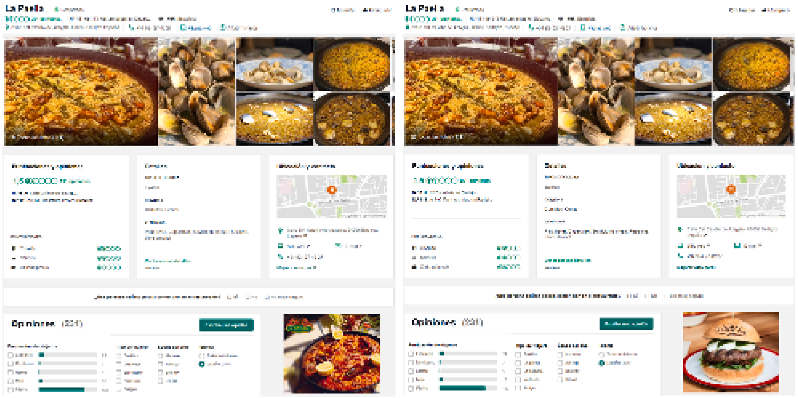

Fig. 3. Example of one of the four stimuli. Left picture: stimulus with a congruent ad. Right picture: stimulus with an incongruent ad.

did not recall the ad) and controlled for restaurant type. This analysis showed a main significant effect of congruence, congruent ads being recalled more than incongruent ($F(1, 1174) = 37.234$, $p < .001$). There was neither an interaction effect of valence and congruence, nor a main effect of valence. Fig. 4 shows the percentages of ads correctly recalled per condition. A separate analysis of each restaurant type revealed that the congruence effect was not found in restaurant 3 (Fig. 5).

RQ4 investigates if congruence between social media content and embedded ads increases ad recall. The findings showed that congruence affects ad recall. We showed that congruence increases percentage of ad recall compared to the incongruent condition. We also found that valence was not statistically significant for increasing ad recall. Our findings support previous studies on the positive effects of congruence on ad recall (Segev, Wang, & Fernandes, 2014; Simola et al., 2013).

3.3. *Study 3 – Eye-tracking study*

The laboratory study was designed to obtain unbiased insights into the effects of ad congruence on visual attention (RQ5). To this end, we collected neurophysiological data through eye-tracking.

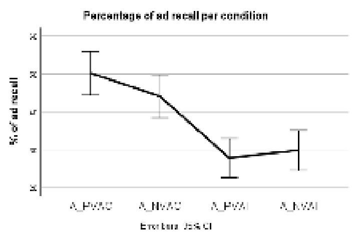

Fig. 4. Percentage of ads correctly recalled per condition. Error bars represent 95% confidence interval.

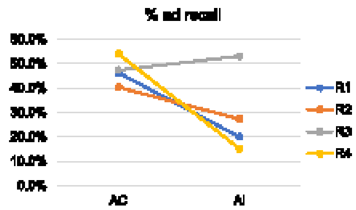

Fig. 5. Percentage of ads correctly recalled per restaurant type. Data were combined based on valence (AC = PVAC + NVAC, AI = PVAI + NVI). The error bars are omitted to facilitate visualization.

3.3.1. *Experimental design*

We used the same task and design as for Study 2. In addition to the metrics already described in Study 2, in Study 3 we measured the subjects' eye-tracking responses. The ET metrics selected were: time to first fixation, time spent in fixations (ms), number of fixations, and number of revisits to the ad AOI.

3.3.2. *Data collection, sample, and procedure*

128 participants living in Spain (51.6% female; mean age = 32.97, $SD_{age} = 10.14$; age range: 18–56; 68.5% employed; 26% students; 5.5% unemployed) were recruited via an external agency (100) and by internal means (28). The procedure was as follows. The participants arrived in the laboratory and signed the informed consent form. They viewed the instructions for the experiment on the computer screen. Calibration of the eye-tracking operation was performed before the experiment. The experiment used iMotions software (iMotions 8.1, København V, Denmark) for the presentations and synchronization of the stimuli. The participants viewed the stimuli through a 23-inch 1920 × 1080-pixel monitor. The Tobii X2-30 Compact device was used to monitor eye movements (eye-tracking), and the ET metrics were recorded using iMotions software. To obtain good quality eye-tracking data, instead of the self-paced visualization of the TripAdvisor stimuli

used in Study 2, in Study 3 the participants viewed each TripAdvisor stimulus for 30 s.

3.3.3. Results

First, we assessed the percentage of ad recall to further correlate it with the results of the eye-tracking measures. For this, a within-subject binary logistic regression was carried out, using ad recall as the dependent variable (binary variable, 1: participant recalled the ad; 0: participant did not recall the ad), controlled for restaurant type. This analysis showed that neither congruence nor valence had a significant main effect, and there was no interaction effect between the two variables. On average, participants recalled the ad 55.9% of the time in the congruent conditions and 53.5% in the incongruent condition (this difference is not statistically significant). Therefore, the results of Study 3 did not replicate the results of Study 2. This supports previous research on the inconclusive effects of ad-context congruency on consumer ad recall (De Pelsmacker et al., 2002; Kononova et al., 2020; Simola et al., 2013).

For the eye-tracking measure, due to poor data quality (percentage of recording below 70%), four participants were excluded from the analysis, and another five had only part of their data considered. The stimuli were divided into seven AOIs (see Fig. 6). The following variables were analyzed for the third-party ad AOI (AOI number 7): time to first fixation (ms), time spent fixated on the AOI (ms), number of visits, and number of fixations. The results of the within-subjects ANOVA demonstrated that there was no significant main effect of congruence nor valence in all metrics. The interaction effect between the two variables was not significant. The non-parametric Friedman related samples test confirmed a non-significant effect of valence and congruence for all metrics. The average means for all the metrics for congruent versus incongruent conditions (grouping restaurants and valence) were: time to first fixation (ms) $M_{cong} = 11,915$, $SD_{cong} = 6,912$, $M_{incong} = 12,360$, $SD_{incong} = 7,137$, time spent fixating the AOI (ms) $M_{cong} = 1,014$, $SD_{cong} = 877$, $M_{incong} = 983$, $SD_{incong} = 842$, number of visits $M_{cong} = 2.35$, $SD_{cong} = 1.82$, $M_{incong} = 2.38$, $SD_{incong} = 1.98$, and number of fixations $M_{cong} = 5.09$, $SD_{cong} = 4.03$, $M_{incong} = 5.07$, $SD_{incong} = 4.44$. In addition, the ad AOI was the last to be fixated on across all conditions. Therefore, ad-context congruence does not influence attention paid to the ad.

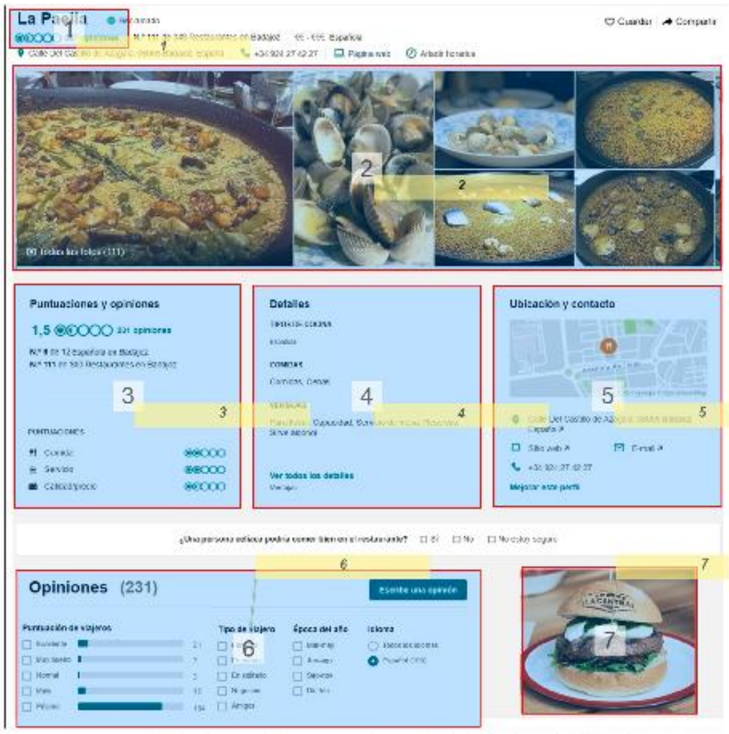

Fig. 6. Example of the distribution of the AOIs in one of the stimuli. The numbers indicate the label of each AOI.

The laboratory results found no differences in the percentage of ad recall across the conditions. The eye-tracking also showed no differences in the attention paid to the ads measured through the time to first fixation and number of visits metrics, and no difference in the attention paid to the ads, measured through the time spent in fixations and number of fixations. This result may be due to the different conditions under which the consumers processed the ads. As De Pelsmacker et al. (2002) pointed out, the environmental conditions faced by the subject at the time of exposure may influence message processing. In the online study, participants performed the experiment in a non-controlled environment. Moreover, the experiment was self-paced. In the laboratory study the participants had to view each stimulus for 30 s, and were in a higher-pressure environment than were the online participants. The data showed that the online participants spent less than 30 s on each stimulus.

4. Conclusions

4.1. Theoretical contributions

In this study we analyzed the influence of: (i) heuristic information UGC cues on TripAdvisor by disaggregating the main informative content of their AOIs and (ii) an online advertisement embedded in a TripAdvisor page. Using eye-tracking we examined how consumers allocate visual attention in social media. The EEG metrics showed that the cognitive load of consumers viewing UGC about a restaurant in TripAdvisor does not increase when an online ad is embedded in the page. Therefore, the sum of the cognitive load imposed on the subjects in processing the information in the ad embedded in the social media webpage, and their evaluation of the social media content, did not exceed their overall cognitive capacity (Duff & Sar, 2015).

Our findings provide new insights into consumers' visual processing behaviors. First, users follow visual patterns when looking at tourism services' content. Not surprisingly, the size of the AOI affects visual attention. However, attention is not totally driven by size; rather, particular heuristics attract the user's attention. Specifically, the area of the TripAdvisor page which attracts the most visual attention is the top central part.

Second, this study extends knowledge of the operationalization of HSM and significantly contributes to the identification of the role of heuristic cues in consumers' visual attention in social media. The heuristic cues that attracted higher visual attention were the scores for specific restaurant attributes (atmosphere, service, value for money, food), followed by the general breakdown of the comments in low-consensus situations, and star ratings and headings of individual reviews about specific restaurant attributes. The star ratings of online reviews are heuristic informational cues that facilitate the customer's evaluation of specific attributes of products and services. The results about the impact of specific scores of online reviews on visual attention complements previous research that showed that the level of detail in a message plays a powerful role in the persuasion process (Bigne et al., 2019). The breakdown of the overall comments in low consensus scenarios also attracted visual attention. This supports previous research (Kim & Lee, 2015) that showed that consensus in online reviews plays a pivotal role in influencing how potential consumers incorporate UGC into their evaluations about companies. Where reviewers provide conflicting opinions, this can induce uncertainty in consumers, and result in them rejecting all the assessments. Consequently, the visual attention paid to the presence/absence of consensus in overall star ratings is high, as consensus is a strong communication cue of persuasiveness and trustworthiness (Kim & Lee, 2015). However, volume of comments had a low impact on visual attention.

Third, this research highlights the effectiveness of the advertising content embedded in TripAdvisor pages, as the attention paid to ads is not at the expense of the attention paid to other content. Indeed, the gain in terms of percentage of attention paid to the ad was around 6%.

Fourth, the online study (Study 2) showed that ad recall was greater when the social media content and the third-party ad were congruent, than when they were incongruent, supporting the results of some previous ad congruence studies (Moorman et al., 2002; Rieger et al., 2015; Segev et al., 2014; Simola et al., 2013). The present study adds to earlier research into the effects of congruence by showing that, in low-involvement situations, ad-context congruence impacts positively on memory in terms of recalling previously viewed ads. Furthermore, rating valence had no main effect on ad recall. In addition, no interaction effect of UGC valence-ad congruence was found on ad recall. From a methodological point of view, the findings of the online study and the eye-tracking study improve our understanding of congruency effects in ad processing in different environments. This is important because previous empirical evidence regarding ad-context congruency effects on ad processing is contradictory (Kononova et al., 2020; Simola et al., 2013). Our findings support previous research on the priming principle; in low-involvement situations, a congruent context serves as a cue that enhances peripheral processing. We demonstrated that consumers exposed to online ads for a very limited time period (short and self-paced exposure) rely on less effortful, more heuristic, context-based processing strategies. A congruent ad-media context can act as a peripheral cue, activating knowledge structures and facilitating message processing (Petty & Cacioppo, 1986). In contrast, consumers exposed to online ads for longer periods of time are geared toward processing the message centrally. Priming the relevant associative structures, in this case, is not important.

4.2. Managerial implications

This study provides insights into which online advertising content (incongruent /congruent) to use, and where to place it, in social media such as TripAdvisor. These insights will help practitioners capture consumers' visual attention, which should be a primary objective in marketing communications, given the information overload faced by consumers. Our findings have implications for different professional groups involved in online advertising through social media, as we propose ideas for more effective distribution of items in TripAdvisor webpages.

As to our first goal (i.e. to identify which heuristic UGC information cues most attract viewer attention), advertisers should consider placing their ads in the central part of webpages. The information placed in the center of webpages attracts the greatest attention; in TripAdvisor, the central part of pages contains the overall ratings, and specific ratings for the different attributes, of the evaluated locations (Study 1 used the 2018 TripAdvisor layout). Since users spend more time on these specific AOIs, it would make sense, in order to maximize ad effectiveness: (1) to use medium-to-large sized ads, and (2) to place them as close as possible to the areas that attract most attention.

It is also worth highlighting the conclusions regarding our second goal (i.e. to analyze how online advertising competes with heuristic UGC cues to influence consumer visual attention and engagement). The presence of ads does not reduce the attention paid to the other AOIs. In other words, restaurant review sites should welcome the presence of advertisements as they do not detract from the attention paid to adjacent UGC. This result is in line with previous studies (e.g. Guitart, Hervet, & Hildebrand, 2019) that supported the effectiveness of banner advertising, even when users do not look directly at the ads (due to multitasking), since they still perceive the information through their peripheral vision. This, in turns, might positively affect brand recognition.

Regarding our third goal (i.e. to analyze the effect of online advertising of congruent/incongruent products on visual attention and ad recall), ad congruence, editorial content, and viewing time should be taken into consideration. When consumers peripherally process, subtle types of congruence can make a difference to ad recall. In order to increase ad recall and, thus, to enhance ad effectiveness, congruence should be high. This finding shows that ads should match their surrounding online content.

4.3. Limitations and future research lines

This study has some limitations that can open up new lines of research. As the study stimuli were presented statically, further analyses using dynamic ads (animated GIFs and videos) could provide more insights. Although the location of the ad in the webpage followed the original TripAdvisor format, it would be interesting to change its location and/or size. Second, in the three studies the layout of the stimuli reflected only the desktop version of TripAdvisor advertisements; future research should test other forms of incongruence and use mobile devices. Third, the length of exposure to the social media content needs further research. For example, an interesting research line would be to assess the impact of time spent visualizing advertisements on ad recall. More specifically, future research should address the impact of the different ways consumers process the information in ads on visual attention and ad recall. Fourth, in our research we explored social media content at an aggregate level, which summarized the average ratings and only some of the comments viewed. A further research line might analyze the effect of ad congruency on a comment from one reviewer and, thereafter, the reply given by the company. A comparison might then be made of how is was processed, based on the profile of the poster (e.g., expert versus non-expert); a similar comparison might also be made of match-ups between posters and lurkers. Last, our study pays no attention to type of reader. As a recent study posited (Rita, Ramos, Moro, Menlha, & Radu, 2020), younger generations are more accepting of social media advertising, thus it might of interest to conduct experiments based on product type and participant age.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Babić-Rosario, A., de Valck, K., & Sotgiu, F. (2020). Conceptualizing the electronic word-of-mouth process: What we know and need to know about eWOM creation, exposure, and evaluation. *Journal of the Academy of Marketing Science, 48*, 422–448.

Bagdziunaite, D., Nasri, K., Clement, J., & Ramsøy, T. Z. (2014). An added value of neuroscientific tools to understand consumers' in-store behaviour. In *Conference Proceedings EMAC 2014. European Marketing Academy 43rd Annual Conference: Paradigm Shifts & Interactions* (p. 171). EMAC.

Belanche, D., Flavián, C., & Pérez-Rueda, A. (2017). Understanding interactive online advertising: Congruence and product involvement in highly and lowly arousing, skippable video ads. *Journal of Interactive Marketing, 37*, 75–88.

Bigne, E., Ruiz, C., & Curras-Perez, R. (2019). Destination appeal through digitalized comments. *Journal of Business Research, 101*, 447–453.

BrightLocal. (2018). Local Consumer Review Survey | Online Reviews Statistics & Trends. https://www.brightlocal.com/research/local-consumer-review-survey/ **Accessed 16 March 2020.**

Cabiedes-Miragaya, L. (2017). Analysis of the economic structure of the eating-out sector: The case of Spain. *Appetite, 119*, 64–76.

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of personality and social psychology, 39*(5), 752–766.

Chu, S. C., Lien, C. H., & Cao, Y. (2019). Electronic word-of-mouth (eWOM) on WeChat: Examining the influence of sense of belonging, need for self-enhancement, and consumer engagement on Chinese travellers' eWOM. *International Journal of Advertising, 38*(1), 26–49.

Dahlén, M., Rosengren, S., Törn, F., & Öhman, N. (2008). Could placing ads wrong be right?: Advertising effects of thematic incongruence. *Journal of Advertising, 37*(3), 57–67.

De Pelsmacker, P., Geuens, M., & Anckaert, P. (2002). Media context and advertising effectiveness: The role of context appreciation and context/ad similarity. *Journal of Advertising, 31*(2), 49–61.

Duff, B. R. L., & Sar, S. (2015). Seeing the big picture: Multitasking and perceptual processing influences on ad recognition. *Journal of Advertising, 44*(3), 173–184.

Guitart, I. A., Hervet, G., & Hildebrand, D. (2019). Using eye-tracking to understand the impact of multitasking on memory for banner ads: The role of attention to the ad. *International Journal of Advertising, 38*(1), 154–170.

Hernández-Méndez, J., & Muñoz-Leiva, F. (2015). What type of online advertising is most effective for eTourism 2.0? An eye-tracking study based on the characteristics of tourists. *Computers in Human Behavior, 50*, 618–625.

Kim, D. Y., & Kim, H. Y. (2020). Influencer advertising on social media: The multiple inference model on influencer-product congruence and sponsorship disclosure. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.02.020.

Kim, E. K., & Lee, C. H. (2015). How do consumers process online hotel reviews? *Journal of Hospitality and Tourism Technology, 6*(2), 113–126.

Kononova, A., Kim, W., Joo, E., & Lynch, K. (2020). Click, click, ad: The proportion of relevant (vs. irrelevant) ads matters when advertising within paginated online content. *International Journal of Advertising*, 1–28. https://doi.org/10.1080/02650487.2020.1732114.

MacInnis, D. J., & Park, C. W. (1991). The differential role of characteristics of music on high-and low-involvement consumers' processing of ads. *Journal of Consumer Research, 18*(2), 161–173.

Markowitz, D. A., Shewcraft, R. A., Wong, Y. T., & Pesaran, B. (2011). Competition for visual selection in the oculomotor system. *Journal of Neuroscience, 31*(25), 9298–9306.

Moorman, M., Neijens, P. C., & Smit, E. G. (2002). The effects of magazine-induced psychological responses and thematic congruence on memory and attitude toward the ad in a real-life setting. *Journal of Advertising, 31*(4), 27–40.

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.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and Persuasion* (pp. 1–24). New York, NY: Springer.

Pfiffelmann, J., Dens, N., & Soulez, S. (2020). Personalized advertisements with integration of names and photographs: An eye-tracking experiment. *Journal of Business Research, 111*, 196–207.

Plassmann, H., Venkatraman, V., Huettel, S., & Yoon, C. (2015). Consumer neuroscience: Applications, challenges, and possible solutions. *Journal of Marketing Research, 52*(4), 427–435.

Rieger, D., Bartz, F., & Bente, G. (2015). Reintegrating the ad. Effects of context congruency banner advertising in hybrid media. *Journal of Media Psychology, 27*, 64–77.

Rita, P., Ramos, R. F., Moro, S., Mealha, M., & Radu, L. (2020). Online dating apps as a marketing channel: A generational approach. *European Journal of Management and Business Economics*. https://doi.org/10.1108/EJMBE-10-2019-0192.

Scott, N., Zhang, R., Le, D., & Moyle, B. (2019). A review of eye-tracking research in tourism. *Current Issues in Tourism, 22*(10), 1244–1261.

Segev, S., Wang, W., & Fernandes, J. (2014). The effects of ad–context congruency on responses to advertising in blogs. *International Journal of Advertising, 33*(1), 17–36.

Simola, J., Kivikangas, M., Kuisma, J., & Krause, C. M. (2013). Attention and memory for newspaper advertisements: Effects of ad–editorial congruency and location. *Applied Cognitive Psychology, 27*(4), 429–442.

Strong, E. K., Jr (1925). Theories of selling. *Journal of Applied Psychology, 9*(1), 75.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285.

Underwood, G., Humphreys, L., & Cross, E. (2007). Congruency, saliency and gist in the inspection of objects in natural scenes. In R. P. G. Gompel, M. H. Fischer, W. S. Murray, & R. L. Hill (Eds.), *Eye movements: A window on mind and brain* (pp. 563–579). Amsterdam: Elsevier.

Vecchiato, G., Toppi, J., Astolfi, L., Fallani, F. D. V., Cincotti, F., Mattia, D., & Babiloni, F. (2011). Spectral EEG frontal asymmetries correlate with the experienced pleasantness of TV commercial advertisements. *Medical & Biological Engineering & Computing, 49*(5), 579–583.

Verhulst, N., De Keyser, A., Gustafsson, A., Shams, P., & Van Vaerenbergh, Y. (2019). Neuroscience in service research: An overview and discussion of its possibilities. *Journal of Service Management, 30*(5), 621–649.

Wedel, M., & Pieters, R. (2014). Looking at vision: Eye/face/head tracking of consumers for improved marketing decisions. In *The Routledge Companion to the Future of Marketing* (pp. 212–225). Routledge.

Wiese, M., Martínez-Climent, C., & Botella-Carrubi, D. (2020). A framework for Facebook advertising effectiveness: A behavioral perspective. *Journal of Business Research, 109*, 76–87.

Wojdynski, B. W., & Bang, H. (2016). Distraction effects of contextual advertising on online news processing: An eye-tracking study. *Behaviour & Information Technology, 35*(8), 654–664.

Yang, S. S. (2012). Eye movements on restaurant menus: A revisitation on gaze motion and consumer scanpaths. *International Journal of Hospitality Management, 31*(3), 1021–1029.

Yoon, Y., Kim, A. J., Kim, J., & Choi, J. (2019). The effects of eWOM characteristics on consumer ratings: Evidence from TripAdvisor.com. *International Journal of Advertising, 38*(5), 684–703.

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APPENDIX 2

MOTIVATION IN METAVERSE: A DUAL-PROCESS APPROACH TO CONSUMER CHOICE IN A VIRTUAL REALITY SUPERMARKET

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This is the second out of three published Appendices. The study uses electroencephalography to examine differences brain signals during planned and unplanned decisions in virtual supermarket. As part of this thesis, we are reproducing the online version of the study published in Frontiers in Neuroscience. Saffari, F., Kakaria, S., Bigné, E**.,** Bruni, L. E., Zarei, S., & Ramsøy, T. Z. (2023). Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket. *Frontiers in Neuroscience*, 17. https://doi.org/10.3389/fnins.2023.1062980

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Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket

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Introduction: Consumer decision-making processes involve a complex interrelation between perception, emotion, and cognition. Despite a vast and diverse literature, little effort has been invested in investigating the neural mechanism behind such processes.

Methods: In the present work, our interest was to investigate whether asymmetrical activation of the frontal lobe of the brain could help to characterize consumer's choices. To obtain stronger experimental control, we devised an experiment in a virtual reality retail store, while simultaneously recording participant brain responses using electroencephalogram (EEG). During the virtual store test, participants completed two tasks; first, to choose items from a predefined shopping list, a phase we termed as "planned purchase". Second, subjects were instructed that they could also choose products that were not on the list, which we labeled as "unplanned purchase." We assumed that the planned purchases were associated with a stronger cognitive engagement, and the second task was more reliant on immediate emotional responses.

Results: By analyzing the EEG data based on frontal asymmetry measures, we find that frontal asymmetry in the gamma band reflected the distinction between planned and unplanned decisions, where unplanned purchases were accompanied by stronger asymmetry deflections (relative frontal left activity was higher). In addition, frontal asymmetry in the alpha, beta, and gamma ranges illustrate clear differences between choices and no-choices periods during the shopping tasks.

Discussion: These results are discussed in light of the distinction between planned and unplanned purchase in consumer situations, how this is reflected in the relative cognitive and emotional brain responses, and more generally how this can influence research in the emerging area of virtual and augmented shopping.

KEYWORDS
electroencephalogram, virtual reality, frontal asymmetry, consumer neuroscience, decision making

Introduction

Our everyday behaviors and choices result from a complex interplay between our perceptions, emotions, and cognition. Choices we make range from highly planned to direct and impulsive behaviors. This distinction is often seen in well-controlled studies in psychological and cognitive neuroscience. The distinction between decisions as ranging from cognitive to emotional responses has been investigated in various disciplines, i.e., neuroscience, philosophy, psychology, and commercial studies (Schall, 2001). Most notably, behavioral studies have long held a view of a split between an emotional and impulsive system, and a more cognitively driven deliberation system (Frankish, 2010). This has also been demonstrated in neuroimaging studies showing a distinction between two separate neural systems for immediate and delayed rewards (McClure et al., 2004).

However, less is known about the role of dual-process (an interplay between our emotion and cognition) decisions in real-life situations, especially in the ubiquitous digital reality in which consumer behaviors are embedded in our days. Numerous studies in neuroscience have been examining consumers' shopping behavior (Martin and Potts, 2009; Ravaja et al., 2013; Gable et al., 2015; Ramsøy et al., 2018; Goto et al., 2019; Liao et al., 2019; Shih et al., 2019; Ozkara and Bagozzi, 2021). With the help of quantitative measurement in neuroscience such as electroencephalogram (EEG), these relatively vague concepts can be analyzed and furtherly explore consumer decisions. The most recent studies in neuromarketing have been focused on consumer's purchase intention and decisions (purchase vs. no-purchase) (Shang et al., 2020; Wang et al., 2021), or predicting consumer's purchases (Golnar-Nik et al., 2019; Bak et al., 2022). But fewer studies have gone beyond "buy" and "no buy" and the relative contribution of cognitive and emotional process on consumer motivation (Aditya and Sarno, 2018; Royo-Vela and Varga, 2022) and the distinction of consumers decisions have not been thoroughly investigated.

Human emotion plays a central role in our everyday decisions (Rutherford and Lindell, 2011; Harmon-Jones et al., 2012). Previous research has shown that our positive or negative perceptions could be explained by approach\avoidance behavior (Rutherford and Lindell, 2011; Harmon-Jones et al., 2012). When it comes to human shopping behavior, the reasoning behind our decision becomes more complex and difficult to explain (Ohme et al., 2010; Wixted, 2018; Karmarkar and Plassmann, 2019; Neal and Gable, 2019; Sänger, 2019).

Lateralized function of the brain has been the core of many neuroscientific studies on emotion (Petrantonakis and Hadjileontiadis, 2011; Gable et al., 2015), motivation (Coan et al., 1997; Poole and Gable, 2014), neurological and psychiatric disorders (Keune et al., 2015; Lin et al., 2021). Specifically, frontal asymmetry scores are one of the most promising features that have been extracted from EEG data to quantify our valence and approach-avoidance behavior (Coan et al., 1997; Davidson, 2004; Ravaja et al., 2013; Poole and Gable, 2014; Wixted, 2018).

Frontal asymmetry has been traditionally used by neuroscientists as an indicator of human emotions (Smith et al., 2017), which relies on the theory that the left prefrontal cortex is more activated for emotions with positive valence compared to those with negative valence, which induce relatively less left prefrontal activity. Moreover, the approach/avoidance behavior has been studied in this manner as a motivation index. Most of these studies have been focused on the alpha frequency band, which relates to the inhibitory function of the brain and a higher relative power in this band indicates less cortical activation (Smith et al., 2017). However, less attention has been paid to the other EEG frequency bands such as beta and gamma (Ravaja et al., 2013; Ramsøy et al., 2018; Spironelli et al., 2021).

The theta-alpha ratio (TAR) has been recently used as a cognitive load index which is sensitive to task difficulty and cognitive processing (Trammell et al., 2017; Cabañero et al., 2019; Wang et al., 2020). Here, we assumed that the TAR index would vary as participants switched their shopping behavior from decisions that were mainly emotion-based, and hence frontal asymmetry based, to a more cognitive state of planned behavior, which we expected to be related to stronger TAR scores.

Consumer behaviors have recently changed from being physically based in brick-and-mortar stores to moving online (Cheung et al., 2005), and finally now on the verge of moving fully into mixed reality (MR) (Shen et al., 2021). Recent research in Virtual Reality (VR) tried to combine VR and supermarket as a research tool (Peschel et al., 2022), or as a teaching application for Autistic patients (Thomsen and Adjorlu, 2021). Also, VR supermarkets have been used to investigate consumers' behavior in choosing healthy food (Eichhorn et al., 2021; Melendrez-Ruiz et al., 2021), or with the help artificial intelligence, virtual supermarket has been studied as a "shopping at home" avenue (Shravani et al., 2021). However, to the best of our knowledge, the effect of virtual supermarkets on consumers' subconscious response has not been thoroughly investigated *via* psychophysiological tools such as EEG. Thus, there is a need for a better understanding of consumer behaviors and relative underlying neural responses in general, as well as in the new digital interfaces that consumers are currently moving into.

Recently, different effects of VR on our brain responses have been measured through EEG (D'Errico et al., 2020; Dini et al., 2022). Due to VR engagement and the semi-real environment that these technologies provide, they could facilitate examining neural responses in a more realistic way. In Schaefer et al. (2016) a VR shopping task has been conducted to investigate the effect of price expectation violation on the P300 component of EEG and in Rosenlacher et al. (2018) the effects of a VR store on human shopping behavior have been studied. Besides consumer neuroscience, VR and MR have been used as a treatment tool (Tran et al., 2022), or as an educational avenue (Makransky et al., 2019) in neuroscientific studies. Specifically, as there is now a surge in interest for implementing MR worlds as a solution for everyday situations (Bazzani et al., 2020)—increasingly referred to as the "metaverse"—our knowledge about attentional, emotional, and cognitive responses is woefully lacking. While we can, *a priori*, assume that the responses we see inside MR are the same as those that we see outside MR, few studies have been conducted to test this assumption. Hence, although numerous neuroscientific studies tried to investigate the neural mechanism behind consumers' decision-making process, the validity of the finding of those studies have not been tested in a real-life scenario.

In this study, we designed an experiment in a VR supermarket, with minimal experimental control and high ecological validity, to investigate whether there is a difference in consumers' relative involvement of cognitive and emotional processes in planned vs. unplanned decisions, respectively. Participants went through two experimental phases while being in the VR store. First, they were asked to buy products following a predefined shopping list. Second, they were instructed to also buy whatever they wanted from the store.

We posed two main hypotheses. First, following prior research on frontal asymmetry and choice, we expected stronger frontal asymmetry responses when consumers made choices, compared to phases of product inspection with no choice, regardless of whether the choice was planned or unplanned. More specifically, frontal asymmetry, as a representation of participants' approach behavior, is assumed to be higher in choice trials compared to the no-choice trials, i.e., periods of the experiment in which participants are navigating or searching for products.

Second, we assumed that planned purchases would rely more on cognitive brain responses implying higher cognitive load, while spontaneous, unplanned purchases would be more driven by emotional brain responses. Therefore, we hypothesized that unplanned purchases would be related to a stronger frontal asymmetry score during product choice, compared to planned purchases. Conversely, we hypothesized that planned purchases would be associated with a relatively lower frontal asymmetry and a higher degree of cognitive load.

Materials and methods

A total of 30 (14 female, 16 male) right-handed subjects (age range 23–44, mean = 31.8, std = 6.6) were recruited in the experiment using Neurons Inc[1] online recruitment procedures. Since we aimed to compare the EEG responses in two conditions, we only included the data from the subjects who fulfilled both tasks in the experiment which reduced the number of subjects to 27 (age range 23–44, mean = 31.6, std = 6.9). From these participants that we consider the data for the study, eight of them have previous experience with VR and using the controllers and two of them have participated in a study with virtual supermarket previously. All participants read and signed the consent form, and they were informed about the experimental procedure prior to the data collection. This study was performed in accordance with the Declaration of Helsinki, the rules and laws of the Danish Data Protection Agency, the European Union law of the General Data Protection Regulation, as well as the ethical regulations imposed by the Neuromarketing Science and Business Association, Article 64. Each person's biometric data, survey responses, and other types of data were anonymized and only contained the log number as the unique identifier. No personally relevant data could be extracted from the log number.

Experimental design

A supermarket environment was designed in Unreal Engine V4.1[2] and implemented in a VR HTC Vive 5.[3] The VR supermarket was comparable to the supermarkets in Denmark in terms of appearance. Participants had two controllers (which appeared as hands in the VR) that they can use to choose the items and teleport through the VR. They could also walk (for one or two steps in the physical space), but we asked them to limit their movement in order to keep them in VR environments. All of the items in the supermarket were accessible and participants could choose whatever they see in the store through free navigation. We have allocated a budget of 250 Danish Kroner (DKK) (~$35) for each participant to spend on these two shopping tasks. Therefore, participants were free to distribute their budget between these two shopping tasks and prevent the neurological effect of product price suggested by Tang and Song (2019) in online context. We provided a list of products in the VR for the participants, which contained six items (Broccoli, Milk, Cheese, Soda, Cereal, and Chocolate). The range of the cost of these items was between 80 and 120 DKK. Participants need to purchase all of these items, which we call as planned purchase condition. With the remaining amount of budget, they could buy whatever they wanted in the store (Unplanned Purchase Condition). They could leave the environment as soon as they had bought the items they wanted. The number of planned purchases (items from the list) was fixed, and the number of unplanned purchases could be different among the subjects, as they were free to choose any item they wanted if it was within their budget. In Figure 1, the experimental procedure of the experiment is illustrated. In the upper side of the figure, the environment for the virtual supermarket is presented.

The EEG data were recorded during the whole shopping task. After mounting the VR and EEG cap, we instructed the participant on how to use the VR so they could start the experiment and navigate through the store. The list of the products that they needed to purchase was available for them by hitting a button on the controller. In the first phase, they were required to buy all the products from the list. Afterward, we informed them about the remaining budget. Then, they could start the second phase of the experiment. On average, participants spent 238.87 ± 85.57 s on the planned purchase condition, and 228.00 ± 107.20 s on the unplanned purchase condition. The time-points of each purchase (i.e., when the participants choose an item) have been recorded during the experiment.

EEG recording

Electroencephalogram data were collected using a monopolar 32 channels (gel-based) EEG device (Brain Products, ActiCap) with 500 Hz sampling rate. The EEG sensor locations with the standard 10–20 system were positioned at Fp1, Fp2, F8, F4, Fz, F3, F7, FT9, FT10, FC5, FC1, FC2, FC6, T7, T8, C3, Cz, C4, CP5, CP1, CP2, CP6, TP9, TP10, P7, P3, Pz, P4, P8, O1, Oz, O2. The ground and reference electrodes were located at Afz and FCz, respectively, for online processing. The data were transmitted wirelessly from the amplifier (LiveAmp32) to a PC using a USB module. The impedance of the electrodes was monitored prior to the data collection, and it was maintained below 15 KΩ.

EEG analysis

For the EEG data analysis, we used the MNE tool (Gramfort, 2013). First, the data were filtered using a FIR bandpass filter

1 https://www.neuronsinc.com

2 https://www.unrealengine.com

3 https://www.vive.com

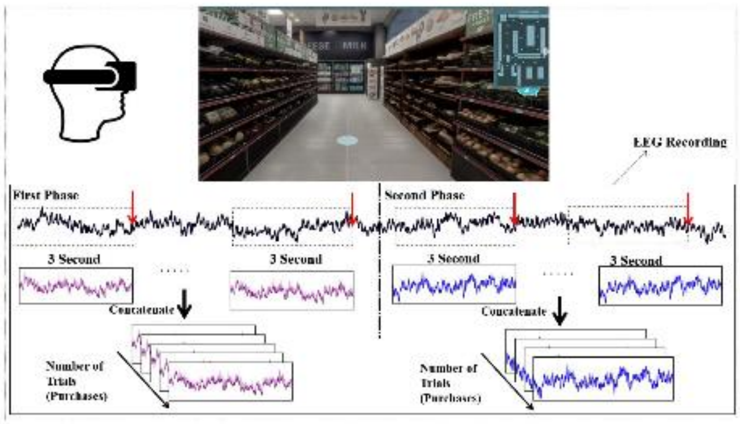

FIGURE 1
The environment for virtual supermarket and EEG data collection procedure is presented. The red arrows show the time points in which they choose a product. We consider the 3 s data before that event as a trial. Afterward the trials for each condition have been concatenated for further analysis.

with a hamming window for the 0.1 and 100 Hz frequency bands. A notch filter at 50 Hz was also applied to remove the power line noises. Independent Component Analysis (Jung et al., 1998) was applied to clean the data and manually remove the "bad" components by visual inspection. Afterward, common average referencing and baseline correction methods were used for pre-processing procedures.

Based on a recent study (Ramsøy et al., 2018), we considered 3 s epochs of the data before each participant chose an item (in both conditions) for our analysis. The rest of the data, which was not included in choosing the products was also epoched with 3 s length for the consistency of the analysis. The power spectrum of the signal was calculated using a welch method (with 256 numbers of FFT points equivalent to 512 milliseconds) for each frequency band (theta [4–8], alpha [8–13], beta [13–25], gamma [30–40]). For each epoch, the power spectrum was calculated by averaging over frequency bins and then averaged over all epochs to represent the power spectrum of that condition for each subject.

EEG feature extraction

Frontal asymmetry

The frontal asymmetry score is a well-established EEG feature to indicate the lateralization effect of emotional processing in the brain (Lee et al., 2020; Lin et al., 2021; Yang et al., 2021). Frontal asymmetry is calculated by subtracting the log-transformed power values of frontal channel F7 from frontal channel F8 and divided by the sum of the power of both electrodes, as shown in Equation 1. Frontal asymmetry was measured for alpha, beta, and gamma frequency bands. It should be noted that the alpha scores are not multiplied by -1 to indicate the "de-activation" of the alpha band.

$$\frac{Log\ (power(F7)) - Log\ (power(F8))}{Log\ (power(F7)) + Log\ (power\ (F8))} \tag{1}$$

Theta-alpha ratio

TAR indexes the cognitive load value by using cross-frequency activity in the frontal and parietal lobes. As shown in Equation 2, power values in the theta frequency band from F7 and F8 channels were normalized to power values in the alpha frequency band at the parietal lobe (P3 and P4) (Wang et al., 2020).

$$\frac{Power\ (F7(theta)) + Power\ (F8(theta)}{Power\ (P3(alpha)) + Power\ (P4(alpha)} \tag{2}$$

Statistical method

As described in the experimental design section, we asked each participant to purchase six items from a predefined list, and then they could purchase whatever they wanted with the remaining budget. Accordingly, this led to an imbalance of trials, both within each subject (between each condition) and between subjects. To solve this imbalance, we applied a permutation test, which previously has been applied to resolve the imbalance of trials issue in an ERP study (Files et al., 2016). As shown in Figure 2, for each participant, we first calculated the desired feature (asymmetry score in different frequency bands) from the trials of each condition. We subtracted those values of one condition from the other to calculate

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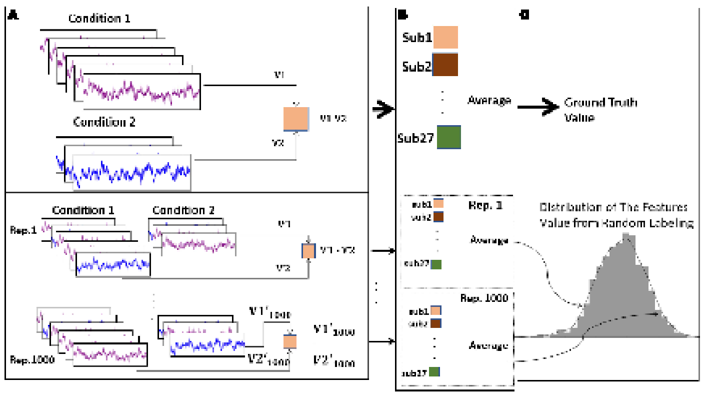

FIGURE 2
The implemented statistical method for considering the imbalanced trials. In section (A), the calculation of feature values has been shown. In the upper section, features from the actual conditions (V1, V2) have been calculated and then subtracted for each subject. In the lower section of (A) the same procedure is happening but with random shuffling of the labels across trials for 1,000 iterations. In section (B) we averaged the outcome of section (A) over subjects which the upper section shows for the actual condition and the lower section is for each iteration. In section (C) the ground truth value from the actual conditions and null distribution from the random shuffling is illustrated in the upper and lower side respectively.

the difference between the features. By repeating this procedure for all subjects, we computed the average of these values for all the participants to build up the "ground truth" values for that comparison.

Next, for generating data-driven null distribution, we randomly shuffled the trial's labels between conditions for each subject, and then repeated the same procedure that we did to calculate the ground truth. By performing this procedure 1,000 times, we could have a null distribution to compare the ground truth value in the two conditions. Ultimately, if the ground truth is far enough (based on the significance level which here is 0.05 before Bonferroni's correction) from the mean of this distribution, we could state that our findings are not due to randomness. Due to multiple comparisons, the significance level is $0.05/3 = 0.01$.

We applied this statistical method to compare the asymmetry scores in alpha, beta, and gamma frequency bands, in the two given conditions: purchase vs. non-purchase, and planned purchase vs. unplanned purchase.

Results

Frontal asymmetry

Looking at the distinction between purchase and non-purchase conditions, we find a significant difference in alpha, beta, and gamma asymmetry scores (F7, and F8 channels) between the two conditions. The results of the beta asymmetry scores for these two conditions are presented in Figure 3A as an illustrative example to show the significance level (P-value < 0.01). For the rest of the frequency bands, the significance plots were similar to Figure 3, therefore, we are not presenting the plots here to avoid repetition. As it is shown in Figure 3, the ground truth of asymmetry scores was far from the mean of null distribution which makes the ground truth value statistically significant.

In the alpha frequency band, the asymmetry mean scores for purchase and non-purchase conditions over all subjects were negative and the score for the purchase phase (-0.001 ± 0.008) was higher (p-value < 0.001, 1000 permutations) than the non-purchase phase (-0.005 ± 0.006). For beta and gamma frequency bands, the mean asymmetry scores were positive for the purchase phase (0.0001 ± 0.009 and 0.0008 ± 0.011) and negative for the non-purchase phase (-0.005 ± 0.007 and -0.006 ± 0.008) with p-value < 0.001 and 1,000 permutations. The violin plots of these results are presented in Figure 4.

For the comparison between planned and unplanned purchase, there was a trend toward a significant difference in the range of alpha (P-value $= 0.08$) and beta (P-value $= 0.04$) asymmetry scores before correction, between these two conditions. However, in the gamma band, the difference between mean asymmetry scores of the unplanned purchase (0.001 ± 0.011) and planned purchase (-0.002 ± 0.012) was statistically significant (P-value < 0.001, 1000 permutations). The results of the statistical method for the gamma frequency band are presented in Figure 3B, and the violin plots of asymmetry scores for different frequency bands are presented in Figure 5.

The asymmetry scores in alpha, beta, and gamma frequency bands for each of the products in planned purchase are presented in Figure 6 (averaged for all subjects). For each of the six products, the

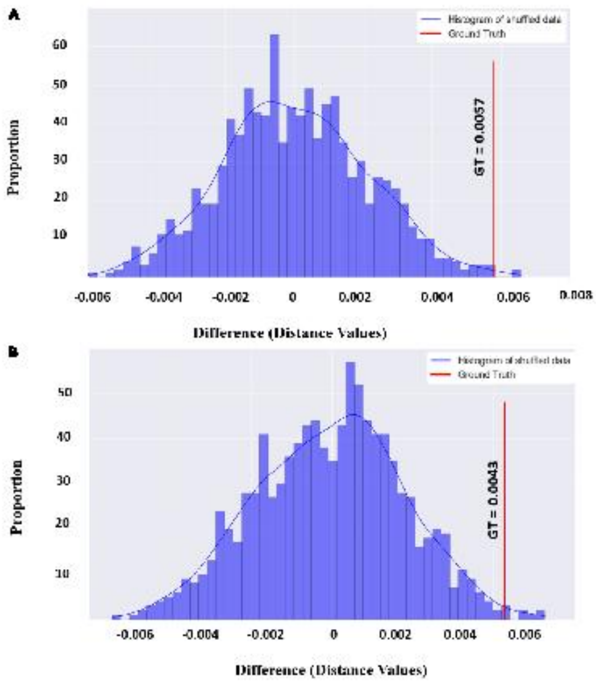

FIGURE 5
(A) The distribution and ground truth values of the beta asymmetry score differences in the two conditions (purchase vs. Non-purchase). The distribution derives from calculating the difference of the beta asymmetry score between two conditions for 1,000 times and shuffling the labels among trials. The blue vertical line is our ground truth which indicates the same difference but for the actual conditions. (B) Same as the above plot but for planned and unplanned conditions in gamma frequency band.

alpha asymmetry scores are positive (considering the multiplication by -1) and chocolate has the highest alpha asymmetry. For beta and gamma asymmetry, the scores are both negative and positive. Cereal and chocolate have the highest beta and gamma asymmetry scores respectively.

In addition, we have compared the asymmetry score in the gamma frequency band of each second (from the 3-s time window) before choosing an item. As it is shown in Figure 7, for both planned and unplanned purchases, as participants become closer to choosing an item, the gamma asymmetry score increases. For unplanned purchase, the asymmetry score starts from negative and become positive when there is a 2 s before choosing an item. However, for the planned purchases, even though the asymmetry score increased as we get closer to choosing a product, the asymmetry score remains negative for each of the three phases before choosing an item.

Theta alpha ratio

Comparing TAR values of planned and unplanned purchase, we found a significant difference between the given conditions with p-value < 0.0001. As represented in Figure 8, the averaged TAR index over all subjects was 7.04 ± 4.35 for planned condition and 4.28 ± 1.92 for unplanned condition.

Discussion

In this study, we sought to test whether consumer choices in a VR supermarket can modulate brain frontal asymmetry in alpha, beta, and gamma frequency bands. In addition, we were interested in testing whether planned and unplanned choices would be related

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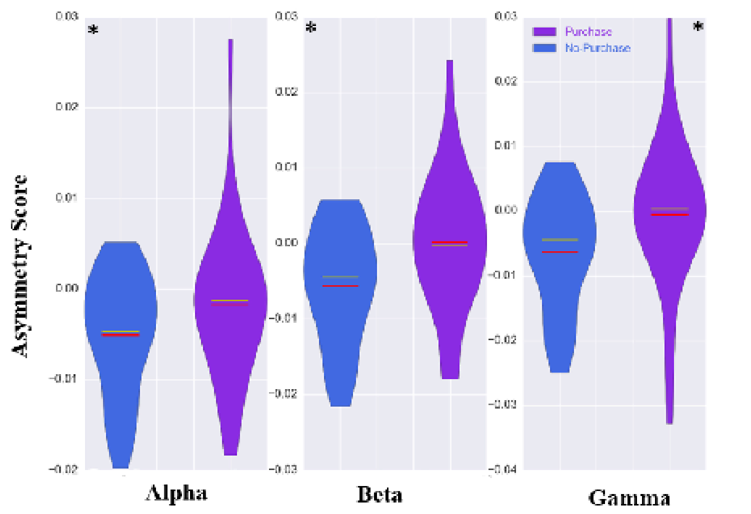

FIGURE 4
The violin plots of asymmetry scores of three frequency bands for all subjects. The purchase and non-purchase conditions are shown with blue and purple colors, respectively. The red and yellow line in the middle illustrating the mean and median values, respectively. The difference between the asymmetry scores were statistically significant (*p-value < 0.001) in all tree frequency bands.

to similar changes in emotional and cognitive responses such as frontal asymmetry and TAR, respectively.

In doing so, we found that regardless of the types of participants' purchases, there was a significant difference in alpha, beta, and gamma asymmetry scores comparing trials that involved choosing a product, compared to other phases of store task completion, such as navigating the environment. We also showed that different types of consumer choices (planned and unplanned), were related to a modulation of the gamma asymmetry scores but not the alpha or beta frontal asymmetries.

Our findings for comparison of "choice vs. no-choice" were partially in line with the previous studies regarding frontal asymmetry and approach behavior. Previous research has shown that since alpha oscillation is more correlated with inhibitory activities, relatively higher right frontal activity is related to the approach behavior in this frequency band (Harmon-Jones and Allen, 1998; Pizzagalli et al., 2005; Ravaja et al., 2013; Smith et al., 2017). However, our results showed a contrast in alpha frontal asymmetry, in which there was a relatively higher right frontal activity in the no-choice phase. For the beta and gamma frequency bands, there was a relatively higher frontal asymmetry during the "choice" conditions, which was in line with previous research that relates higher left frontal beta activity compared to right frontal activity to consumers' purchase decisions (Aftanas et al., 2006; Ramsøy et al., 2018; Zhao et al., 2018; Alarcão and Fonseca, 2019; Lin et al., 2021; Yuan et al., 2022).

Our second hypothesis was concerned with the comparison between planned and unplanned choices. Here, our results confirmed our hypothesis as there was a significantly higher left than right frontal activity in the gamma frequency band during unplanned conditions, relative to planned choices. As some recent studies suggested (Ramsøy et al., 2018; Tarrant and Cope, 2018), we found a greater gamma asymmetry score for unplanned choices compared to planned choices. These findings provide new insights into the role of gamma frequency band activity in decision making particularly in consumer neuroscience.

Moreover, when looking at the cognitive index of the TAR score for the planned and unplanned conditions, our results show that planned purchases were associated with relatively higher levels of the cognitive load than unplanned purchases. This is in line with our assumption and prior findings and suggests that planned behavior is reflected as a theta-alpha activity ratio even in a virtual shopping environment. As opposed to most of the research in the field of consumer neuroscience, which mainly focus on consumers' "purchase" and "no purchase" (Rosenlacher et al., 2018; Golnar-Nik et al., 2019; Goto et al., 2019; Eichhorn et al., 2021; Melendrez-Ruiz et al., 2021; Horr et al., 2022) we have extended this view by looking deeper to the relative contribution of cognitive and emotional response and the dual-process of consumer's decision-making process. Additionally, one of the important contributions of this study is that, compared to highly controlled lab experiments, it adds a higher ecological validity to the research by using an immersive

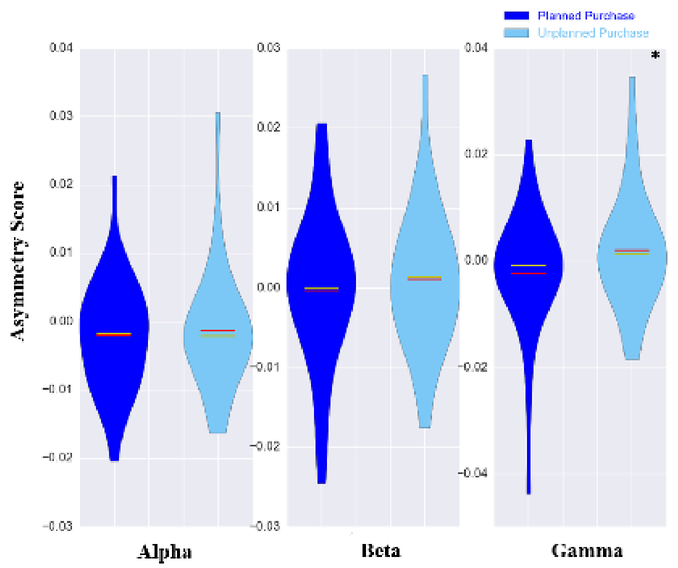

FIGURE 5
The violin plots of asymmetry scores of three frequency bands for all subjects. The planned purchase and unplanned purchase conditions are shown with dark-blue and light-blue colors, respectively. The red and yellow line in the middle illustrating the mean and median values, respectively. The difference between the asymmetry scores was statistically significant (*p-value < 0.001) in gamma frequency band.

VR supermarket. Most previous studies that have investigated emotions and frontal asymmetry have been customarily conducted in lab settings. However, with the current study we can expand the interpretation more widely into our daily decisions. Also, little is known about the effects of MR systems on human emotional and cognitive responses. The present research shows that those findings can be partially reproduced in a VR-based experiment which is a closer simulation of real-life conditions.

As for the limitations of this study that also prompt future research, it should be noted that these findings should be tested in other VR settings to eliminate the sensitivity of the results to a specific environment. Additionally, other studies should seek to do a direct comparison of virtual and real store environments to ensure that there is indeed a high degree of reliability of the identified emotional and cognitive scores across environments. In addition, although the feedback we got from the participants was overally positive, there were some limitations to the environment (e.g., they could not carry the products to the cashier, or they could not find some types of products in the supermarket) which should be improved and lead us to novel hypotheses such as the role of product type on frontal asymmetry.

Another limitation of this is study is that we did not consider personal preferences (which lead to a higher motivation) of the participants for each product. Collecting the data on personal preferences for each product that participants have bought within both planned and unplanned purchases, a comprehensive comparison of participants' motivation resulted from EEG for each item and its relation to their behavioral response could be conducted.

Another limitation of this study is the imbalance of trials and fewer number of trials for one condition. This limitation was mainly because of our attempt to keep a high degree of ecological validity and thereby providing a shopping experience as realistic as possible for a daily shopping routine. Also, we sought to limit the experiment duration, as we had to consider elements of fatigue which is often caused by staying in a VR environment for a relatively long time. In our analysis, we fill this "gap" with the aforementioned statistical methods, to overcome the imbalance trials comparison. To further abate this, another solution could be to increase the number of participants and make a between-subject study. By doing so, there would be more trials for each condition, and the outcome of the statistical analysis would be less affected by imbalance trials. As a result, the participants would be less likely to experience fatigue during the VR experiments.

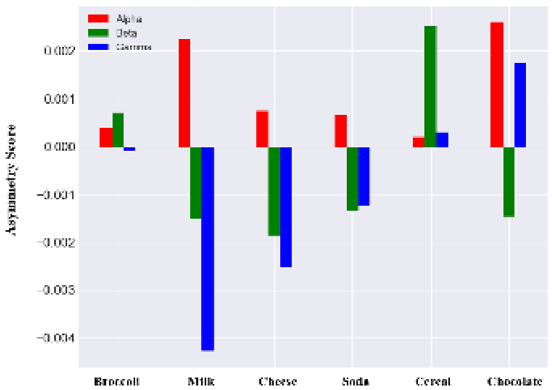

FIGURE 6
Asymmetry scores in alpha, beta, and gamma frequency bands for each item in planned purchase. Asymmetry scores in alpha have been multiply by negative 1 to represent a same behavior as other frequency bands.

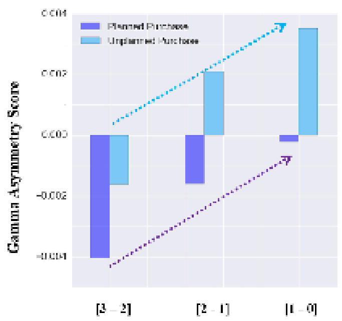

FIGURE 7
Gamma asymmetry score (averaged for all subject over all purchased items) for the three 1-s epochs before choosing a product. The horizontal axis shows the three time-intervals (within the 3 s window) before choosing a product.

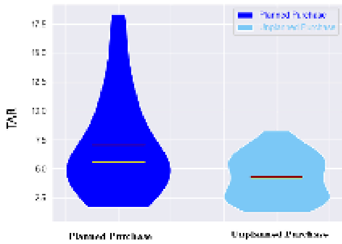

FIGURE 8
The violin plots of TAR index across all subjects. The planned purchase and unplanned purchase conditions are shown with dark-blue and light-blue colors, respectively. The red and yellow lines in the middle illustrate the mean and median values, respectively.

Conclusion

In conclusion, we investigated the role of frontal asymmetry and TAR in explaining consumer choices in a virtual store. Although most previous studies have focused on frontal asymmetry in the alpha frequency band, we showed that information in the gamma band can explain consumers' behavior more precisely. By conducting an experiment in a VR supermarket and two shopping tasks (planned and unplanned purchases) first we compared trials related to consumer choices and trials related to their navigation and searching products. We found a clear difference in alpha, beta, and gamma frontal asymmetry. In addition, we compared trials within the consumer choices (planned and unplanned choices), and results showed that gamma information in frontal asymmetry and TAR could discriminate those choices, which neither alpha nor beta frequency information would be apt to explain the difference.

The presented study tested previous findings related to frontal asymmetry in the consumer decision-making process. In addition, we confirmed previous finding in a semi-realistic VR environment, which makes the current study fruitful for consumer neuroscience and the VR research field. These findings and further research on the dual-process nature of consumer choices in MR systems will become increasingly important as emerging technological paradigms such as the Metaverse become distributed at the level that non-immersive social media have reached today.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by the Technical Faculty of IT and Design, Aalborg University. The patients/participants provided their written informed consent to participate in this study.

Author contributions

FS was responsible for designing the experiment, collecting the data, pre-processing and analyzing the data, interpreting the result, writing the manuscript, and preparing the figures. SK was being responsible for designing the experiment and collecting the data. EB worked on the study design and contributed to the manuscript. LB and SZ contributed to the manuscript. TR was responsible for study design and interpreting the results contributed to the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

FS, SZ, and TR were employed by Neurons Inc.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Aditya, D., and Sarno, R. (2018). Neuromarketing: State of the arts. *Adv. Sci. Lett.* 24, 9307–9310. doi: 10.1166/asl.2018.12261

Aftanas, L. I., Reva, N. V., Savotina, L. N., and Makhnev, V. P. (2006). Neurophysiological correlates of induced discrete emotions in humans: An individually oriented analysis. *Neurosci. Behav. Physiol.* 36, 119–130. doi: 10.1007/s11055-005-0170-6

Alarcão, S. M., and Fonseca, M. J. (2019). Emotions recognition using EEG signals: A survey. *IEEE Trans. Affect. Comput.* 10, 374–393. doi: 10.1109/TAFFC.2017.2714671

Bak, S., Jeong, Y., Yeu, M., and Jeong, J. (2022). Brain–computer interface to predict impulse buying behavior using functional near-infrared spectroscopy. *Sci. Rep.* 12:18024. doi: 10.1038/s41598-022-22653-8

Bazzani, A., Ravaioli, S., Trieste, L., Faraguna, U., and Turchetti, G. (2020). Is EEG suitable for marketing research? A systematic review. *Front. Neurosci.* 14:594566. doi: 10.3389/fnins.2020.594566

Cabañero, L., Hervás, R., González, I., Fontecha, J., Mondéjar, T., and Bravo, J. (2019). "Analysis of cognitive load using EEG when interacting with mobile devices," in *13th international conference on ubiquitous computing and ambient intelligence UCAmI 2019*, (Basel: MDPI), 70. doi: 10.3390/proceedings2019031070

Cheung, C. M. K., Chan, G. W. W., and Limayem, M. (2005). A critical review of online consumer behavior. *J. Electron. Commer. Organ.* 3, 1–19. doi: 10.4018/jeco.2005100101

Coan, J. A., B Allen, J. J., Harmon-Jones, E., and B Allen, J. J. (1997). Frontal EEG asymmetry and the behavioral activation and inhibition systems. *Psychophysiology* 40, 106–114.

D'Errico, F., Leone, G., Schmid, M., and D'Anna, C. (2020). Prosocial virtual reality, empathy, and EEG measures: A pilot study aimed at monitoring emotional processes in intergroup helping behaviors. *Appl. Sci.* 10:1196. doi: 10.3390/app10041196

Davidson, R. J. (2004). What does the prefrontal cortex "do" in affect: Perspectives on frontal EEG asymmetry research. *Biol. Psychol.* 67, 219–234. doi: 10.1016/j.biopsycho.2004.03.008

Dini, H., Simonetti, A., Bigne, E., and Bruni, L. E. (2022). EEG theta and N400 responses to congruent versus incongruent brand logos. *Sci. Rep.* 12:4490. doi: 10.1038/s41598-022-08363-1

Eichhorn, C., Lurz, M., Plecher, D. A., Weber, S., Wintergerst, M., Kaiser, B., et al. (2021). "Inspiring healthy food choices in a virtual reality supermarket by adding a tangible dimension in the form of an augmented virtuality smartphone," in *2021 IEEE conference on virtual reality and 3D user interfaces abstracts and workshops (VRW)*, (Lisbon: IEEE), 548–549. doi: 10.1109/VRW52623.2021.00156

Files, B. T., Lawhern, V. J., Ries, A. J., and Marathe, A. R. (2016). A permutation test for unbalanced paired comparisons of global field power. *Brain Topogr.* 29, 345–357. doi: 10.1007/s10548-016-0477-3

Frankish, K. (2010). Dual-process and dual-system theories of reasoning. *Philos. Compass* 5, 914–926. doi: 10.1111/j.1747-9991.2010.00330.x

Gable, P. A., Mechin, N. C., Hicks, J. A., and Adams, D. L. (2015). Supervisory control system and frontal asymmetry: Neurophysiological traits of emotion-based impulsivity. *Soc. Cogn. Affect. Neurosci.* 10, 1310–1315. doi: 10.1093/scan/nsv017

Golnar-Nik, P., Farashi, S., and Safari, M.-S. (2019). The application of EEG power for the prediction and interpretation of consumer decision-making: A neuromarketing study. *Physiol. Behav.* 207, 90–98. doi: 10.1016/j.physbeh.2019.04.025

Goto, N., Lim, X. L., Shee, D., Hatano, A., Khong, K. W., Buratto, L. G., et al. (2019). Can brain waves really tell if a product will be purchased? Inferring consumer preferences from single-item brain potentials. *Front. Integr. Neurosci.* 13:19. doi: 10.3389/fnint.2019.00019

Gramfort, A. (2013). MEG and EEG data analysis with MNE-Python. *Front. Neurosci.* 7:267. doi: 10.3389/fnins.2013.00267

Harmon-Jones, E., and Allen, J. J. B. (1998). Anger and frontal brain activity: EEG asymmetry consistent with approach motivation despite negative affective valence. *J. Pers. Soc. Psychol.* 74, 1310–1316. doi: 10.1037/0022-3514.74.5.1310

Harmon-Jones, E., Gable, P. A., and Price, T. F. (2012). The influence of affective states varying in motivational intensity on cognitive scope. *Front. Integr. Neurosci.* 6:73. doi: 10.3389/fnint.2012.00073

Horr, N. K., Han, K., Mousavi, B., and Tang, R. (2022). Neural signature of buying decisions in real-world online shopping scenarios – An exploratory electroencephalography study series. *Front. Hum. Neurosci.* 15:797064. doi: 10.3389/fnhum.2021.797064

Jung, T. P., Humphries, C., Lee, T. W., Makeig, S., McKeown, M. J., Iragui, V., et al. (1998). "Removing electroencephalographic artifacts: Comparison between ICA and PCA," in *Neural networks for signal processing - Proceedings of the IEEE workshop*, (Cambridge: IEEE), 63–72. doi: 10.1109/nnsp.1998.710633

Karmarkar, U. R., and Plassmann, H. (2019). Consumer neuroscience: Past, present, and future. *Organ. Res. Methods* 22, 174–195. doi: 10.1177/1094428117730598

Keune, P. M., Wiedemann, E., Schneidt, A., and Schönenberg, M. (2015). Frontal brain asymmetry in adult attention-deficit/hyperactivity disorder (ADHD): Extending the motivational dysfunction hypothesis. *Clin. Neurophysiol.* 126, 711–720. doi: 10.1016/j.clinph.2014.07.008

Lee, M., Shin, G. H., and Lee, S. W. (2020). Frontal EEG asymmetry of emotion for the same auditory stimulus. *IEEE Access* 8, 107200–107213. doi: 10.1109/ACCESS.2020.3000788

Liao, W., Zhang, Y., and Peng, X. (2019). Neurophysiological effect of exposure to gossip on product endorsement and willingness-to-pay. *Neuropsychologia* 132:107123. doi: 10.1016/j.neuropsychologia.2019.107123

Lin, I. M., Chen, T. C., Lin, H. Y., Wang, S. Y., Sung, J. L., and Yen, C. W. (2021). Electroencephalogram patterns in patients comorbid with major depressive disorder and anxiety symptoms: Proposing a hypothesis based on hypercortical arousal and not frontal or parietal alpha asymmetry. *J. Affect. Disord.* 282, 945–952. doi: 10.1016/j.jad.2021.01.001

Makransky, G., Terkildsen, T. S., and Mayer, R. E. (2019). Adding immersive virtual reality to a science lab simulation causes more presence but less learning. *Learn. Instr.* 60, 225–236. doi: 10.1016/j.learninstruc.2017.12.007

Martin, L. E., and Potts, G. F. (2009). Impulsivity in decision-making: An event-related potential investigation. *Pers. Individ. Dif.* 46, 303–308. doi: 10.1016/j.paid.2008.10.019

McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., and Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. *Neuron* 44, 379–387. doi: 10.1016/j.neuron.2004.09.019

Melendrez-Ruiz, J., Goisbault, I., Charrier, J.-C., Pagnat, K., Dujourdy, L., Arvisenet, G., et al. (2021). An exploratory study combining eye-tracking and virtual reality: Are pulses good "eye-catchers" in virtual supermarket shelves?. *Front. Virtual Real.* 2:655273. doi: 10.3389/frvir.2021.655273

Neal, L. B., and Gable, P. A. (2019). Shifts in frontal asymmetry underlying impulsive and controlled decision-making. *Biol. Psychol.* 140, 28–34. doi: 10.1016/j.biopsycho.2018.11.002

Ohme, R., Reykowska, D., Wiener, D., and Choromanska, A. (2010). Application of frontal EEG asymmetry to advertising research. *J. Econ. Psychol.* 31, 785–793. doi: 10.1016/j.joep.2010.03.008

Ozkara, B. Y., and Bagozzi, R. (2021). The use of event related potentials brain methods in the study of Conscious and unconscious consumer decision making processes. *J. Retail. Consum. Serv.* 58:102202. doi: 10.1016/j.jretconser.2020.102202

Peschel, A. O., Jacobsen, L. F., Frank, D.-A., and Steinmann, S. (2022). "VR retail lab: An immersive virtual reality (VR) supermarket as a flexible research infrastructure," in *Adjunct proceedings of the 2022 Nordic human-computer interaction conference*, (New York, NY: ACM), 1–2. doi: 10.1145/3547522.3547711

Petrantonakis, P. C., and Hadjileontiadis, L. J. (2011). A novel emotion elicitation index using frontal brain asymmetry for enhanced EEG-based emotion recognition. *IEEE Trans. Inform. Technol. Biomed.* 15, 737–746. doi: 10.1109/TITB.2011.2157933

Pizzagalli, D. A., Sherwood, R. J., Henriques, J. B., and Davidson, R. J. (2005). Frontal brain asymmetry and reward responsiveness. *Psychol. Sci.* 16, 805–813. doi: 10.1111/j.1467-9280.2005.01618.x

Poole, B. D., and Gable, P. A. (2014). Affective motivational direction drives asymmetric frontal hemisphere activation. *Exp. Brain Res.* 232, 2121–2130. doi: 10.1007/s00221-014-3902-4

Ramsøy, T. Z., Skov, M., Christensen, M. K., and Stahlhut, C. (2018). Frontal brain asymmetry and willingness to pay. *Front. Neurosci.* 12:138. doi: 10.3389/fnins.2018.00138

Ravaja, N., Somervuori, O., and Salminen, M. (2013). Predicting purchase decision: The role of hemispheric asymmetry over the frontal cortex. *J. Neurosci. Psychol. Econ.* 6, 1–13. doi: 10.1037/a0029949

Rosenlacher, P., Tomcik, M., and Brùna, M. (2018). EEG study of the effect of virtual reality. *AD ALTA J. Interdiscip. Res.* 8, 216–218. doi: 10.33543/0802216218

Royo-Vela, M., and Varga, Á. (2022). Unveiling neuromarketing and its research methodology. *Encyclopedia* 2, 729–751. doi: 10.3390/encyclopedia2020051

Rutherford, H. J. V., and Lindell, A. K. (2011). Thriving and surviving: Approach and avoidance motivation and lateralization. *Emot. Rev.* 3, 333–343. doi: 10.1177/1754073911402392

Sänger, J. (2019). Can't take my eyes off you – How task irrelevant pictures of food influence attentional selection. *Appetite* 133, 313–323. doi: 10.1016/j.appet.2018.11.030

Schaefer, A., Buratto, L. G., Goto, N., and Brotherhood, E. V. (2016). The feedback-related negativity and the P300 brain potential are sensitive to price expectation violations in a virtual shopping task. *PLoS One* 11:e0163150. doi: 10.1371/journal.pone.0163150

Schall, J. D. (2001). Neural basis of deciding, choosing and acting. *Nat. Rev. Neurosci.* 2, 33–42. doi: 10.1038/35049054

Shang, Q., Jin, J., Pei, G., Wang, C., Wang, X., and Qiu, J. (2020). Low-order webpage layout in online shopping facilitates purchase decisions: Evidence from event-related potentials. *Psychol. Res. Behav. Manag.* 13, 29–39. doi: 10.2147/PRBM.S238581

Shen, B., Tan, W., Guo, J., Zhao, L., and Qin, P. (2021). How to promote user purchase in metaverse? A systematic literature review on consumer behavior research and virtual commerce application design. *Appl. Sci.* 11:11087. doi: 10.3390/app112311087

Shih, D. H., Lu, K. C., and Shih, P. Y. (2019). Exploring shopper's browsing behavior and attention level with an EEG biosensor cap. *Brain Sci.* 9:301. doi: 10.3390/brainsci9110301

Shravani, D., Prajwal, Y. R., Atreyas, P. V., and Shobha, G. (2021). "VR supermarket: A virtual reality online shopping platform with a dynamic recommendation system," in *2021 IEEE International conference on artificial intelligence and virtual reality (AIVR)*, (Taichung: IEEE), 119–123. doi: 10.1109/AIVR52153.2021.00028

Smith, E. E., Reznik, S. J., Stewart, J. L., and Allen, J. J. B. (2017). Assessing and conceptualizing frontal EEG asymmetry: An updated primer on recording, processing, analyzing, and interpreting frontal alpha asymmetry. *Int. J. Psychophysiol.* 111, 98–114. doi: 10.1016/j.ijpsycho.2016.11.005

Spironelli, C., Fusina, F., Bortolomasi, M., and Angrilli, A. (2021). EEG frontal asymmetry in dysthymia, major depressive disorder and euthymic bipolar disorder. *Symmetry* 13:2414. doi: 10.3390/sym13122414

Tang, X., and Song, Z. (2019). Neurological effects of product price and evaluation on online purchases based on event-related potentials. *Neurosci. Lett.* 704, 176–180. doi: 10.1016/j.neulet.2019.04.019

Tarrant, J., and Cope, H. (2018). Combining frontal gamma asymmetry neurofeedback with virtual reality: A proof-of-concept case study. *NeuroRegulation* 5, 57–66. doi: 10.15540/nr.5.2.57

Thomsen, L. A., and Adjorlu, A. (2021). "A collaborative virtual reality supermarket training application to teach shopping skills to young individuals with autism spectrum disorder," in *2021 IEEE conference on virtual reality and 3D user interfaces abstracts and workshops (VRW)*, (Lisbon: IEEE), 50–55. doi: 10.1109/VRW52623.2021.00015

Trammell, J. P., MacRae, P. G., Davis, G., Bergstedt, D., and Anderson, A. E. (2017). The relationship of cognitive performance and the theta-alpha power ratio is age-dependent: An EEG study of short term memory and reasoning during task and resting-state in healthy young and old adults. *Front. Aging Neurosci.* 9:364. doi: 10.3389/fnagi.2017.00364

Tran, Y., Austin, P., Lo, C., Craig, A., Middleton, J. W., Wrigley, P. J., et al. (2022). An exploratory EEG analysis on the effects of virtual reality in people with neuropathic pain following spinal cord injury. *Sensors* 22:2629. doi: 10.3390/s22072629

Wang, J., Wang, A., Zhu, L., and Wang, H. (2021). The effect of product image dynamism on purchase intention for online aquatic product shopping: An EEG Study. *Psychol. Res. Behav. Manag.* 14, 759–768. doi: 10.2147/PRBM.S313742

Wang, Y., Wang, Q., Du, J., and Lin, Y. (2020). "Quantifying cognitive load in wayfinding information review using EEG," in *Construction research congress 2020*, (Reston, VA: American Society of Civil Engineers), 594–602. doi: 10.1061/9780784482865.063

Wixted, J. T. (ed.) (2018). *Stevens' handbook of experimental psychology and cognitive neuroscience*. Hoboken, NJ: Wiley, doi: 10.1002/9781119170174

Yang, M., Deng, X., and An, S. (2021). The relationship between habitual use and real-time emotion regulation strategies in adolescents: Evidence from frontal EEG asymmetry. *Neuropsychologia* 162:108056. doi: 10.1016/j.neuropsychologia.2021.108056

Yuan, G., He, W., and Liu, G. (2022). Is male preference recognizable based on electroencephalogram signals? Machine learning applied to initial romantic attraction. *Front. Neurosci.* 16:830820. doi: 10.3389/fnins.2022.830820

Zhao, G., Zhang, Y., and Ge, Y. (2018). Frontal EEG asymmetry and middle line power difference in discrete emotions. *Front. Behav. Neurosci.* 12:225. doi: 10.3389/fnbeh.2018.00225

APPENDIX 3

THE ROLE OF STIMULI- DRIVEN AND GOAL- DRIVEN ATTENTION IN SHOPPING DECISION-MAKING BEHAVIOURS— AN EEG AND VR STUDY

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This is the second out of three published Appendices. The study examines measurements derived from electroencephalography to examine differences in goal-directed and stimulus-driven attention in a virtual supermarket. As part of this thesis, we are reproducing the online version of the study published in Brain Sciences. Saffari, F., Zarei, S**.,** Kakaria, S., Bigné, E., Bruni, L. E., & Ramsøy, T. Z. (2023). The Role of Stimuli-Driven and Goal-Driven Attention in Shopping Decision-Making Behaviors—An EEG and VR Study. *Brain Sciences*, *13*(6), 928. https://doi.org/10.3390/brainsci13060928

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The Role of Stimuli-Driven and Goal-Driven Attention in Shopping Decision-Making Behaviors—An EEG and VR Study

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Abstract: The human attention system, similar to other networks in the brain, is of a complex nature. At any moment, our attention can shift between external and internal stimuli. In this study, we aimed to assess three EEG-based measures of attention (Power Spectral Density, Connectivity, and Spectral Entropy) in decision-making situations involving goal-directed and stimulus-driven attention using a Virtual Reality supermarket. We collected the EEG data of 29 participants in 2 shopping phases, planned and unplanned purchases. The three mentioned features were extracted and a statistical analysis was conducted. We evaluated the discriminatory power of these features using an SVM classifier. The results showed a significant (p-value < 0.001) increase in theta power over frontal, central, and temporal lobes for the planned purchase phase. There was also a significant decrease in alpha power over frontal and parietal lobes in the unplanned purchase phase. A significant increase in the frontoparietal connectivity during the planned purchase was observed. Additionally, an increase in spectral entropy was observed in the frontoparietal region for the unplanned purchase phase. The classification results showed that spectral entropy has the highest discriminatory power. This study can provide further insights into the attentional behaviors of consumers and how their type of attentional control can affect their decision-making processes.

Keywords: EEG; virtual reality; attention; coherency; spectral entropy

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1. Introduction

The human attention system has been traditionally divided into two modes. At any given moment, our attention has the ability to shift between external stimuli in our environment and internal cognitive processes, such as memories [1]. Our attention systems have the capacity to be directed toward internal thoughts, such as our memories or plans [2], or can be captured by an external stimulus. Based on this division in cognition, attention is typically distinguished as belonging to one of two types: bottom-up (i.e., externally directed/stimuli-driven/exogenous) and top-down (i.e., internally directed/schema-driven/goal-driven/endogenous) attention [1,3,4].

People rely either on external or internal information when making decisions [2,5]. The decision maker's goals, intentions, and previous knowledge drive top-down attention. By contrast, decision-making based on bottom-up attention is determined by the lower-level perceptual properties of a stimulus. Additionally, recent studies demonstrate that the bottom-up process is more activated during human "free" choices, where decisions are made without any external forces [6–8].

For decades, electrophysiological research has been assessing the underlying neural mechanisms of attention processes [9–13]. Two major brain oscillatory rhythms have been studied in electroencephalogram (EEG) for their functional role in attentional processes:

theta (roughly between 4 and 8 Hz) and alpha (roughly between 8 and 12 Hz) [13,14]. Power modulations of these oscillations have been found to be strongly correlated with attentional state alteration in specific regions, as well as interregional synchronization within these frequency bands (measuring functional connectivity) [15–18]. We briefly review recent studies here that concern the modulation of EEG (particularly in the theta and alpha bands) in top-down and bottom-up attention.

1.1. Theta Activity

Theta activity has been observed mainly in the frontal midline region (around Fz) in goal-driven tasks which involve internal attention, such as internal planning [19] and working memory tasks [20–22]. In order to retrieve information from multiple items/cues, the mentioned tasks require integrating, updating, organizing, and holding information. These studies suggest that theta activity is associated with internally directed attention toward information/intention stored in the memory and that it helps with information retrieval [13,16]. The evidence from theta oscillations mediating the orchestration between the temporal lobe and medial prefrontal cortex (MPFC) also supports its role in memory integration [21]. Interestingly, an increase in theta activity in the MPFC is also observed in prospective memory tasks [23], which is remembering to execute the planned task and ignoring the irrelevant stimuli [24,25]. This requires orienting attention toward internal intentions in the memory and successful retrieval of that information. In addition, an increase in the theta synchronization between frontal, temporal, and posterior regions of the brain has been observed in those tasks [22].

1.2. Alpha Activity

Alpha-band oscillations regulate attention processes both inside and outside of the focus of attention. The most prominent role of alpha-band oscillations in attention is the inhibition of task-irrelevant information that can interfere with task goals [15,26] and enhancing the processing of relevant information. This function is important for the selection and suppression processes required in attention and therefore modulates knowledge access and orientation [27,28]. Moreover, an increase in alpha activity has been found during retention intervals in visual working memory tasks [29]. The increase in alpha power in memory tasks is associated with task difficulty and memory load, which itself supports the inhibitory role of alpha for the maintenance and protection of task-relevant information and filtering external interrupting information [15,27,29]. As a filter mechanism, through a progressive increase in power, alpha oscillations inhibit the distractors. The higher the attention to task-relevant stimuli, the higher the suppression of distracting information [27]. Therefore, the alpha increase has been associated with internal attention, while external attention has been linked mainly to alpha decrease [26,30,31].

More recently, there has been a rise in more advanced methods for studying and understanding the brain mechanisms of attentional processes. Here, we focus on two analysis methods that also represent underlying brain mechanisms that may be relevant for understanding attentional processes in the brain: synchronous brain activity, and entropy-based measures of brain activity.

1.3. Synchronized Intra-Regional Activity

The dorsal frontoparietal attention network is one of the executive networks that mediate goal-directed behaviors [4,32,33]. A combination of this inhibitory mechanism and an excitatory baseline shift that orients attention sharpens visual spatial focus [34]. Studies that have assessed connectivity between parietal and dorsofrontal attentional regions have shown that voluntary vs. involuntary attention have different attentional networks (the dorsal attention networks) depending on the type of attention. The role of bottom-up and top-down processes in action comprehension has been investigated in previous studies [35]. They suggest that there exists a distinct interactivity among brain regions indicating the degree of bottom-up vs. top-down attention. In addition to that, a large amount of research has suggested that synchronized activity in the aforementioned networks in the theta frequency band is modulated by internally directed attention and sustained attention [22,36–40]. Having said that, an increase in low-frequency coupled activity in the frontoparietal network has been considered an indicator of working memory and top-down brain activity [22,36]. However, these well-established concepts and neural behaviors have not been discussed or investigated in the consumer neuroscience context. Particularly, to what extent the underlying neural response of humans' attentional process could explain consumers' shopping behavior is still missing.

1.4. Spectral Entropy

Entropy (e.g., Shannon entropy) is a concept in stochastic signals that quantifies the irregularity of random variables by measuring proportion distribution [41]. Since its first debut in EEG [42], Shannon or spectral entropy (SpE) has been used as an irregularity index of EEG signals where higher values correspond to more irregular or unpredictable signals (more "flat" distribution) and lower values correspond to more predictable signals (power spectrum is bounded in specific frequency band) [43]. Recently, spectral entropy has been utilized as an attention index [43] to develop a more accurate attention-based diagnostic tool. Moreover, modulation of SpE in focused attention when exposed to auditory stimuli has been investigated, and a decrease in SpE has been observed in active attention compared with passive attention in response to audio stimuli [44,45]. To our knowledge, only one study of attention to visual objects has been published [46], where the researchers report a greater approximate entropy for externally operative attention compared with internally operative attention. In spite of this discussion around the role of entropy in the human attention system, it has not been tested whether the activation of different attention modalities such as top-down or bottom-up will modulate SpE.

Extended reality technologies such as Virtual Reality (VR) have been found to be useful in marketing, retail, and consumer behavior analyses, such as of attention [47–50]. VR has a multidimensional framework with real-time graphics. Interactivity, imagination, and immersion are the essential features of VR; therefore, using VR for testing consumer behavior provides the participants with a 3D dynamic purchase experience that is closer to real life [47,51,52].

Previous studies that have explored the relationship between brain oscillations and attentional control have generally not focused on consumer behavior. Furthermore, although numerous studies have investigated the effect of attention level on the SpE of EEG, to the best of our knowledge, the effect of goal-driven and stimulus-driven attention on SpE has not been previously examined. Additionally, no prior study has assessed brain activity related to different modes of attention in (a VR) environment, making the present study particularly ecologically valid. To understand the impact of distractors in the environment or visual field, it is also important to investigate connectivity and power across brain regions when attention is directed toward task-relevant stimuli versus when it is directed toward distractors or external stimuli.

Therefore, the aim of the present study was to assess three types of EEG-based measures of attention and their discriminatory power in decision-making situations involving goal-directed and stimulus-driven attention using a VR supermarket. The experiment consisted of two phases: a planned purchase phase (or listed condition, in which participants shopped from a list) and an unplanned purchase phase (in which participants were free to buy what they wanted). We hypothesized that the unplanned purchase phase would elicit more bottom-up attention, while the planned purchase phase would elicit more top-down attention. Accordingly, we expected to see higher theta activity over frontal, central, and temporal lobes during the planned purchase phase and lower alpha activity in frontal and parietal lobes during the unplanned purchase phase. Furthermore, during the planned purchase phase, we predicted a higher level of synchronized activity within the frontoparietal network Additionally, we hypothesized that there would be a more distinct alternation of SpE in the frontal, parietal, and occipital lobes, reflecting shifts between goal-directed and stimulus-driven attention. At a data analysis level, this means that we expected to observe an increase in SpE in the frontal, parietal, and occipital lobes, from planned to unplanned purchase phases. Furthermore, we evaluated the discriminatory power of the three mentioned features using an SVM classifier.

2. Materials and Methods

2.1. Participants

A total number of 29 (14 women and 15 men) volunteers (age range: 23 to 44; mean = 31.8; SD = 6.6) without any prior psychiatric or neurological conditions were recruited in the experiment via the Neurons Inc. online recruitment system. Among these participants that we considered as the data for the study, eight of them had previous experience with VR and using controllers and two of them had participated in a study with a virtual supermarket previously. All participants were informed about the experiment and had read and signed the consent form prior to the experiment. The experiment was approved by the ethical committee of the University of Aalborg. All data were analyzed and reported anonymously.

2.2. Experimental Procedure

The experiment was performed in a virtual reality environment designed in Unreal Engine V4.1 and run using HTC Vive 5 in a machine with 16 GB of RAM (Intel(R) Core (TM) i7-10875H CPU 2.30 GHz) and NVIDIA GeForce RTX 2070 GPU on Microsoft Windows 10 operating system. A supermarket was designed in VR (similar to Danish supermarkets), and we asked participants to perform a shopping task. We allocated 250 Danish Kroner, DKK (~USD 35), to each participant. We first asked them to buy six items from a predefined list (the planned purchase phase), and then they could buy whatever they wanted with the remaining budget (the unplanned purchase phase). The cost of the items on the list added up to DKK 120, which left half of the budget for unplanned purchases. Overall, 172 items were chosen as unplanned purchases, which is almost equal to 174 planned purchases.

First, we collected 30 s of resting-stage EEG data (with eyes closed and a black screen) while the participants had the VR headset on. Afterward, we instructed participants on how to use the controller to navigate through the supermarket, find the list of products, and choose a product. In the physical space, participants could have limited movement (one or two steps for getting closer to a product) but in general, they were instructed to teleport with the controller to navigate through the supermarket, which they could do by pointing to a location and reaching there with a short delay (200 ms), to ensure they would experience a "flow" in the supermarket. The list of the required products was provided for them in VR and participants could look at the list whenever they needed using a button in the controller. The products had price labels and the prices were according to the actual price ranges for products in Danish supermarkets.

When participants were completely familiar with the tasks, we started to record the data, and they needed to first purchase six items from the list (i.e., broccoli, milk, cheese, soda, cereal, and chocolate). This phase was considered as the "Planned Purchase Phase". We expected "goal-driven" or "top-down" attention to be activated in this phase. When the participants had purchased all the items on the list, we asked them to buy whatever they wanted with the remaining budget, or they could leave the environment immediately. The remaining time that the participants spent buying the items they wanted using the leftover money was considered the "unplanned purchase phase". We expected "stimuli-driven" or "bottom-up" attention to be activated in this phase. After participants were done with the shopping task, they had to go to the cashier, which was taking them out of the environment.

2.3. EEG Recording and Processing

EEG data were recorded via Brain Product EEG device with 32 electrodes (Fp1, Fp2, F8, F4, Fz, F3, F7, FT9, FT10, FC5, FC1, FC2, FC6, T7, T8, C3, Cz, C4, CP5, CP1, CP2, CP6, TP9, TP10, P7, P3, Pz, P4, P8, O1, Oz, and O2). The ground and reference electrodes were located at AFz and FCz, respectively, for online processing. The data were transmitted wirelessly from the amplifier to a PC using a USB module. The EEG data were digitalized with a 500 Hz sampling frequency and then exported to the MNE Python library for pre-processing and further analysis. For each participant, 30 s of the rest data were recorded, but the time spent for each condition varied among participants. The following pre-processing steps were applied for the EEG data of each participant (the whole analysis for the data from pre-processing to statistical analysis was carried out via different Python libraries). First, the data were filtered using an FIR bandpass filter with a hamming window for the 0.1 and 100 Hz frequency bands, and then a 50 Hz notch filter was applied to remove the power line artifact.

Independent Component Analysis (ICA) was used to manually remove "bad" components with a visual inspection. The components that contain the eye-blink and eye-movement patterns were eliminated based on visual inspection. Furthermore, components with an increasing pattern of power distributions with regard to the frequency were removed during ICA. On average, 9.5 components out of 32 were removed during ICA for each subject. Thereafter, we changed the EEG reference to average all electrodes for the rest of the analysis. Then, we segmented data into 5 s epochs for consistency of the analysis and computational convenience.

2.4. Power Spectral Density Computation

Power spectrum density (PSD) was computed via the Welch method with a window size of 256 samples, equal to 512 milliseconds (ms) for each phase (i.e., rest, planned purchase, and unplanned purchase). Theta (4–8 Hz) and alpha (8–13 Hz) frequency bands were considered for PSD analysis. For each channel, first, we averaged power values over frequency bins, and then we took the average over epochs to represent the PSDs of that condition for the corresponding channel. To compute PSD over regions, we averaged the PSD of channels included in those regions. The underlying regions of each EEG channel are shown in Table 1.

Table 1. EEG channels allocated for each region.

Regions	Channels
Frontal	FP1, FP2, F8, F4, Fz, F3, F7
Parietal	P7, P3, Pz, P4, P8
Temporal	T7, T8, TP9, TP10, FT9, FT10
Occipital	O1, O2, Oz
Central	FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6

2.5. Functional Connectivity

Spectral coherency is a synchronization metric that has been widely used to measure functional connectivity in neuroscientific studies [53–57]. As is shown in Equation (1), coherency shows variance explainability of signal X with regard to signal Y by measuring cross-spectral density of X and Y (S_{XY}), normalized by power estimates of X and Y (S_X, S_Y).

Equation (1):

$$Coh_{XY}(\omega) = \frac{|S_{XY}(\omega)|}{\sqrt{S_{XX}(\omega)S_{YY}(\omega)}} \quad (1)$$

where coherence coefficient is a value between 0 and 1; 0 indicates no synchronization, and 1 indicates perfectly synchronized signals.

Due to spurious connectivity caused by volume conduction [54,58], we conducted current source density [59,60] to reduce the volume conduction effect. Afterward, we used the Fourier method to transform the data from a time domain to a frequency domain with 256 points (equal to 512 ms) in the theta frequency band (4–8 Hz). Thereafter, by computing coherence between two given signals, we averaged coherency measurement over frequency bins to represent the connectivity values for each of the two channels. Lastly, by averaging pairwise connectivity values in regions of interest (especially the frontoparietal networks), the final connectivity values were computed and ready for statistical analysis.

2.6. Spectral Entropy

In information theory, entropy and spectral entropy are analytical techniques to quantify irregularity and (un)predictability in a stochastic signal such as EEG [41]. As noted in Equation (2), spectral entropy (SpE) uses power spectrum density to quantify EEG irregularity between 0 and 1, where '0' means no irregularity (totally predictable) and '1' means a completely random sequence.

Equation (2):

$$SE[f_1, f_2] = \frac{1}{log(N[f_1, f_2])} \sum_{f_i=f_1}^{f_2} P_n(f_i) \cdot log\left(\frac{1}{P_n(f_i)}\right) \quad (2)$$

where $P_n(f_i)$ represents normalized power spectrum at the frequency of f_i, which, by dividing the power spectrum at each frequency by total power spectrum, yields the normalized power spectrum. f_1 and f_2 are the boundaries of the frequency range, and $N[f_1, f_2]$ is the number of frequency bins within that range.

We considered a frequency range of 0.5 to 32 Hz and used FFT (Welch's method) to compute the PSD with a window of 256 points, which is equal to a 512 ms time window. In addition, since attention mainly activates frontal and parieto-occipital networks [4], our focus for entropy analysis was mainly on these areas.

2.7. Statistical and Classification Analysis

As noted, the time spent in each condition varied among the participants. Therefore, in order to have a valid comparison, we used a permutation-based statistical method that previously had been used in an ERP study for imbalance trial comparison [61]. First, desired features (PSD, connectivity, and SpE) were calculated from the trial of each condition. Then, those values of one condition were subtracted from the other to calculate the difference between the features. By repeating this procedure for all subjects, the average of the relevant feature was computed to provide the "ground truth" values. Next, for generating data-driven null distribution, we randomly shuffled trail labels between conditions and repeated the same procedure of calculating the ground truth. By repeating this procedure 1000 times, we conducted a null distribution to compare the ground truth value in the two conditions. Ultimately, if the ground truth was far enough from the mean of this distribution, we could conclude that our findings are not due to randomness and are statistically significant.

To compare the discriminatory power of PSD, connectivity, and SpE in classifying goal-directed or stimulus-driven attention, we implemented a support vector machine (SVM) classifier [62] and used these features as inputs. In addition, by measuring the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) for each feature, the performance of those features was evaluated in a 5-fold cross-validation setting.

3. Results

Since the duration of the experiment was subject-dependent, we provided the time length of the data here to show the amount of EEG data we used for the analysis. In Figure 1, box plots of the time that each participant spent on the two phases are provided. The mean duration of the planned and the unplanned purchase phases across participants are 238.87 ± 85.57, and 228.00 ± 107.20 s, respectively.

To evaluate the subjective experience of the VR supermarket, two survey questionnaires with a 7-point Likert chart were administered to inquire about participant satisfaction with the store and their sense of presence. We found a significant correlation between "Sense of presence" and "Store Satisfaction" $r(27) = 0.54$, p-value < 0.01. The results are reported in Figure 2.

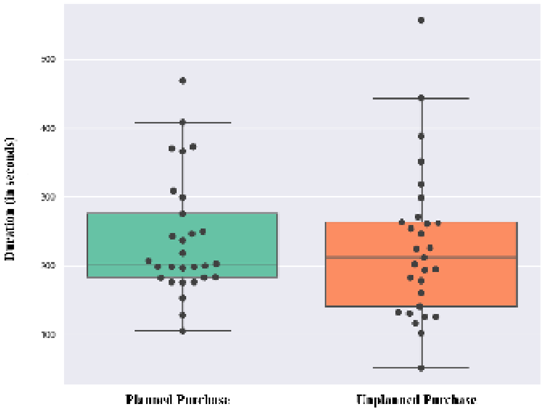

Figure 1. Box plot of the time spent under planned and unplanned conditions for each participant per second. Each dot represents the time spent by each subject and the horizontal line in the boxes represents the median for each condition (202.54 s for planned and 211.86 s for unplanned conditions).

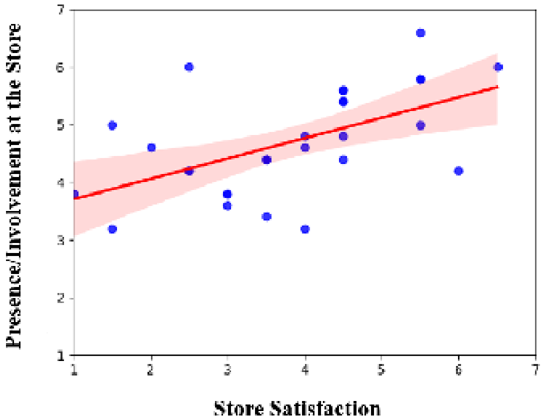

Figure 2. A moderate correlation (0.5) between store satisfaction and sense of presence resulted from the questionnaire.

As mentioned, participants were free to choose whatever they wanted under the unplanned purchase condition, and therefore, a range of choices were made that differed from fixed purchases under the planned condition. In Figure 3, the distribution of the unplanned purchases is illustrated.

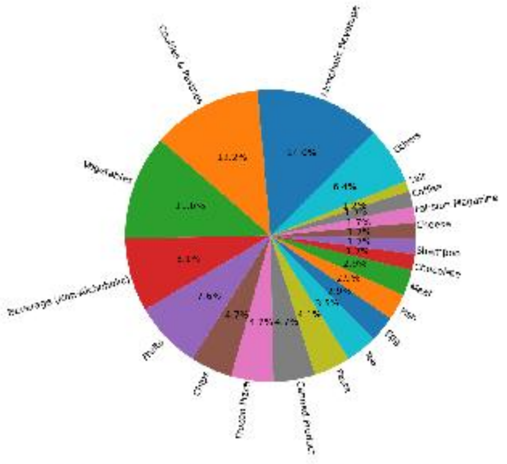

Figure 3. The distribution of product categories that were chosen under unplanned condition.

3.1. Power Spectrum Analysis

The distribution of theta and alpha power over the scalp during the rest, planned purchase, and unplanned purchase phases are presented in Figures 4 and 5 (averaged across all subjects). Figure 6 presents the regional statistical comparison for the theta frequency band, focusing on the frontal and parietal regions. During the planned purchase phase, there was an increase in Fz activity compared with the rest and unplanned purchase phases. In the fronto-central regions (Fz, Cz, Fc1, Fc2), theta power during the planned phase was higher than during the rest and unplanned purchase phases. In the temporal lobe (T7, T8, TP9, TP10, FT9, FT10), an increase in theta activity was observed under the planned condition compared with the rest and unplanned conditions. This increase was also seen under the unplanned condition compared with the rest. In addition, a similar pattern of variation was observed in T7 and T8.

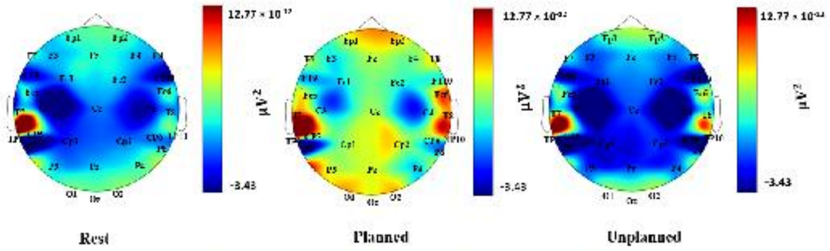

Figure 4. Topographical heatmap of theta activation during the rest, planned, and unplanned phases.

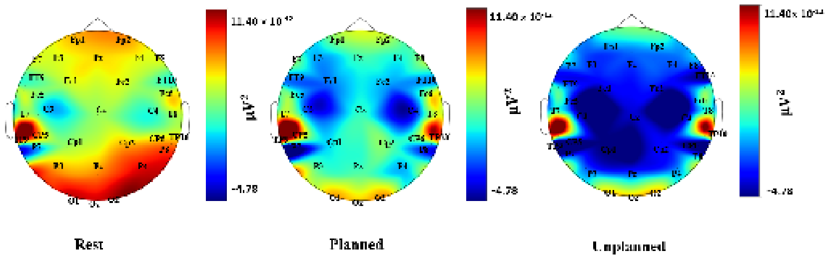

Figure 5. Topographical heatmap of alpha activation during the rest, planned, and unplanned phases.

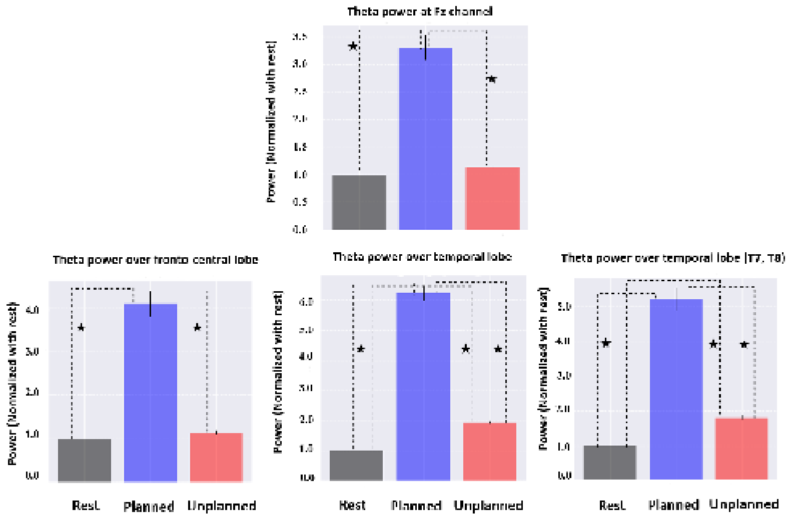

Figure 6. Comparison of theta activity for frontal, central, and temporal regions (normalized by rest). Statistically significant results are shown by ★.

A statistical comparison of the three conditions for the alpha frequency band in the frontal and parietal lobes is presented in Figure 7. A decrease in alpha power over the parietal lobe occurred for the unplanned phase and was not observed in the rest and planned phases. In the frontal lobe, a stronger decrease in alpha activity was found for the unplanned condition, in comparison with the rest and planned purchase phases. We observed an increase in alpha activity in the planned phase compared with the rest, but it was not statistically significant.

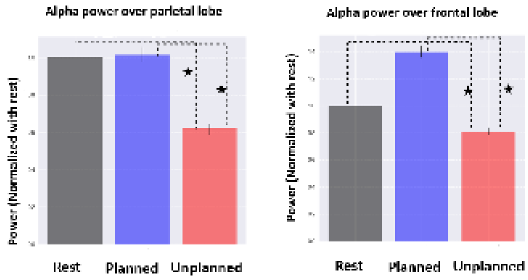

Figure 7. Comparison of alpha activity for frontal and parietal regions (normalized by rest). Statistically significant results are shown by ★.

3.2. Functional Connectivity Analysis

Table 2 and Figure 8 show the results of a connectivity analysis for the frontal–parietal networks after applying the current source density. In Table 2, the coherency values in the theta frequency band for both the planned and unplanned conditions are presented. For all pairs (frontal–frontal, fontal–parietal, and parietal–parietal), the coherency values for the planned phase were significantly higher (*p*-value < 0.0001, *p*-value < 0.000, *p*-value < 0.001, respectively) than for the unplanned phase.

Table 2. Coherency values (mean ± std) for inter-regional (frontal–frontal, parietal–parietal) and intra-regional (frontal–parietal) for each condition.

	Coherency Values		
	Frontal–Frontal	**Parietal–Parietal**	**Frontal–Parietal**
Planned Purchase Phase	0.52 ± 0.09	0.51 ± 0.11	0.39 ± 0.10
Unplanned Purchase Phase	0.45 ± 0.08	0.45 ± 0.05	0.31 ± 0.08

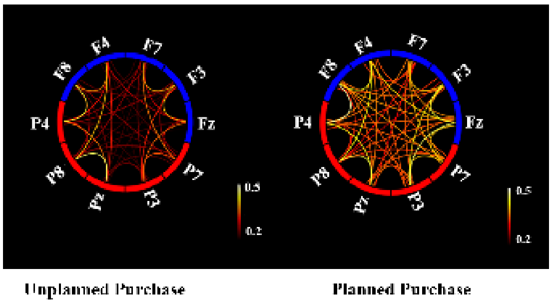

Figure 8. Connectivity circle plots for the planned and unplanned conditions. EEG sensors located in frontal areas are indicated by blue blocks, while sensors in parietal regions are shown by red blocks. The intensity of the color of the links between each block represents the connectivity values between those locations.

Appendix 3

In Figure 8, the circle of coherency values between and within the frontal and parietal lobes is illustrated. For both phases, coherency values were averaged over all epochs, and for visualization in Figure 8, the mean of coherency values was averaged over all participants. A stronger synchronization, both locally and regionally, was found in the planned purchase phase compared with the unplanned purchase phase.

3.3. Spectral Entropy Analysis

The spectral entropy values for 32 channels are presented in Table 3. For each channel, the spectral entropy for the planned purchase phase (Entropy 1), the unplanned purchase phase (Entropy 2), the difference (Entropy 2–Entropy 1), and the p-value (with a significance level being $0.05/32 = 0.001$) are reported. For Fp1 and F7, sensors that are placed in the frontal region, spectral entropy in the unplanned purchase phase was significantly higher (p-value < 0.0001) than in the planned purchase phase. In the parietal and occipital lobes, P8 and Oz channels showed a higher spectral entropy for the planned purchase phase than the unplanned purchase phase, and they were statistically significant (p-value < 0.0001). In Figure 9, entropy values and topography plots are provided for the planned purchase phase, the unplanned purchase phase, and their differences.

Table 3. SpE values of each EEG channel. SpE for the planned and unplanned conditions are indicated with Entropy 1 and Entropy 2, respectively. The Difference column shows the subtraction of Entropy 2 from Entropy 1. Channels with statistically significant different values are indicated with *.

Channels	Entropy 1	Entropy 2	Difference	p-Value
* Fp1	0.855	0.933	0.078	<0.0001
Fz	0.935	0.933	−0.002	0.578
F3	0.930	0.934	0.003	0.423
* F7	0.843	0.939	0.096	<0.0001
FT9	0.936	0.935	0.0	0.567
FC5	0.929	0.936	0.006	0.154
FC1	0.925	0.937	0.011	0.161
C3	0.934	0.926	−0.007	0.655
T7	0.935	0.934	−0.001	0.575
TP9	0.929	0.934	0.005	0.359
CP5	0.936	0.925	−0.01	0.92
CP1	0.929	0.929	0.0	0.571
Pz	0.934	0.930	−0.003	0.644
P3	0.937	0.925	−0.011	0.821
P7	0.931	0.929	−0.002	0.522
O1	0.934	0.932	−0.002	0.687
* Oz	0.815	0.939	0.124	<0.0001
O2	0.938	0.930	−0.007	0.825
P4	0.925	0.935	0.01	0.088
* P8	0.887	0.933	0.046	<0.0001
TP10	0.936	0.933	−0.003	0.625
CP6	0.930	0.936	0.005	0.283
CP2	0.923	0.933	0.009	0.253
Cz	0.936	0.930	−0.005	0.687
C4	0.932	0.935	0.002	0.452
T8	0.930	0.935	0.004	0.35
FT10	0.938	0.928	−0.01	0.832
FC6	0.934	0.929	−0.004	0.691
FC2	0.936	0.935	0.0	0.524
F4	0.934	0.930	−0.003	0.645
F8	0.932	0.930	−0.001	0.679
Fp2	0.933	0.932	0.0	0.58

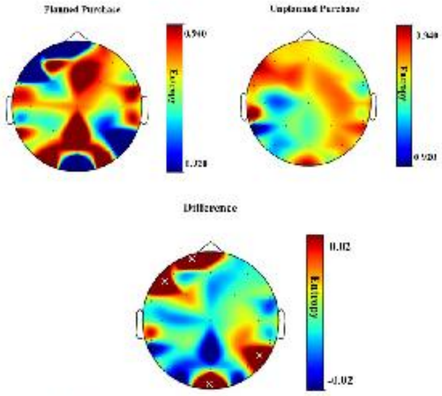

Figure 9. Distribution of SpE values over the scalp for each condition and difference (unplanned and planned). Areas with statistically significant increases in SpE for unplanned purchases are indicated with ×.

3.4. Classification Results

The results of this subject-independent model are shown in Figures 10 and 11. The highest accuracy was achieved when all three features were used as inputs, and other metrics were also relatively high, indicating a balanced performance of the model in predicting between the two classes. Among the individual features, SpE resulted in the highest accuracy, with comparably high precision, recall, and F1 score, indicating that the model was not biased toward either class. When using PSD as the sole input, the classifier exhibited an imbalanced performance, with the highest sensitivity (91%) but low accuracy and precision, indicating a bias toward the goal-directed attention class. The model performed worst in terms of accuracy when using connectivity as the sole input, but the other metrics showed a balanced performance between the two classes.

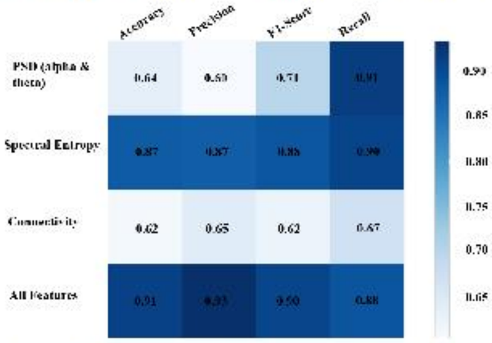

Figure 10. The classification report of the model using different features as input.

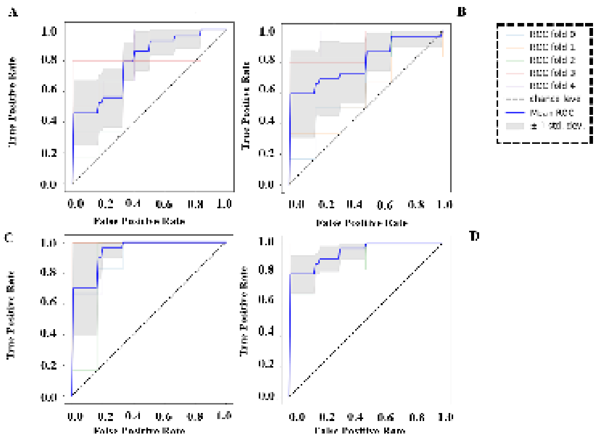

Figure 11. The AUC of ROC in 5-fold cross-validation using **(A)** PSD, **(B)** connectivity, **(C)** SpE, and **(D)** all features as input to the model.

To compare these features more thoroughly, we conducted a five-fold cross-validation analysis and calculated the AUC of the ROC for each feature and for all features combined as inputs to the model. As shown in Figure 11, the ROC of the model using all features as input had the highest AUC of 0.94 ± 0.04 (average across five folds). This result was similar to the AUC of the model using SpE alone, which was 0.94 ± 0.05, but with a slightly higher standard deviation. Using connectivity as the sole input resulted in an AUC of 0.80 ± 0.15 on average across five folds, which was slightly higher than the AUC of the model using PSD alone, which was 0.79 ± 0.05.

4. Discussions

In this study, we investigated to what extent goal-driven versus stimulus-driven attention is involved in different shopping behaviors, i.e., planned, and unplanned decisions. By labeling different decision types as planned and unplanned, we were able to observe a higher activity in both alpha and theta bands over frontal and parietal lobes in the planned purchase phase compared with the unplanned purchase and rest phases. On the other hand, for unplanned purchases, we observed a decrease in both theta and alpha activity in comparison with planned purchases. Stronger connectivity over the frontoparietal network was found in the planned purchase compared with the unplanned purchase phase. However, in the unplanned condition, SpE was higher in the frontal, parietal, and occipital regions.

4.1. Theta Power Changes in Frontal, Central, and Temporal Lobes

Compared with the unplanned and the rest phase, an increase in theta power was observed in the frontocentral regions (Fz, Cz, Fc1, Fc2) during the planned purchase phase. This increase was also observed in the temporal region (T7, T8, TP9, TP10, FT9, FT10). The increase in theta band activity, as compared with the rest, was also observed in the unplanned phase for some temporal regions (T7, T8). These findings are in line with the previous studies that support an increase in theta power during goal-driven attention, mainly over frontal, central, and temporal lobes. More specifically an increase in theta power in the frontal midline regions has been found for tasks that require goal-driven control of attention, such as information retrieval and planning [63,64]. This is consistent with our findings, which show a substantial increase in the theta frequency band in the frontocentral region and signify a goal-directed mode of attention in the planned phase. It is worth noting that an increase in theta power in the mentioned regions has been observed in various cognitive tasks, with a stronger increase for more demanding conditions [65]. Similarly, a stronger theta activity has been reported in the temporal region while performing tasks that require the activation of prospective memory (that is, directing the attention toward intentions stored in the memory to execute the planned intention) [13,66]. An increase in the frontal midline has been also observed in the tasks that require sustained internal attention, such as working memory tasks [22]. One of the explanations for the higher activity of theta during these tasks is the necessity for updating and organizing information, a feature presented in our planned purchase phase.

4.2. Alpha Power Changes in Frontal and Parietal Lobes

We observed a weaker alpha activity in the parietal lobe for the unplanned phase in comparison with the planned and the rest phases. Similarly, there was also a lower alpha activity during the unplanned phase in the frontal lobe. However, a stronger alpha activity was observed in both the frontal and the parietal regions for planned purchases compared with unplanned purchases. These findings support the previous studies that suggest that an increase in alpha band activity is observable in goal-driven attention or during the processing of "task-relevant information" [15,26,67,68], whereas lower alpha activity has been observed during "sensory-intake tasks", which require the processing of external sensory information [26]. An alpha power decrease has been found to be the most prominent feature in tasks that require the direction of attention to external stimuli—in our study, the unplanned purchases—and it has been found over occipitoparietal and frontotemporal regions, as well as over left dorsal frontoparietal regions [1,13]. An increase in alpha-band oscillations, however, has been observed in tasks that require internal attention, or in goal-driven tasks. In fact, alpha activity plays an important role in information processing by inhibiting task-irrelevant information and suppressing the distractors that interfere with the task's goals.

4.3. Increased Synchronized Activity over the Frontoparietal Network in Theta for Goal-Driven Attention

We found stronger connectivity both between frontal and parietal regions and within the regions themselves during planned purchases compared with unplanned purchases. This supports our hypothesis that in the planned purchase phase, the goal-driven attentional network is more activated in comparison with the unplanned purchase phase, which is a stimulus-driven process.

The frontoparietal network has been considered as a control network for internally directed attention [37]. Goal-directed attention modulates an increase in the synchronized activity in the frontoparietal network compared with stimulus-driven attention, according to recent findings in the theta frequency band [22,36,37]. Research also shows that top-down control signals may emerge from the dorsoparietal attention network as well as other higher-order executive regions that mediate behavior directed toward goals [4,69,70].

4.4. Spectral Entropy Increase in Frontal and Parietal Sites for Stimulus-Driven Attention

A higher SpE was observed in the frontal and parietal regions during the unplanned condition compared with the planned condition. These results suggest that while participants are in a more predictable situation, such as a planned purchase compared with an unplanned purchase, this regularity pattern has its own neural signature in EEG signals. However, due to a lack of adequate evidence in this field, further research is required to investigate the modulation of SpE in goal-driven and stimulus-driven attention.

As mentioned before, the application of SpE as an objective measurement of attention is relatively a new approach [44,45]. SpE has been utilized as an index for attention level [43,44], in which an increase in SpE is associated with "active attention" compared with "passive attention", especially in the frontal and the parietal regions. However, to the best of our knowledge, the SpE role has not been investigated for comparison of goal-directed versus stimulus-driven attention.

4.5. The Discriminatory Power of SpE Is Almost Equal to the Combination of PSD, Connectivity, and SpE

As the classification results suggested, SpE has the highest discriminatory power among the three features to classify goal-directed and stimulus-driven attention. Considering both sensitivity and specificity, using SpE as an input for the predictive model would result in equal performance while using all of the features combined. In addition, although the PSD feature will lead to the highest sensitivity (recall) since will result in poor specificity, the overall performance (AUC) of the model is worse than when using connectivity to feed the model. It is worth mentioning that the train and test sets of the model derive from different subjects, which results in a subject-independent and more generalized performance.

4.6. Limitations

Some limitations are worth mentioning for consideration in future studies. One of the limitations of the present study is the uneven duration of the unplanned and planned purchase phases, which could potentially cause a bias in the results. Even though we tried to reduce the bias with the mentioned statistical method, it should be taken into consideration for future research. Another point is that, since we needed to consider the "budget" that each participant could spend on each purchase, the planned phase was always the first phase of the experiment. Nevertheless, considering that the phases were not very long, we assume that this should not have had a major impact on the findings of the study. Moreover, we had no rest phase before the unplanned purchase phase as it started immediately after the planned phase. Having no pause between the phases, however, contributed to the ecological validity of our study.

5. Conclusions

In conclusion, this study analyzed alpha and theta activity during planned and unplanned purchase tasks in a VR environment. The findings revealed distinct neural oscillation patterns associated with different phases of the purchase process. During the planned purchase phase, both alpha and theta powers increased, indicating heightened cognitive engagement. In contrast, the unplanned phase showed a decrease in both theta and alpha activity, suggesting reduced cognitive engagement.

Moreover, our investigation provided insights into the functional connectivity within the frontoparietal network during the planned and unplanned purchase phases. Specifically, we observed greater connectivity within the frontoparietal network during the planned purchase phase compared with the unplanned purchase phase. This finding suggests the involvement of coordinated activity between the frontal and parietal regions, which are crucial for attentional control and decision-making processes. Interestingly, the SpE analysis yielded contrasting results, with higher SpE observed in the frontal and parietal regions during the unplanned purchase phase compared with the planned purchase phase, which shows the capability of SpE in examining the human attention system. This suggests a shift in attentional dynamics, potentially reflecting a transition from goal-directed attention to stimulus-driven attention during unplanned purchasing.

Overall, this study expands our knowledge of the neural mechanisms underlying planned and unplanned purchase tasks, offering insights into attentional behaviors in consumer decision-making. These findings have implications for marketers aiming to influence consumer behavior and guide purchase decisions by understanding the neural mechanisms involved in attentional control and decision-making processes.

Future research directions include exploring larger and more diverse samples to enhance the generalizability of the findings. Additionally, investigating the impact of individual differences, such as personality traits or prior purchasing experiences, could provide a comprehensive understanding of consumer behavior. Incorporating other neurophysiological measures, such as event-related potentials (ERPs) or functional magnetic resonance imaging (fMRI), would offer a more detailed characterization of the brain mechanisms underlying purchase decisions. Furthermore, studying real-world purchasing scenarios and considering contextual factors could provide a more ecologically valid understanding of consumer attention and decision-making processes.

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Institutional Review Board Statement: The study was approved by the local ethics committee (Technical Faculty of IT and Design, Aalborg University) and performed in accordance with the Danish Code of Conduct for research and the European Code of Conduct for Research Integrity.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Magosso, E.; Ricci, G.; Ursino, M. Alpha and theta mechanisms operating in internal-external attention competition. *J. Integr. Neurosci.* **2021**, *20*, 1–19. [CrossRef] [PubMed]
2. Rolls, E.T. *Memory, Attention, and Decision-Making*; Oxford University Press: Oxford, UK, 2007.
3. Connor, C.E.; Egeth, H.E.; Yantis, S. Visual attention: Bottom-up versus top-down. *Curr. Biol.* **2004**, *14*, R850–R852. [CrossRef] [PubMed]
4. Corbetta, M.; Shulman, G.L. Control of goal-directed and stimulus-driven attention in the brain. *Nat. Rev. Neurosci.* **2002**, *3*, 201–215. [CrossRef]
5. Dixon, M.L.; Fox, K.C.R.; Christoff, K. A framework for understanding the relationship between externally and internally directed cognition. *Neuropsychologia* **2014**, *62*, 321–330. [CrossRef] [PubMed]
6. Brosch, T.; Pourtois, G.; Sander, D.; Vuilleumier, P. Additive effects of emotional, endogenous, and exogenous attention: Behavioral and electrophysiological evidence. *Neuropsychologia* **2011**, *49*, 1779–1787. [CrossRef] [PubMed]
7. Masciocchi, C.M.; Mihalas, S.; Parkhurst, D.; Niebur, E. Everyone knows what is interesting: Salient locations which should be fixated. *J. Vis.* **2009**, *9*, 25. [CrossRef] [PubMed]
8. Meyerding, S.G.H. Combining eye-tracking and choice-based conjoint analysis in a bottom-up experiment. *J. Neurosci. Psychol. Econ.* **2018**, *11*, 28–44. [CrossRef]
9. Liu, N.-H.; Chiang, C.-Y.; Chu, H.-C. Recognizing the degree of human attention using EEG signals from mobile sensors. *Sensors* **2013**, *13*, 10273–10286. [CrossRef] [PubMed]
10. Rashal, E.; Senoussi, M.; Santandrea, E.; Ben-Hamed, S.; Macaluso, E.; Chelazzi, L.; Boehler, C.N. An EEG study of the combined effects of top-down and bottom-up attentional selection under varying task difficulty. *Psychophysiology* **2021**, *59*, e14002. [CrossRef] [PubMed]
11. Sarter, M.; Givens, B.; Bruno, J.P. The cognitive neuroscience of sustained attention: Where top-down meets bottom-up. *Brain Res. Rev.* **2001**, *35*, 146–160. [CrossRef]
12. Shipp, S. The brain circuitry of attention. *Trends Cogn. Sci.* **2004**, *8*, 223–230. [CrossRef]
13. Cona, G.; Chiossi, F.; di Tomasso, S.; Pellegrino, G.; Piccione, F.; Bisiacchi, P.; Arcara, G. Theta and alpha oscillations as signatures of internal and external attention to delayed intentions: A magnetoencephalography (MEG) study. *Neuroimage* **2020**, *205*, 116295. [CrossRef] [PubMed]
14. Klimesch, W.; Doppelmayr, M.; Russegger, H.; Pachinger, T.; Schwaiger, J. Induced alpha band power changes in the human EEG and attention. *Neurosci. Lett.* **1998**, *244*, 73–76. [CrossRef]
15. Klimesch, W. Alpha-band oscillations, attention, and controlled access to stored information. *Trends Cogn. Sci.* **2012**, *16*, 606–617. [CrossRef]
16. Klimesch, W. EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Res. Rev.* **1999**, *29*, 169–195. [CrossRef]

17. Dijkstra, N.; Zeidman, P.; Ondobaka, S.; van Gerven, M.A.J.; Friston, K. Distinct top-down and bottom-up brain connectivity during visual perception and imagery. *Sci. Rep.* **2017**, *7*, 5677. [CrossRef] [PubMed]
18. Vossel, S.; Geng, J.J.; Fink, G.R. Dorsal and ventral attention systems: Distinct neural circuits but collaborative roles. *Neuroscientist* **2014**, *20*, 150–159. [CrossRef]
19. Domic-Siede, M.; Irani, M.; Valdés, J.; Perrone-Bertolotti, M.; Ossandón, T. Theta activity from frontopolar cortex, mid-cingulate cortex and anterior cingulate cortex shows different roles in cognitive planning performance. *Neuroimage* **2021**, *226*, 117557. [CrossRef] [PubMed]
20. Jensen, O.; Tesche, C.D. Frontal theta activity in humans increases with memory load in a working memory task. *Eur. J. Neurosci.* **2002**, *15*, 1395–1399. [CrossRef]
21. O'Neill, P.-K.; Gordon, J.A.; Sigurdsson, T. Theta oscillations in the medial prefrontal cortex are modulated by spatial working memory and synchronize with the hippocampus through its ventral subregion. *J. Neurosci.* **2013**, *33*, 14211–14224. [CrossRef] [PubMed]
22. Ratcliffe, O.; Shapiro, K.; Staresina, B.P. Fronto-medial theta coordinates posterior maintenance of working memory content. *Curr. Biol.* **2022**, *32*, 2121–2129. [CrossRef]
23. Kesner, R.P. Retrospective and prospective coding of information: Role of the medial prefrontal cortex. *Exp. Brain Res.* **1989**, *74*, 163–167. [CrossRef]
24. Einstein, G.O.; McDaniel, M.A. Normal aging and prospective memory. *J. Exp. Psychol. Learn Mem. Cogn.* **1990**, *16*, 717. [CrossRef]
25. Kliegel, M.; Martin, M. Prospective memory research: Why is it relevant? *Int. J. Psychol.* **2003**, *38*, 193–194. [CrossRef]
26. Benedek, M.; Schickel, R.J.; Jauk, E.; Fink, A.; Neubauer, A.C. Alpha power increases in right parietal cortex reflects focused internal attention. *Neuropsychologia* **2014**, *56*, 393–400. [CrossRef] [PubMed]
27. Jensen, O.; Mazaheri, A. Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Front. Hum. Neurosci.* **2010**, *4*, 186. [CrossRef] [PubMed]
28. Foxe, J.J.; Snyder, A.C. The role of alpha-band brain oscillations as a sensory suppression mechanism during selective attention. *Front. Psychol.* **2011**, *2*, 154. [CrossRef] [PubMed]
29. Wianda, E.; Ross, B. The roles of alpha oscillation in working memory retention. *Brain Behav.* **2019**, *9*, e01263. [CrossRef]
30. O'Connell, M.E.; Boat, T.; Warner, K.E. Committee on the prevention of mental disorders and substance abuse among children, youth, and young adults: Research advances and promising interventions. In *Preventing Mental, Emotional, and Behavioral Disorders Among Young People: Progress and Possibilities*; The National Academies Press: Washington, DC, USA, 2009.
31. Pfurtscheller, G.; Stancak, A., Jr.; Neuper, C. Event-related synchronization (ERS) in the alpha band—An electrophysiological correlate of cortical idling: A review. *Int. J. Psychophysiol.* **1996**, *24*, 39–46. [CrossRef]
32. Spreng, R.N.; Stevens, W.D.; Chamberlain, J.P.; Gilmore, A.W.; Schacter, D.L. Default network activity, coupled with the frontoparietal control network, supports goal-directed cognition. *Neuroimage* **2010**, *53*, 303–317. [CrossRef]
33. Corbetta, M.; Shulman, G.L. Spatial neglect and attention networks. *Annu. Rev. Neurosci.* **2011**, *34*, 569. [CrossRef]
34. Aton, S.J.; Broussard, C.; Dumoulin, M.; Seibt, J.; Watson, A.; Coleman, T.; Frank, M.G. Visual experience and subsequent sleep induce sequential plastic changes in putative inhibitory and excitatory cortical neurons. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 3101–3106. [CrossRef] [PubMed]
35. Hanson, S.J.; Hanson, C.; Halchenko, Y.; Matsuka, T.; Zaimi, A. Bottom-up and top-down brain functional connectivity underlying comprehension of everyday visual action. *Brain Struct. Funct.* **2007**, *212*, 231–244. [CrossRef]
36. Buschman, T.J.; Miller, E.K. Top-down versus bottom-up control of attention in the prefrontal and posterior parietal cortices. *Science* **2007**, *315*, 1860–1864. [CrossRef]
37. Kam, J.W.Y.; Lin, J.J.; Solbakk, A.K.; Endestad, T.; Larsson, P.G.; Knight, R.T. Default network and frontoparietal control network theta connectivity supports internal attention. *Nat. Hum. Behav.* **2019**, *3*, 1263–1270. [CrossRef]
38. Sander, M.C.; Lindenberger, U.; Werkle-Bergner, M. Lifespan age differences in working memory: A two-component framework. *Neurosci. Biobehav. Rev.* **2012**, *36*, 2007–2033. [CrossRef] [PubMed]
39. Hummel, F.; Gerloff, C. Larger interregional synchrony is associated with greater behavioral success in a complex sensory integration task in humans. *Cereb. Cortex* **2005**, *15*, 670–678. [CrossRef]
40. Payne, L.; Kounios, J. Coherent oscillatory networks supporting short-term memory retention. *Brain Res.* **2009**, *1247*, 126–132. [CrossRef] [PubMed]
41. Shannon, C.E. A Mathematical Theory of Communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [CrossRef]
42. Inouye, T.; Shinosaki, K.; Sakamoto, H.; Toi, S.; Ukai, S.; Iyama, A.; Katsuda, Y.; Hirano, M. Quantification of EEG irregularity by use of the entropy of the power spectrum. *Electroencephalogr. Clin. Neurophysiol.* **1991**, *79*, 204–210. [CrossRef] [PubMed]
43. Lesenfants, D.; Habbal, D.; Chatelle, C.; Soddu, A.; Laureys, S.; Noirhomme, Q. Toward an Attention-Based Diagnostic Tool for Patients with Locked-in Syndrome. *Clin. EEG Neurosci.* **2018**, *49*, 122–135. [CrossRef] [PubMed]
44. Lesenfants, D.; Francart, T. The interplay of top-down focal attention and the cortical tracking of speech. *Sci. Rep.* **2020**, *10*, 6922. [CrossRef] [PubMed]
45. Holtze, B.; Rosenkranz, M.; Jaeger, M.; Debener, S.; Mirkovic, B. Ear-EEG Measures of Auditory Attention to Continuous Speech. *Front. Neurosci.* **2022**, *16*, 869426. [CrossRef]
46. Kumar, M.; Singh, D.; Deepak, K.K. Identifying the correlation between encephalographic signal irregularity and heart rate variability to differentiate internally and externally operative attention. *Biomed. Eng.* **2020**, *32*, 2050014. [CrossRef]

47. Pizzi, G.; Scarpi, D.; Pichierri, M.; Vannucci, V. Virtual reality, real reactions? Comparing consumers' perceptions and shopping orientation across physical and virtual-reality retail stores. *Comput. Hum. Behav.* **2019**, *96*, 1–12. [CrossRef]
48. Burdea, G.C.; Coiffet, P. *Virtual Reality Technology*; John Wiley & Sons: Hoboken, NJ, USA, 2003.
49. Marín-Morales, J.; Higuera-Trujillo, J.L.; Greco, A.; Guixeres, J.; Llinares, C.; Scilingo, E.P.; Alcañiz, M.; Valenza, G. Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors. *Sci. Rep.* **2018**, *8*, 13657. [CrossRef] [PubMed]
50. Saffari, F.; Kakaria, S.; Bigné, E.; Bruni, L.E.; Zarei, S.; Ramsøy, T.Z. Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket. *Front. Neurosci.* **2023**, *17*, 1062980. [CrossRef]
51. Speicher, M.; Hell, P.; Daiber, F.; Simeone, A.; Krüger, A. A virtual reality shopping experience using the apartment metaphor. In Proceedings of the 2018 International Conference on Advanced Visual Interfaces, Grosseto, Italy, 29 May–1 June 2018; pp. 1–9.
52. Han, S.-L.; An, M.; Han, J.J.; Lee, J. Telepresence, time distortion, and consumer traits of virtual reality shopping. *J. Bus. Res.* **2020**, *118*, 311–320. [CrossRef]
53. Bastos, A.M.; Schoffelen, J.M. A tutorial review of functional connectivity analysis methods and their interpretational pitfalls. *Front. Syst. Neurosci.* **2016**, *9*, 175. [CrossRef]
54. Friston, K.J.; Bastos, A.; Litvak, V.; Stephan, K.E.; Fries, P.; Moran, R.J. DCM for complex-valued data: Cross-spectra, coherence and phase-delays. *Neuroimage* **2012**, *59*, 439–455. [CrossRef] [PubMed]
55. Fries, P. A mechanism for cognitive dynamics: Neuronal communication through neuronal coherence. *Trends Cogn. Sci.* **2005**, *9*, 474–480. [CrossRef]
56. Bokil, H.; Purpura, K.; Schoffelen, J.-M.; Thomson, D.; Mitra, P. Comparing spectra and coherences for groups of unequal size. *J. Neurosci. Methods* **2007**, *159*, 337–345. [CrossRef] [PubMed]
57. Bastos, A.M.; Vezoli, J.; Fries, P. Communication through coherence with inter-areal delays. *Curr. Opin. Neurobiol.* **2015**, *31*, 173–180. [CrossRef]
58. Schoffelen, J.-M.; Gross, J. Source connectivity analysis with MEG and EEG. *Hum. Brain Mapp.* **2009**, *30*, 1857–1865. [CrossRef]
59. Perrin, F.; Bertrand, O.; Pernier, J. Scalp Current Density Mapping: Value and Estimation from Potential Data. *IEEE Trans. Biomed. Eng.* **1987**, *4*, 283–288. [CrossRef] [PubMed]
60. Cohen, M.X. *Analyzing Neural Time Series Data: Theory and Practice*; MIT Press: Cambridge, MA, USA, 2014.
61. Files, B.T.; Lawhern, V.J.; Ries, A.J.; Marathe, A.R. A Permutation Test for Unbalanced Paired Comparisons of Global Field Power. *Brain Topogr.* **2016**, *29*, 345–357. [CrossRef] [PubMed]
62. Cortes, C.; Vapnik, V. Support-vector networks. *Mach. Learn.* **1995**, *20*, 273–297. [CrossRef]
63. Chun, M.M.; Golomb, J.D.; Turk-Browne, N.B. A Taxonomy of External and Internal Attention. *Annu. Rev. Psychol.* **2011**, *62*, 73–101. [CrossRef] [PubMed]
64. Keller, A.S.; Payne, L.; Sekuler, R. Characterizing the roles of alpha and theta oscillations in multisensory attention. *Neuropsychologia* **2017**, *99*, 48–63. [CrossRef] [PubMed]
65. Clayton, M.S.; Yeung, N.; Cohen Kadosh, R. Electrical stimulation of alpha oscillations stabilizes performance on visual attention tasks. *J. Exp. Psychol. Gen.* **2019**, *148*, 203–220. [CrossRef] [PubMed]
66. Cruz, G.; Burgos, P.; Kilborn, K.; Evans, J.J. Involvement of the anterior cingulate cortex in time-based prospective memory task monitoring: An EEG analysis of brain sources using Independent Component and Measure Projection Analysis. *PLoS ONE* **2017**, *12*, e0184037. [CrossRef]
67. Benedek, M.; Bergner, S.; Könen, T.; Fink, A.; Neubauer, A.C. EEG alpha synchronization is related to top-down processing in convergent and divergent thinking. *Neuropsychologia* **2011**, *49*, 3505–3511. [CrossRef] [PubMed]
68. Wen, X.; Xiang, Y.; Cant, J.S.; Wang, T.; Cupchik, G.; Huang, R.; Mo, L. The neural correlates of internal and external comparisons: An fMRI study. *Brain Struct. Funct.* **2017**, *222*, 563–575. [CrossRef] [PubMed]
69. Capotosto, P.; Babiloni, C.; Romani, G.L.; Corbetta, M. Frontoparietal Cortex Controls Spatial Attention through Modulation of Anticipatory Alpha Rhythms. *J. Neurosci.* **2009**, *29*, 5863–5872. [CrossRef] [PubMed]
70. Kastner, S.; Pinsk, M.A.; De Weerd, P.; Desimone, R.; Ungerleider, L.G. Increased Activity in Human Visual Cortex during Directed Attention in the Absence of Visual Stimulation. *Neuron* **1999**, *22*, 751–761. [CrossRef] [PubMed]

REFERENCES

Abratt, R., & Goodey, S. D. (1990). Unplanned buying and in-store stimuli in supermarkets. *Managerial and Decision Economics*, *11*(2), 111–121. https://doi.org/10.1002/MDE.4090110204

Achar, C., So, J., Agrawal, N., & Duhachek, A. (2016). What we feel and why we buy: The influence of emotions on consumer decision-making. In *Current Opinion in Psychology* (Vol. 10, pp. 166–170). Elsevier. https://doi.org/10.1016/j.copsyc.2016.01.009

Acharya, U. R., Joseph, K. P., Kannathal, N., Lim, C. M., & Suri, J. S. (2006). Heart rate variability: A review. *Medical and Biological Engineering and Computing*, *44*(12), 1031–1051. https://doi.org/10.1007/s11517-006-0119-0

Adam, M., Krãmer, J., & Weinhardt, C. (2012). Excitement up! Price down! Measuring emotions in Dutch auctions. *International Journal of Electronic Commerce*, *17*(2), 7–40. https://doi.org/10.2753/JEC1086-4415170201

Adam, M. T. P., Krämer, J., & Müller, M. B. (2015). Auction Fever! How Time Pressure and Social Competition Affect Bidders' Arousal and Bids in Retail Auctions. *Journal of Retailing*, *91*(3), 468–485. https://doi.org/10.1016/j.jretai.2015.01.003

Aghakhani, N., Oh, O., Gregg, D. G., & Karimi, J. (2020). Online Review Consistency Matters: An Elaboration Likelihood Model Perspective. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-020-10030-7

Ahmed, S., & Ting, D. H. (2018). The shopping list in goal-directed shopping: scale development and validation. *Https://Doi.Org/10.1080/02642069.2018.1532997*, *39*(5–6), 319–342. https://doi.org/10.1080/02642069.2018.1532997

Alcañiz, M., Bigné, E., & Guixeres, J. (2019). Virtual Reality in Marketing: A Framework, Review, and Research Agenda. *Frontiers in Psychology*, *10*(July), 1–15. https://doi.org/10.3389/fpsyg.2019.01530

Alexander, V., Tripp, S., & Zak, P. J. (2015). Preliminary Evidence for the Neurophysiologic Effects of Online Coupons: Changes in Oxytocin, Stress, and Mood. *Psychology and Marketing*, *32*(9), 977–986. https://doi.org/10.1002/mar.20831

Alsop, T. (2022). *AR/VR market size worldwide 2021-2028 | Statista*. Statista. https://www.statista.com/statistics/591181/global-augmented-virtual-reality-market-size/

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*(December). https://doi.org/10.3389/fnins.2020.577666

Amos, C., Holmes, G. R., & Keneson, W. C. (2014). A meta-analysis of consumer impulse buying. *Journal of Retailing and Consumer Services*, *21*(2), 86–97. https://doi.org/10.1016/j.jretconser.2013.11.004

Antonenko, P., Paas, F., Grabner, R., & van Gog, T. (2010). Using Electroencephalography to Measure Cognitive Load. *Educational Psychology Review*, *22*(4), 425–438. https://doi.org/10.1007/S10648-010-9130-Y/FIGURES/3

Arghashi, V. (2022). Shopping with augmented reality: How wow-effect changes the equations! *Electronic Commerce Research and Applications*, *54*, 101166. https://doi.org/10.1016/J.ELERAP.2022.101166

Aydınoğlu, N. Z., & Krishna, A. (2019). The power of consumption-imagery in communicating retail-store deals. *Journal of Retailing*, *95*(4), 116–127. https://doi.org/10.1016/J.JRETAI.2019.10.010

Babić Rosario, A., de Valck, K., & Sotgiu, F. (2020). Conceptualizing the electronic word-of-mouth process: What we know and need to know about eWOM creation, exposure, and evaluation. *Journal of the*

Academy of Marketing Science, *48*(3), 422–448. https://doi.org/10.1007/s11747-019-00706-1

Bachen, C. M., Hernández-Ramos, P., Raphael, C., & Waldron, A. (2016). How do presence, flow, and character identification affect players' empathy and interest in learning from a serious computer game? *Computers in Human Behavior*, *64*, 77–87. https://doi.org/10.1016/J.CHB.2016.06.043

Baldo, D., Viswanathan, V. S., Timpone, R. J., & Venkatraman, V. (2022). The heart, brain, and body of marketing: Complementary roles of neurophysiological measures in tracking emotions, memory, and ad effectiveness. *Psychology & Marketing*. https://doi.org/10.1002/mar.21697

Baymard. (2020). 46 Cart Abandonment Rate Statistics. In *Baymard Institute* (Vol. 2013). https://baymard.com/lists/cart-abandonment-rate

Bazzani, A., Ravaioli, S., Trieste, L., Faraguna, U., & Turchetti, G. (2020). Is EEG Suitable for Marketing Research? A Systematic Review. *Frontiers in Neuroscience*, *14*(December). https://doi.org/10.3389/fnins.2020.594566

Bell, D. R., Corsten, D., & Knox, G. (2011). From Point of Purchase to Path to Purchase: How Preshopping Factors Drive Unplanned Buying. *Journal of Marketing*, *75*(1), 31–45. https://doi.org/10.1509/jm.75.1.31

Bell, L., Vogt, J., Willemse, C., Routledge, T., Butler, L. T., & Sakaki, M. (2018). Beyond self-report: A review of physiological and neuroscientific methods to investigate consumer behavior. *Frontiers in Psychology*, *9*(SEP), 1–16. https://doi.org/10.3389/fpsyg.2018.01655

Bellini, S., Cardinali, M. G., & Grandi, B. (2017). A structural equation model of impulse buying behaviour in grocery retailing. *Journal of Retailing and Consumer Services*, *36*, 164–171. https://doi.org/10.1016/J.JRETCONSER.2017.02.001

Bellman, S., Nenycz-Thiel, M., Kennedy, R., Hartnett, N., & Varan, D. (2019). Best measures of attention to creative tactics in TV advertising: When do attention-getting devices capture or reduce attention? *Journal of Advertising Research*, *59*(3), 295–311. https://doi.org/10.2501/JAR-2019-002

Bellman, Steven, Murphy, J., Treleaven-Hassard, S., O'Farrell, J., Qiu, L., & Varan, D. (2013). Using Internet Behavior to Deliver Relevant Television Commercials. *Journal of Interactive Marketing*, *27*(2), 130–140.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the Tribes: Using Text for Marketing Insight. *Journal of Marketing*, *84*(1), 1–25. https://doi.org/10.1177/0022242919873106

Bettman, J. R. (1979). Memory Factors in Consumer Choice: A Review. *Journal of Marketing*, *43*(2), 37–53. https://doi.org/10.1177/002224297904300205

Bialkova, S., Grunert, K. G., & van Trijp, H. (2020). From desktop to supermarket shelf: Eye-tracking exploration on consumer attention and choice. *Food Quality and Preference*, *81*, 103839. https://doi.org/10.1016/J.FOODQUAL.2019.103839

Bigne, E., Chatzipanagiotou, K., & Ruiz, C. (2020). Pictorial content, sequence of conflicting online reviews and consumer decision-making: The stimulus-organism-response model revisited. *Journal of Business Research*, *115*, 403–416. https://doi.org/10.1016/j.jbusres.2019.11.031

Bigné, E., Llinares, C., & Torrecilla, C. (2016). Elapsed time on first buying triggers brand choices within a category: A virtual reality-based study. *Journal of Business Research*, *69*(4), 1423–1427. https://doi.org/10.1016/j.jbusres.2015.10.119

Bigne, E., Ruiz, C., Cuenca, A., Perez, C., & Garcia, A. (2021). What drives the helpfulness of online reviews? A deep learning study of sentiment analysis, pictorial content and reviewer expertise for mature destinations. *Journal of Destination Marketing and Management*, *20*, 2212–2571. https://doi.org/10.1016/j.jdmm.2021.100570

Bigne, E., Ruiz, C., & Curras-Perez, R. (2019). Destination appeal through digitalized comments. *Journal of Business Research*, *101*(January), 447–453. https://doi.org/10.1016/j.jbusres.2019.01.020

Bigne, E., Simonetti, A., Ruiz, C., & Kakaria, S. (2021). How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach. *Journal of Business Research*, *123*, 279–288. https://doi.org/10.1016/J.JBUSRES.2020.10.010

Bigné, E., William, E., & Soria-Olivas, E. (2020). Similarity and Consistency in Hotel Online Ratings across Platforms. *Journal of Travel Research*, *59*(4), 742–758. https://doi.org/10.1177/0047287519859705

Biswas, D. (2019). Sensory Aspects of Retailing: Theoretical and Practical Implications. *Journal of Retailing*, *95*(4), 111–115. https://doi.org/10.1016/J.JRETAI.2019.12.001

Blasco-Arcas, L., Kastanakis, M. N., Alcañiz, M., & Reyes-Menendez, A. (2023). Leveraging user behavior and data science technologies for management: An overview. *Journal of Business Research*, *154*, 113325. https://doi.org/10.1016/J.JBUSRES.2022.113325

Block, L. G., & Morwitz, V. G. (1999). Shopping Lists as an External Memory Aid for Grocery Shopping: Influences on List Writing and List Fulfillment. *Journal of Consumer Psychology*, *8*(4), 343–375. https://doi.org/10.1207/S15327663JCP0804_01

Bloemer, J., & de Ruyter, K. (1998). On the relationship between store image, store satisfaction and store loyalty. *European Journal of Marketing*, *32*(5/6), 499–513. https://doi.org/10.1108/03090569810216118

Bos, M. G. N., Jentgens, P., Beckers, T., & Kindt, M. (2013). Psychophysiological Response Patterns to Affective Film Stimuli. *PLoS ONE*, *8*(4). https://doi.org/10.1371/journal.pone.0062661

Brachten, F., Brünker, F., Frick, N. R. J., Ross, B., & Stieglitz, S. (2020). On the ability of virtual agents to decrease cognitive load: an experimental study. *Information Systems and E-Business Management*, *18*(2), 187–207. https://doi.org/10.1007/S10257-020-00471-7/TABLES/4

Breuer, C., Boronczyk, F., & Rumpf, C. (2021). Message personalization and real-time adaptation as next innovations in sport sponsorship management? How run-of-play and team affiliation affect viewer response. *Journal of Business Research*, *133*, 309–316. https://doi.org/10.1016/j.jbusres.2021.05.003

Bruwer, J., Chrysochou, P., & Lesschaeve, I. (2017). Consumer involvement and knowledge influence on wine choice cue utilisation. *British Food Journal*, *119*(4), 830–844. https://doi.org/10.1108/BFJ-08-2016-0360

Buckley, P. G. (1991). An S-O-R Model of the Purchase of an Item in a Sore. *Advances in Consumer Research*, *18*.

Bulagang, A. F., Weng, N. G., Mountstephens, J., & Teo, J. (2020). A review of recent approaches for emotion classification using electrocardiography and electrodermography signals. *Informatics in Medicine Unlocked*, *20*, 100363. https://doi.org/10.1016/j.imu.2020.100363

Burnkrant, R. E. (1978). Cue Utilization in Product Perception. *ACR North American Advances*, *NA-05*. https://www.acrwebsite.org/volumes/9512/volumes/v05/NA-05/full

Cahlíková, J., Cingl, L., & Levely, I. (2020). How stress affects performance and competitiveness across gender. *Management Science*, *66*(8), 3295–3310. https://doi.org/10.1287/mnsc.2019.3400

Candia-Rivera, D., Catrambone, V., Thayer, J. F., Gentili, C., & Valenza, G. (2022). Cardiac sympathetic-vagal activity initiates a functional brain–body response to emotional arousal. *Proceedings of the National Academy of Sciences*, *119*(21). https://doi.org/10.1073/PNAS.2119599119

Carter, C. (2008). Healthcare performance and the effects of the binaural beats on human blood pressure and heart rate. *Journal of Hospital Marketing and Public Relations*, *18*(2), 213–219. https://doi.org/10.1080/15390940802234263

Casado-Aranda, L.-A., & Sanchez-Fernandez, J. (2022). Advances in neuroscience and marketing: analyzing tool possibilities and research opportunities. *Spanish Journal of Marketing - ESIC*, *26*(1), 3–22. https://doi.org/10.1108/SJME-10-2021-0196

Casado-Aranda, L. A., Sánchez-Fernández, J., Bigne, E., & Smidts, A. (2023). The application of neuromarketing tools in communication research: A comprehensive review of trends. *Psychology and Marketing*. https://doi.org/10.1002/MAR.21832

Catai, A. M., Pastre, C. M., Godoy, M. F. de, Silva, E. da, Takahashi, A. C. de M., & Vanderlei, L. C. M. (2020). Heart rate variability: are you using it properly? Standardisation checklist of procedures. In *Brazilian Journal of Physical Therapy* (Vol. 24, Issue 2, pp. 91–102). Elsevier. https://doi.org/10.1016/j.bjpt.2019.02.006

Catrambone, V., Wendt, H., Scilingo, E. P., Barbieri, R., Abry, P., & Valenza, G. (2019). Heartbeat Dynamics Analysis under Cold-Pressure Test using Wavelet p-Leader Non-Gaussian Multiscale Expansions. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2023–2026. https://doi.org/10.1109/EMBC.2019.8856653

Chaiken, S., Liberman, A., & Eagly, A. H. H. (1989). Heuristic and systematic information processing within and beyond the persuasion context. In *Unintentent Thought*.

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

Chen, J., Fan, W., Wei, J., & Liu, Z. (2021). Effects of linguistic style on persuasiveness of word-of-mouth messages with anonymous vs. identifiable sources. *Marketing Letters*, *0123456789*. https://doi.org/10.1007/s11002-021-09602-7

Chen, J. V., Ha, Q. A., & Vu, M. T. (2022). The Influences of Virtual Reality Shopping Characteristics on Consumers' Impulse Buying Behavior. *International Journal of Human-Computer Interaction*, *0*(0), 1–19. https://doi.org/10.1080/10447318.2022.2098566

Chen, Z., & Yuan, M. (2020). Psychology of word of mouth marketing. *Current Opinion in Psychology*, *31*, 7–10. https://doi.org/10.1016/j.copsyc.2019.06.026

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chevalier, S. (2021a). *• U.S. leading online shopping attributes 2018 | Statista*. https://www.statista.com/statistics/973413/most-important-attributes-online-shopping-shoppers-usa/

Chevalier, S. (2021b, November 16). *• Global social media purchases by type 2021 | Statista*. https://www.statista.com/statistics/1276367/online-consumers-purchase-decision-behavior/

Chi, M., Pan, M., & Huang, R. (2021). Examining the direct and interaction effects of picture color cues and textual cues related to color on accommodation-sharing platform rental purchase. *International Journal of Hospitality Management*, *99*. https://doi.org/10.1016/J.IJHM.2021.103066

Choi, H. S., Ko, M. S., Medlin, D., & Chen, C. (2018). The effect of intrinsic and extrinsic quality cues of digital video games on sales: An empirical investigation. *Decision Support Systems*, *106*, 86–96. https://doi.org/10.1016/j.dss.2017.12.005

Chonpracha, P., Ardoin, R., Gao, Y., Waimaleongoraek, P., Tuuri, G., & Prinyawiwatkul, W. (2020). Effects of intrinsic and extrinsic visual cues on consumer emotion and purchase intent: A case of ready-to-eat salad. *Foods*, *9*(4). https://doi.org/10.3390/foods9040396

Christoforou, C., Christou-Champi, S., Constantinidou, F., & Theodorou, M. (2015). From the eyes and the heart: A novel eye-gaze metric that predicts video preferences of a large audience. *Frontiers in Psychology*, *6*(MAY). https://doi.org/10.3389/fpsyg.2015.00579

Clark, K. R., Leslie, K. R., Garcia-Garcia, M., & Tullman, M. L. (2018). How Advertisers Can Keep Mobile Users Engaged and Reduce Video-Ad Blocking. *Journal of Advertising Research*, *58*(3), 311–325. https://doi.org/10.2501/JAR-2018-036

Constantinides, E. (2010). The Marketing Mix Revisited: Towards the 21st Century Marketing. *Https://Doi.Org/10.1362/026725706776861190*, *22*(3–4), 407–438. https://doi.org/10.1362/026725706776861190

Cowan, K., & Ketron, S. (2019). Prioritizing marketing research in virtual reality: development of an immersion/fantasy typology. *European Journal of Marketing*, *53*(8), 1585–1611.

https://doi.org/10.1108/EJM-10-2017-0733

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555/METRICS

Csikszentmihalyi, M., & LeFevre, J. (1989). Optimal Experience in Work and Leisure. *Journal of Personality and Social Psychology*, *56*(5), 815–822. https://doi.org/10.1037/0022-3514.56.5.815

Daisy, J., Krasonikolakis, I., & Vrontis, D. (2022). A systematic literature review of store atmosphere in alternative retail commerce channels. *Journal of Business Research*, *153*(December 2021), 412–427. https://doi.org/10.1016/j.jbusres.2022.08.050

Daugherty, T., & Hoffman, E. (2014). eWOM and the importance of capturing consumer attention within social media. *Journal of Marketing Communications*, *20*(1–2), 82–102. https://doi.org/10.1080/13527266.2013.797764

Davydenko, M., & Peetz, J. (2020). Shopping less with shopping lists: Planning individual expenses ahead of time affects purchasing behavior when online grocery shopping. *Journal of Consumer Behaviour*, *19*(3), 240–251. https://doi.org/10.1002/cb.1812

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, *78*, 97–119. https://doi.org/10.1016/J.EUROECOREV.2015.05.004

Dincelli, E., & Yayla, A. (2022). Immersive virtual reality in the age of the Metaverse: A hybrid-narrative review based on the technology affordance perspective. In *Journal of Strategic Information Systems* (Vol. 31, Issue 2, p. 101717). North-Holland. https://doi.org/10.1016/j.jsis.2022.101717

Dobbs, W. C., Fedewa, M. V, Macdonald, H. V, Clifton, ·, Holmes, J., Cicone, Z. S., Daniel, ·, Plews, J., & Esco, M. R. (2019). The Accuracy of Acquiring Heart Rate Variability from Portable Devices: A Systematic Review and Meta-Analysis. *Sports Medicine*, *49*, 417–435. https://doi.org/10.1007/s40279-019-01061-5

Donovan, R. J., Rossiter, J. R., Marcoolyn, G., & Nesdale, A. (1994). Store atmosphere and purchasing behavior. *Journal of Retailing*, *70*(3), 283–294. https://doi.org/10.1016/0022-4359(94)90037-X

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

Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis. *Journal of Business Research*, *135*, 758–773. https://doi.org/10.1016/j.jbusres.2021.07.015

Dulleck, U., Ristl, A., Schaffner, M., & Torgler, B. (2011). Heart Rate Variability, the Autonomic Nervous System, and Neuroeconomic Experiments. *Journal of Neuroscience, Psychology, and Economics*, *4*(2), 117–124. https://doi.org/10.1037/a0022245

Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., Dennehy, D., Metri, B., Buhalis, D., Cheung, C. M. K., Conboy, K., Doyle, R., Dubey, R., Dutot, V., Felix, R., Goyal, D. P., Gustafsson, A., Hinsch, C., Jebabli, I., … Wamba, S. F. (2022). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *66*, 102542. https://doi.org/10.1016/J.IJINFOMGT.2022.102542

Dwivedi, Y. K., Hughes, L., Wang, Y., Alalwan, A. A., Ahn, S. J. (Grace), Balakrishnan, J., Barta, S., Belk, R., Buhalis, D., Dutot, V., Felix, R., Filieri, R., Flavián, C., Gustafsson, A., Hinsch, C., Hollensen, S., Jain, V., Kim, J., Krishen, A. S., … Wirtz, J. (2022). Metaverse marketing: How the metaverse will shape the future of consumer research and practice. *Psychology & Marketing*. https://doi.org/10.1002/mar.21767

Eberhard, K. (2021). The effects of visualization on judgment and decision-making: a systematic literature review. *Management Review Quarterly*. https://doi.org/10.1007/S11301-021-00235-8

Elboudali, A., Aoussat, A., Mantelet, F., Bethomier, J., & Leray, F. (2020). A customised virtual reality shopping experience framework based on consumer behaviour: 3DR3CO. *International Journal on Interactive Design and Manufacturing*, *14*(2), 551–563. https://doi.org/10.1007/S12008-020-00645-0/FIGURES/12

Elmashhara, M. G., & Soares, A. M. (2022). Linking atmospherics to shopping outcomes: The role of the desire to stay. *Journal of Retailing and Consumer Services*, *64*, 102744. https://doi.org/10.1016/j.jretconser.2021.102744

Falk, A., Kosse, F., Menrath, I., Verde, P. E., & Siegrist, J. (2018). Unfair pay and health. *Management Science*, *64*(4), 1477–1488. https://doi.org/10.1287/mnsc.2016.2630

Fan, X., Chai, Z., Deng, N., & Dong, X. (2020). Adoption of augmented reality in online retailing and consumers' product attitude: A cognitive perspective. *Journal of Retailing and Consumer Services*, *53*(October 2019), 101986. https://doi.org/10.1016/j.jretconser.2019.101986

Fang, D., Nayga, R. M., West, G. H., Bazzani, C., Yang, W., Lok, B. C., Levy, C. E., & Snell, H. A. (2021). On the Use of Virtual Reality in Mitigating Hypothetical Bias in Choice Experiments. *American Journal of Agricultural Economics*, *103*(1), 142–161. https://doi.org/10.1111/AJAE.12118

Figini, P., Vici, L., & Viglia, G. (2020). A comparison of hotel ratings between verified and non-verified online review platforms. *International Journal of Culture, Tourism, and Hospitality Research*, *14*(2), 157–171. https://doi.org/10.1108/IJCTHR-10-2019-0193

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261–1270. https://doi.org/10.1016/j.jbusres.2014.11.006

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research*, *58*, 46–64. https://doi.org/10.1016/j.annals.2015.12.019

Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How Online Product Reviews Affect Retail Sales: A Meta-analysis. *Journal of Retailing*, *90*(2), 217–232. https://doi.org/10.1016/j.jretai.2014.04.004

Forte, G., Favieri, F., & Casagrande, M. (2019). Heart rate variability and cognitive function: A systematic review. In *Frontiers in Neuroscience* (Vol. 13, Issue JUL, p. 710). Frontiers Media S.A. https://doi.org/10.3389/fnins.2019.00710

Gangadharbatla, H., Bradley, S., & Wise, W. (2013). Psychophysiological responses to background brand placements in video games. *Journal of Advertising*, *42*(2–3), 251–263. https://doi.org/10.1080/00913367.2013.775800

García-Madariaga, J., Moya, I., Recuero, N., & Blasco, M. F. (2020). Revealing Unconscious Consumer Reactions to Advertisements That Include Visual Metaphors. A Neurophysiological Experiment. *Frontiers in Psychology*, *11*, 760. https://doi.org/10.3389/FPSYG.2020.00760/BIBTEX

Gaur, S. S., Herjanto, H., & Makkar, M. (2014). Review of emotions research in marketing, 2002-2013. *Journal of Retailing and Consumer Services*, *21*(6), 917–923. https://doi.org/10.1016/j.jretconser.2014.08.009

Giang Barrera, K., & Shah, D. (2023). Marketing in the Metaverse: Conceptual understanding, framework, and research agenda. *Journal of Business Research*, *155*, 113420. https://doi.org/10.1016/j.jbusres.2022.113420

Golnar-Nik, P., Farashi, S., & Safari, M. S. (2019). The application of EEG power for the prediction and interpretation of consumer decision-making: A neuromarketing study. *Physiology and Behavior*, *207*(August 2018), 90–98. https://doi.org/10.1016/j.physbeh.2019.04.025

Granbois, D. H. (1968). Improving the Study of Customer In-store Behavior. *Journal of Marketing*, *32*(4_part_1), 28–33. https://doi.org/10.1177/002224296803200406

Grassini, S., & Laumann, K. (2020). Questionnaire Measures and Physiological Correlates of Presence: A Systematic Review. *Frontiers in Psychology*, *0*, 349. https://doi.org/10.3389/FPSYG.2020.00349

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing*, *93*(1), 1–6.

https://doi.org/10.1016/j.jretai.2016.12.008

Guixeres, J., Bigné, E., Azofra, J. M. A., Raya, M. A., Granero, A. C., Hurtado, F. F., & Ornedo, V. N. (2017). Consumer neuroscience-based metrics predict recall, liking and viewing rates in online advertising. *Frontiers in Psychology*, *8*(OCT), 1808. https://doi.org/10.3389/fpsyg.2017.01808

Guo, Y., Lu, Z., Kuang, H., & Wang, C. (2020). Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure. *International Journal of Information Management*, *52*, 102067. https://doi.org/10.1016/J.IJINFOMGT.2020.102067

Ha-Brookshire, J., & Bhaduri, G. (2014). Disheartened consumers: impact of malevolent apparel business practices on consumer's heart rates, perceived trust, and purchase intention. *Fashion and Textiles*, *1*(1). https://doi.org/10.1186/s40691-014-0010-9

Halbig, A., & Latoschik, M. E. (2021). A Systematic Review of Physiological Measurements, Factors, Methods, and Applications in Virtual Reality. *Frontiers in Virtual Reality*, *2*, 89. https://doi.org/10.3389/frvir.2021.694567

Halkias, G., Florack, A., Diamantopoulos, A., & Palcu, J. (2022). Eyes Wide Shut? Understanding and Managing Consumers' Visual Processing of Country-of-Origin Cues. *British Journal of Management*, *33*(3), 1432–1446. https://doi.org/10.1111/1467-8551.12545

Hamilton, R., Vohs, K. D., & McGill, A. L. (2014). We'll Be Honest, This Won't Be the Best Article You'll Ever Read: The Use of Dispreferred Markers in Word-of-Mouth Communication. *Journal of Consumer Research*, *41*(1), 197–212. https://doi.org/10.1086/675926

Han, S. L., An, M., Han, J. J., & Lee, J. (2020). Telepresence, time distortion, and consumer traits of virtual reality shopping. *Journal of Business Research*, *118*, 311–320. https://doi.org/10.1016/J.JBUSRES.2020.06.056

Hao, Y. Y., Ye, Q., Li, Y. J., & Cheng, Z. (2010). How does the valence of online consumer reviews matter in consumer decision making? Differences between search goods and experience goods. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 1–10. https://doi.org/10.1109/HICSS.2010.455

Hariharan, A., Adam, M. T. P. M. T. P., Teubner, T., & Weinhardt, C. (2016). *Think, feel, bid: the impact of environmental conditions on the role of bidders' cognitive and affective processes in auction bidding*. *26*(4), 339–355. https://link.springer.com/article/10.1007/s12525-016-0224-3

Hart, S. G. (2016). Nasa-Task Load Index (NASA-TLX); 20 Years Later: *Http://Dx.Doi.Org/10.1177/154193120605000909*, 904–908. https://doi.org/10.1177/154193120605000909

Hattke, F., Hensel, D., & Kalucza, J. (2020). Emotional Responses to Bureaucratic Red Tape. *Public Administration Review*, *80*(1), 53–63. https://doi.org/10.1111/puar.13116

He, J., Wang, X., Vandenbosch, M. B., & Nault, B. R. (2020). Revealed preference in online reviews: Purchase verification in the tablet market. *Decision Support Systems*, *132*(March), 113281. https://doi.org/10.1016/j.dss.2020.113281

He, Y., & Oppewal, H. (2018). See How Much We've Sold Already! Effects of Displaying Sales and Stock Level Information on Consumers' Online Product Choices. *Journal of Retailing*, *94*(1), 45–57. https://doi.org/10.1016/J.JRETAI.2017.10.002

Herman, A. M., Critchley, H. D., & Duka, T. (2018). The role of emotions and physiological arousal in modulating impulsive behaviour. *Biological Psychology*, *133*, 30–43. https://doi.org/10.1016/J.BIOPSYCHO.2018.01.014

Hernandez, M. D., & Minor, M. S. (2011). Investigating the effect of arousal on brand memory in advergames: Comparing qualitative and quantitative approaches. *Qualitative Market Research*, *14*(2), 207–217. https://doi.org/10.1108/13522751111120701

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly: Management Information Systems*, *28*(1), 75–105. https://doi.org/10.2307/25148625

Hilken, T., Keeling, D. I., Chylinski, | Mathew, Ko De Ruyter, |, Golf Papez, M., Heller, J., Dominik Mahr, |, & Alimamy, S. (2022). Disrupting marketing realities: A research agenda for investigating the psychological mechanisms of next-generation experiences with reality-enhancing technologies. *Psychology & Marketing*. https://doi.org/10.1002/MAR.21678

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. *Journal of Marketing*, *60*(3), 50–68. https://doi.org/10.2307/1251841

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). Communication and persuasion; psychological studies of opinion change. In *Communication and persuasion; psychological studies of opinion change.* Yale University Press.

Hu, H. fen, & Krishen, A. S. (2019). When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. *Journal of Business Research*, *100*(March), 27–37. https://doi.org/10.1016/j.jbusres.2019.03.011

Huang, H., Liu, S. Q., & Lu, Z. (2022). When and why Language Assertiveness Affects Online Review Persuasion: *Https://Doi.Org/10.1177/10963480221074280*, *XX*, *No. X*, 109634802210742. https://doi.org/10.1177/10963480221074280

Huang, J., & Zhou, L. (2019). The dual roles of web personalization on consumer decision quality in online shopping: The perspective of information load. *Internet Research*, *29*(6), 1280–1300. https://doi.org/10.1108/INTR-11-2017-0421

Huang, M. H. (2000). Information load: its relationship to online exploratory and shopping behavior. *International Journal of Information Management*, *20*(5), 337–347. https://doi.org/10.1016/S0268-4012(00)00027-X

Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for Experience on the Web: An Empirical Examination of Consumer Behavior for Search and Experience Goods. *Journal of Marketing*, *73*(2), 55–69. https://doi.org/10.1509/jmkg.73.2.55

Huddleston, P. T., Behe, B. K., Driesener, C., & Minahan, S. (2018). Inside-outside: Using eye-tracking to investigate search-choice processes in the retail environment. *Journal of Retailing and Consumer Services*, *43*, 85–93. https://doi.org/10.1016/j.jretconser.2018.03.006

Hui, S. K., Bradlow, E. T., & Fader, P. S. (2009). Testing behavioral hypotheses using an integrated model of grocery store shopping path and purchase behavior. *Journal of Consumer Research*, *36*(3), 478–493. https://doi.org/10.1086/599046/2/M_36-3-478-EQ017.JPEG

Hui, S. K., Huang, Y., Suher, J., & Jeffrey Inman, J. (2013). Deconstructing the "First Moment of Truth": Understanding Unplanned Consideration and Purchase Conversion Using In-Store Video Tracking. *Journal of Marketing Research*, *50*(4), 445–462. https://doi.org/10.1509/jmr.12.0065

Hui, S. K., Inman, J. J., Huang, Y., & Suher, J. (2013). On unplanned spending: Applications to mobile promotion strategies. *Journal of Marketing*, *77*(2), 1–16. https://doi.org/10.1509/jm.11.0436

Humphreys, A., & Wang, R. J. H. (2018). Automated text analysis for consumer research. *Journal of Consumer Research*, *44*(6), 1274–1306. https://doi.org/10.1093/jcr/ucx104

Igartua, J. J., & Hayes, A. F. (2021). Mediation, Moderation, and Conditional Process Analysis: Concepts, Computations, and Some Common Confusions. *The Spanish Journal of Psychology*, *24*(6), 49. https://doi.org/10.1017/SJP.2021.46

Inman, J. J., Winer, R. S., & Ferraro, R. (2009). The Interplay among Category Characteristics, Customer Characteristics, and Customer Activities on in-Store Decision Making: *Https://Doi.Org/10.1509/Jmkg.73.5.19*, *73*(5), 19–29. https://doi.org/10.1509/JMKG.73.5.19

Ishaque, S., Khan, N., & Krishnan, S. (2021). Trends in Heart-Rate Variability Signal Analysis. *Frontiers in Digital*

Health, *3*(February), 1–18. https://doi.org/10.3389/fdgth.2021.639444

Ismagilova, E., Slade, E. L., Rana, N. P., & Dwivedi, Y. K. (2020a). The Effect of Electronic Word of Mouth Communications on Intention to Buy: A Meta-Analysis. *Information Systems Frontiers*, *22*(5), 1203–1226. https://doi.org/10.1007/s10796-019-09924-y

Ismagilova, E., Slade, E., Rana, N. P., & Dwivedi, Y. K. (2020b). The effect of characteristics of source credibility on consumer behaviour: A meta-analysis. *Journal of Retailing and Consumer Services*, *53*. https://doi.org/10.1016/j.jretconser.2019.01.005

Iyer, G. R., Blut, M., Xiao, S. H., & Grewal, D. (2020). Impulse buying: a meta-analytic review. *Journal of the Academy of Marketing Science*, *48*(3), 384–404. https://doi.org/10.1007/s11747-019-00670-w

Jacoby, J. (2002). Stimulus-Organism-Response Reconsidered: An Evolutionary Step in Modeling (Consumer) Behavior. *Journal of Consumer Psychology*, *12*(1), 51–57. https://doi.org/10.1207/s15327663jcp1201_05

Jacoby, J., Szybillo, G. J., & Berning, C. K. (1976). Time and Consumer Behavior: An Interdisciplinary Overview. *Journal of Consumer Research*, *2*(4), 320. https://doi.org/10.1086/208644

Jiménez, F. R., & Mendoza, N. A. (2013). Too popular to ignore: The influence of online reviews on purchase intentions of search and experience products. *Journal of Interactive Marketing*, *27*(3), 226–235. https://doi.org/10.1016/j.intmar.2013.04.004

Jimmy Xie, H., Miao, L., Kuo, P. J., & Lee, B. Y. (2011). Consumers’ responses to ambivalent online hotel reviews: The role of perceived source credibility and pre-decisional disposition. *International Journal of Hospitality Management*, *30*(1), 178–183. https://doi.org/10.1016/j.ijhm.2010.04.008

Jin, B., Kim, G., Moore, M., & Rothenberg, L. (2021). Consumer store experience through virtual reality: its effect on emotional states and perceived store attractiveness. *Fashion and Textiles*, *8*(1). https://doi.org/10.1186/s40691-021-00256-7

Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux. https://books.google.es/books?id=SHvzzuCnuv8C

Kakaria, S., Bigné, E., Catrambone, V., & Valenza, G. (2023). Heart rate variability in marketing research: A systematic review and methodological perspectives. *Psychology & Marketing*, *40*(1), 190–208. https://doi.org/10.1002/mar.21734

Kakaria, S., Simonetti, A., & Bigne, E. (2023). Interaction between extrinsic and intrinsic online review cues: perspectives from cue utilization theory. *Electronic Commerce Research*, *0123456789*. https://doi.org/10.1007/s10660-022-09665-2

Karmarkar, U. R., & Plassmann, H. (2019). Consumer Neuroscience: Past, Present, and Future. *Organizational Research Methods*, *22*(1), 174–195. https://doi.org/10.1177/1094428117730598

Kato, R., & Hoshino, T. (2021). Unplanned purchase of new products. *Journal of Retailing and Consumer Services*, *59*, 102397. https://doi.org/10.1016/J.JRETCONSER.2020.102397

Kaushik, K., Mishra, R., Rana, N. P., & Dwivedi, Y. K. (2018). Exploring reviews and review sequences on e-commerce platform: A study of helpful reviews on Amazon.in. *Journal of Retailing and Consumer Services*, *45*(June), 21–32. https://doi.org/10.1016/j.jretconser.2018.08.002

Kautish, P., & Khare, A. (2022). Investigating the moderating role of AI-enabled services on flow and awe experience. *International Journal of Information Management*, *66*, 102519. https://doi.org/10.1016/J.IJINFOMGT.2022.102519

Kim, A. (2022). The paradox in happiness sales: How can happiness primes backfire? *Journal of Business Research*, *146*, 540–552. https://doi.org/10.1016/J.JBUSRES.2022.04.001

Kim, Daehwan, & Ko, Y. J. (2019). The impact of virtual reality (VR) technology on sport spectators’ flow experience and satisfaction. *Computers in Human Behavior*, *93*, 346–356. https://doi.org/10.1016/J.CHB.2018.12.040

Kim, Dongyeon, Park, K., & Ahn, J. H. (2018). Do verified consumer reviews affect sales? An empirical analysis of mixed review systems in the film industry. *26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change, ECIS 2018*.

Kim, G., Jin, B., & Shin, D. C. (2022). Virtual reality as a promotion tool for small independent stores. *Journal of Retailing and Consumer Services*, *64*. https://doi.org/10.1016/J.JRETCONSER.2021.102822

Kim, J., Fiore, A. M., & Lee, H. H. (2007). Influences of online store perception, shopping enjoyment, and shopping involvement on consumer patronage behavior towards an online retailer. *Journal of Retailing and Consumer Services*, *14*(2), 95–107. https://doi.org/10.1016/J.JRETCONSER.2006.05.001

Kim, M. J., & Hall, C. M. (2019). A hedonic motivation model in virtual reality tourism: Comparing visitors and non-visitors. *International Journal of Information Management*, *46*, 236–249. https://doi.org/10.1016/J.IJINFOMGT.2018.11.016

Kim, M. J., Lee, C.-K., & Jung, T. (2020). Exploring Consumer Behavior in Virtual Reality Tourism Using an Extended Stimulus-Organism-Response Model. *Journal of Travel Research*, *59*(1), 69–89. https://doi.org/10.1177/0047287518818915

Kirwan, C. B., Vance, A., Jenkins, J. L., & Anderson, B. B. (2023). Embracing brain and behaviour: Designing programs of complementary neurophysiological and behavioural studies. *Information Systems Journal*, *33*(2), 324–349. https://doi.org/10.1111/ISJ.12402

Klein, L. R. (1998). Evaluating the Potential of Interactive Media through a New Lens: Search versus Experience Goods. *Journal of Business Research*, *41*(3), 195–203. https://doi.org/10.1016/S0148-2963(97)00062-3

Kleinginna, P. R., & Kleinginna, A. M. (1981). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and Emotion*, *5*(4), 345–379. https://doi.org/10.1007/BF00992553

Koh, N. S., Hu, N., & Clemons, E. K. (2010). Do online reviews reflect a product's true perceived quality? An investigation of online movie reviews across cultures. *Electronic Commerce Research and Applications*, *9*(5), 374–385. https://doi.org/10.1016/j.elerap.2010.04.001

Kokkodis, M., & Lappas, T. (2016). The relationship between disclosing purchase information and reputation systems in electronic markets. *2016 International Conference on Information Systems, ICIS 2016*, 1–20.

Konuk, F. A. (2019). The influence of perceived food quality, price fairness, perceived value and satisfaction on customers' revisit and word-of-mouth intentions towards organic food restaurants. *Journal of Retailing and Consumer Services*, *50*, 103–110. https://doi.org/10.1016/j.jretconser.2019.05.005

Konuk, F. A. (2021). The moderating impact of taste award on the interplay between perceived taste, perceived quality and brand trust. *Journal of Retailing and Consumer Services*, *63*. https://doi.org/10.1016/J.JRETCONSER.2021.102698

Koohang, A., Nord, J. H., Ooi, K. B., Tan, G. W. H., Al-Emran, M., Aw, E. C. X., Baabdullah, A. M., Buhalis, D., Cham, T. H., Dennis, C., Dutot, V., Dwivedi, Y. K., Hughes, L., Mogaji, E., Pandey, N., Phau, I., Raman, R., Sharma, A., Sigala, M., … Wong, L. W. (2023). Shaping the Metaverse into Reality: A Holistic Multidisciplinary Understanding of Opportunities, Challenges, and Avenues for Future Investigation. In *Journal of Computer Information Systems* (pp. 1–31). Taylor & Francis. https://doi.org/10.1080/08874417.2023.2165197

Krell, M., Xu, K. M., Rey, G. D., & Paas, F. (2022). Editorial: Recent Approaches for Assessing Cognitive Load From a Validity Perspective. In *Frontiers in Education* (Vol. 6, p. 588). Frontiers Media SA. https://doi.org/10.3389/feduc.2021.838422

Kristofferson, K., Mcferran, B., Morales, A. C., & Dahl, D. W. (2017). The dark side of scarcity promotions: How exposure to limited-quantity promotions can induce aggression. *Journal of Consumer Research*, *43*(5), 683–706. https://doi.org/10.1093/jcr/ucw056

Kronrod, A., & Danziger, S. (2013). "Wii Will Rock You!" The Use and Effect of Figurative Language in Consumer Reviews of Hedonic and Utilitarian Consumption. *Journal of Consumer Research*, *40*(4), 726–739. https://doi.org/10.1086/671998

Kukar-Kinney, M., & Xia, L. (2017). The effectiveness of number of deals purchased in influencing consumers' response to daily deal promotions: A cue utilization approach. *Journal of Business Research*, *79*, 189–197. https://doi.org/10.1016/J.JBUSRES.2017.06.012

Kunst, A. (2020). How do you search for specific information on a product that you want to buy? In *Sources of information about products in the U.S. 2020*. https://www.statista.com/forecasts/997051/sources-of-information-about-products-in-the-us

Küster, I., Vila, N., & Abad-Tortosa, D. (2021). Orientation response in low-fat foods: Differences based on product category and gender. *International Journal of Consumer Studies*, *46*(2), 515–523. https://doi.org/10.1111/ijcs.12697

Lang, A. (2000). The Limited Capacity Model of Mediated Message Processing. *Journal of Communication*, *50*(1), 46–70. https://doi.org/10.1111/J.1460-2466.2000.TB02833.X

Langan, R., Besharat, A., & Varki, S. (2017). The effect of review valence and variance on product evaluations: An examination of intrinsic and extrinsic cues. *International Journal of Research in Marketing*, *34*(2), 414–429. https://doi.org/10.1016/j.ijresmar.2016.10.004

Laros, F. J. M., & Steenkamp, J. B. E. M. (2005). Emotions in consumer behavior: A hierarchical approach. *Journal of Business Research*, *58*(10), 1437–1445. https://doi.org/10.1016/j.jbusres.2003.09.013

Laukkanen, T., Xi, N., Hallikainen, H., Ruusunen, N., & Hamari, J. (2022). Virtual technologies in supporting sustainable consumption: From a single-sensory stimulus to a multi-sensory experience. *International Journal of Information Management*, *63*, 102455. https://doi.org/10.1016/J.IJINFOMGT.2021.102455

Lavrakas, P. (2012). Encyclopedia of Survey Research Methods. In *Encyclopedia of Survey Research Methods*. Sage Publications, Inc. https://doi.org/10.4135/9781412963947

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. H. (Mark), & Sergueeva, K. (2017). Chewing increases consumers' thought-engagement during retail shopping. *Journal of Retailing and Consumer Services*, *35*, 127–132. https://doi.org/10.1016/J.JRETCONSER.2016.12.010

Lee, W. J. (2020). Use of Immersive Virtual Technology in Consumer Retailing and Its Effects to Consumer. *Journal of Distribution Science*, *8*(2), 5–15. https://doi.org/10.15722/JDS.18.2.202002.5

Lelo de Larrea, G., Park, J. Y., Park, K., & Altin, M. (2022). Cues that Work: Designing the Optimal Restaurant Crowdfunding Campaign in the US. *International Journal of Hospitality and Tourism Administration*. https://doi.org/10.1080/15256480.2022.2038335

Li, K., Chen, Y., & Zhang, L. (2020). Exploring the influence of online reviews and motivating factors on sales: A meta-analytic study and the moderating role of product category. *Journal of Retailing and Consumer Services*, *55*, 102107. https://doi.org/10.1016/J.JRETCONSER.2020.102107

Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. *Journal of Business Research*, *140*, 439–458. https://doi.org/10.1016/J.JBUSRES.2021.11.014

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, S. Q., Ozanne, M., & Mattila, A. S. (2018). Does expressing subjectivity in online reviews enhance persuasion? *Journal of Consumer Marketing*, *35*(4), 403–413. https://doi.org/10.1108/JCM-02-2017-2109

Liu, Y., Jin, J., Ji, P., Harding, J. A., & Fung, R. Y. K. (2013). Identifying helpful online reviews: A product designer's perspective. *Computer-Aided Design*, *45*(2), 180–194. https://doi.org/10.1016/J.CAD.2012.07.008

Liu, Z., Lei, S. hui, Guo, Y. lang, & Zhou, Z. ang. (2020). The interaction effect of online review language style and product type on consumers' purchase intentions. *Palgrave Communications*, *6*(1), 1–8. https://doi.org/10.1057/s41599-020-0387-6

Loureiro, S. M. C., Bilro, R. G., & Angelino, F. J. de A. (2020). Virtual reality and gamification in marketing higher education: a review and research agenda. *Spanish Journal of Marketing - ESIC*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/sjme-01-2020-0013

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*(October 2018), 514–530. https://doi.org/10.1016/j.jbusres.2018.10.055

Loureiro, S. M. C., Guerreiro, J., & Japutra, A. (2021). How escapism leads to behavioral intention in a virtual reality store with background music? *Journal of Business Research*, *134*, 288–300. https://doi.org/10.1016/J.JBUSRES.2021.05.035

Lu, S., Qiu, L., & Wang, K. (2021). The effects of the format of two-sided online reviews: A linguistic perspective. *Information & Management*, *58*(8), 103554. https://doi.org/10.1016/J.IM.2021.103554

Luangrath, A. W. A. W., Peck, J., Hedgcock, W., & Xu, Y. (2022). Observing Product Touch: The Vicarious Haptic Effect in Digital Marketing and Virtual Reality. *Journal of Marketing Research*, *59*(2), 306–326. https://doi.org/10.1177/00222437211059540

Luangrath, A. W., Peck, J., & Barger, V. A. (2017). Textual paralanguage and its implications for marketing communications. *Journal of Consumer Psychology*, *27*(1), 98–107. https://doi.org/10.1016/j.jcps.2016.05.002

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science*, *62*(12), 3412–3427. https://doi.org/10.1287/mnsc.2015.2304

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates. *Journal of Marketing*, *77*(1), 87–103. https://doi.org/10.1509/jm.11.0560

Luna-Nevarez, C., & McGovern, E. (2021). The Rise of the Virtual Reality (VR) Marketplace: Exploring the Antecedents and Consequences of Consumer Attitudes toward V-Commerce. *Journal of Internet Commerce*, *0*(0), 1–28. https://doi.org/10.1080/15332861.2021.1875766

Malhotra, N. K. (1984). Reflections on the Information Overload Paradigm in Consumer Decision Making. *Source: Journal of Consumer Research*, *10*(4), 436–440. https://about.jstor.org/terms

Malhotra, N. K., Jain, A. K., & Lagakos, S. W. (1982). The Information Overload Controversy: An Alternative Viewpoint. *Journal of Marketing*, *46*(2), 27. https://doi.org/10.2307/3203338

Malik, M., Camm, A. J., Bigger, J. T., Breithardt, G., Cerutti, S., Cohen, R. J., Coumel, P., Fallen, E. L., Kennedy, H. L., Kleiger, R. E., Lombardi, F., Malliani, A., Moss, A. J., Rottman, J. N., Schmidt, G., Schwartz, P. J., & Singer, D. H. (1996). Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. In *European Heart Journal* (Vol. 17, Issue 3, pp. 354–381). https://doi.org/10.1093/oxfordjournals.eurheartj.a014868

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

Marchand, A., Hennig-Thurau, T., & Wiertz, C. (2017). Not all digital word of mouth is created equal: Understanding the respective impact of consumer reviews and microblogs on new product success. *International Journal of Research in Marketing*, *34*(2), 336–354. https://doi.org/10.1016/j.ijresmar.2016.09.003

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing*, *39*(4), 755–776. https://doi.org/10.1002/MAR.21619

Martinez-Levy, A. C., Rossi, D., Cartocci, G., Mancini, M., Di Flumeri, G., Trettel, A., Babiloni, F., & Cherubino, P. (2022). Message framing, non-conscious perception and effectiveness in non-profit advertising. Contribution by neuromarketing research. *International Review on Public and Nonprofit Marketing*, *19*(1), 53–75. https://doi.org/10.1007/s12208-021-00289-0

Martínez-Navarro, J., Bigné, E., Guixeres, J., Alcañiz, M., & Torrecilla, C. (2019). The influence of virtual reality in e-commerce. *Journal of Business Research*, *100*(October 2018), 475–482. https://doi.org/10.1016/j.jbusres.2018.10.054

Mas, L., Bolls, P., Rodero, E., Barreda-Ángeles, M., & Churchill, A. (2020). The impact of the sonic logo's acoustic features on orienting responses, emotions and brand personality transmission. *Journal of Product and Brand Management*, *30*(5), 740–753. https://doi.org/10.1108/JPBM-05-2019-2370

Massaro, S., & Pecchia, L. (2019). Heart Rate Variability (HRV) Analysis: A Methodology for Organizational Neuroscience. *Organizational Research Methods*, *22*(1), 354–393. https://doi.org/10.1177/1094428116681072

Maxian, W., Bradley, S. D., Wise, W., & Toulouse, E. N. (2013). Brand Love is in the Heart: Physiological Responding to Advertised Brands. *Psychology and Marketing*, *30*(6), 469–478. https://doi.org/10.1002/mar.20620

Mazzocchi, M. (2011). Statistics for Marketing and Consumer Research. In *Statistics for Marketing and Consumer Research*. SAGE Publications, Ltd. https://doi.org/10.4135/9780857024657

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

Mehta, R., Zhu, R., & Cheema, A. (2012). Is noise always bad? exploring the effects of ambient noise on creative cognition. *Journal of Consumer Research*, *39*(4), 784–799. https://doi.org/10.1086/665048

Mirhoseini, M., Pagé, S. A., Léger, P. M., & Sénécal, S. (2021). What deters online grocery shopping? Investigating the effect of arithmetic complexity and product type on user satisfaction. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(4), 1–18. https://doi.org/10.3390/JTAER16040047

Miyazaki, A. D., Grewal, D., & Goodstein, R. C. (2005). The effect of multiple extrinsic cues on quality perceptions: A matter of consistency. *Journal of Consumer Research*, *32*(1), 146–153. https://doi.org/10.1086/429606

Moore, S. G. (2015). Attitude predictability and helpfulness in online reviews: The role of explained actions and reactions. *Journal of Consumer Research*, *42*(1), 30–44. https://doi.org/10.1093/jcr/ucv003

Moore, S. G., & Lafreniere, K. C. (2020). How online word-of-mouth impacts receivers. *Consumer Psychology Review*, *3*(1), 34–59. https://doi.org/10.1002/arcp.1055

Moore, S. G., & McFerran, B. (2017). She said, she said: Differential interpersonal similarities predict unique linguistic mimicry in online word of mouth. *Journal of the Association for Consumer Research*, *2*(2), 229–245. https://doi.org/10.1086/690942

Morales-Solana, D., Esteban-Millat, I., & Alegret Cotas, A. (2021). Experiences in consumer flow in online supermarkets. *Electronic Commerce Research*, 1–32. https://doi.org/10.1007/s10660-021-09460-5

Morales, A. C., Amir, O., & Lee, L. (2017). Keeping It Real in Experimental Research—Understanding When, Where, and How to Enhance Realism and Measure Consumer Behavior. *Journal of Consumer Research*, *44*(2), 465–476. https://doi.org/10.1093/jcr/ucx048

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on amazon.com. In *MIS Quarterly: Management Information Systems*. https://doi.org/10.2307/20721420

Mukherjee, D., Marc, W., Kumar, S., & Donthu, N. (2022). Guidelines for advancing theory and practice through bibliometric research. *Journal of Business Research*, *148*(May), 101–115. https://doi.org/10.1016/j.jbusres.2022.04.042

Murtazina, M., & Avdeenko, T. (2020). Measuring cognitive load based on EEG data in the intelligent learning systems. *CEUR Workshop Proceedings*, *2861*, 342–350.

Mutlu-Bayraktar, D., Cosgun, V., & Altan, T. (2019). Cognitive load in multimedia learning environments: A systematic review. *Computers & Education*, *141*, 103618. https://doi.org/10.1016/J.COMPEDU.2019.103618

Nakamura, J., & Csikszentmihalyi, M. (2009). Flow Theory and Research. In S. J. Lopez & C. R. Snyder (Eds.), *The Oxford Handbook of Positive Psychology* (pp. 194–206). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195187243.013.0018

Nelson, B. W., Low, C. A., Jacobson, N., Areán, P., Torous, J., & Allen, N. B. (2020). Guidelines for wrist-worn consumer wearable assessment of heart rate in biobehavioral research. In *npj Digital Medicine* (Vol. 3, Issue 1, pp. 1–9). Nature Publishing Group. https://doi.org/10.1038/s41746-020-0297-4

Nelson, P. (1970). Information and Consumer Behavior. *Journal of Political Economy*, *78*(2), 311–329. https://doi.org/10.1086/259630

Nie, Y. Y., Liang, A. R. Da, & Wang, E. C. (2022). Third-party certification labels for organic food: consumers' purchase choice and willingness-to-pay. *British Food Journal*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/BFJ-07-2021-0777/FULL/PDF

Nigam, A., Dewani, P., Behl, A., & Pereira, V. (2022). Consumer's response to conditional promotions in retailing: An empirical inquiry. *Journal of Business Research*, *144*, 751–763. https://doi.org/10.1016/J.JBUSRES.2022.02.051

Noseworthy, T. J., Muro, F. Di, & Murray, K. B. (2014). The Role of Arousal in Congruity-Based Product Evaluation. *Journal of Consumer Research*, *41*(4), 1108–1126. https://doi.org/10.1086/678301

Novak, T. P., Hoffman, D. L., & Yung, Y. F. (2000). Measuring the Customer Experience in Online Environments: A Structural Modeling Approach. *Https://Doi.Org/10.1287/Mksc.19.1.22.15184*, *19*(1), 22–42. https://doi.org/10.1287/MKSC.19.1.22.15184

Nussbaum, E. M. (2014). Categorical and Nonparametric Data Analysis. In *Categorical and Nonparametric Data Analysis: Choosing the Best Statistical Technique*. Routledge. https://doi.org/10.4324/9780203122860

Oliver, R. L. (2014). Satisfaction: A behavioral perspective on the consumer, Second edition. *Satisfaction: A Behavioral Perspective on the Consumer, Second Edition*, 1–519. https://doi.org/10.4324/9781315700892/SATISFACTION-BEHAVIORAL-PERSPECTIVE-CONSUMER-RICHARD-OLIVER

Olson, J., & Jacoby, J. (1972). Cue utilization in the quality perception process. *Proceedings of the Third Annual Conference of the of the Association for Consumer Research*, *SV-02*(1972), 167–179. https://www.acrwebsite.org/volumes/11997/volumes/sv02/SV-02/full

Orazi, D. C., & Nyilasy, G. (2019). Straight to the Heart Of Your Target Audience. *Journal of Advertising Research*, *59*(2), 137–141. https://doi.org/10.2501/JAR-2019-020

Ordenes, F. V., Ludwig, S., De Ruyter, K., Grewal, D., & Wetzels, M. (2017). Unveiling what is written in the stars: Analyzing explicit, implicit, and discourse patterns of sentiment in social media. *Journal of Consumer Research*, *43*(6), 875–894. https://doi.org/10.1093/jcr/ucw070

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*(1), 190–206. https://doi.org/10.1016/j.actpsy.2013.06.003

Owens, A. P., Low, D. A., Iodice, V., Mathias, C. J., & Critchley, H. D. (2017). Emotion and the Autonomic Nervous System—A Two-Way Street: Insights From Affective, Autonomic and Dissociative Disorders. In *Reference Module in Neuroscience and Biobehavioral Psychology*. Elsevier. https://doi.org/10.1016/B978-0-12-809324-5.01799-5

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*(December 2019), 102202. https://doi.org/10.1016/j.jretconser.2020.102202

Packard, G., & Berger, J. (2017). How Language Shapes Word of Mouth's Impact. *Journal of Marketing Research*, *54*(4), 572–588. https://doi.org/10.1509/jmr.15.0248

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, 105906. https://doi.org/10.1016/j.ijsu.2021.105906

Pan, J., & Tompkins, W. J. (1985). A Real-Time QRS Detection Algorithm. *IEEE Transactions on Biomedical Engineering*, *BME-32*(3), 230–236. https://doi.org/10.1109/TBME.1985.325532

Park, C. W., Iyer, E. S., & Smith, D. C. (1989). The Effects of Situational Factors on In-Store Grocery Shopping Behavior: The Role of Store Environment and Time Available for Shopping. *Journal of Consumer Research*, *15*(4), 422–433. https://doi.org/10.1086/209182

Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research*, *50*, 67–83. https://doi.org/10.1016/j.annals.2014.10.007

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., Kaur, D. J., Arora, D. S., & Singh, M. S. V. (2022). Deciphering 'Urge to Buy': A Meta-Analysis of Antecedents. *International Journal of Market Research*, *64*(6), 773–798. https://doi.org/10.1177/14707853221106317/ASSET/IMAGES/LARGE/10.1177_14707853221106317-FIG1.JPEG

Peltola, M. (2012). Role of editing of R-R intervals in the analysis of heart rate variability. *Frontiers in Physiology*, *0*, 148. https://doi.org/10.3389/FPHYS.2012.00148

Pettigrew, S. (2011). Hearts and minds: Children's experiences of Disney world. *Consumption Markets and Culture*, *14*(2), 145–161. https://doi.org/10.1080/10253866.2011.562016

Pham, T., Lau, Z. J., Chen, S. H. A., & Makowski, D. (2021). Heart rate variability in psychology: A review of hrv indices and an analysis tutorial. In *Sensors* (Vol. 21, Issue 12, p. 3998). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/s21123998

Pieters, R., & Warlop, L. (1999). Visual attention during brand choice: The impact of time pressure and task motivation. *International Journal of Research in Marketing*, *16*(1), 1–16. https://doi.org/10.1016/s0167-8116(98)00022-6

Pine, B. J., & Gilmore, J. H. (2011). *The experience economy*. Harvard Business Press.

Piron, F. (1993). A Comparison of Emotional Reactions Experienced By Planned, Unplanned and Impulse Purchasers. *ACR North American Advances*, *NA-20*. https://www.acrwebsite.org/volumes/7468/volumes/v20/NA-20/full

Pizzi, G., Scarpi, D., Pichierri, M., & Vannucci, V. (2019). Virtual reality, real reactions?: Comparing consumers' perceptions and shopping orientation across physical and virtual-reality retail stores. *Computers in Human Behavior*, *96*, 1–12. https://doi.org/10.1016/j.chb.2019.02.008

Pizzi, G., Vannucci, V., & Aiello, G. (2020). Branding in the time of virtual reality: Are virtual store brand perceptions real? *Journal of Business Research*, *119*(December 2019), 502–510. https://doi.org/10.1016/j.jbusres.2019.11.063

Plass, J. L., & Kalyuga, S. (2019). Four Ways of Considering Emotion in Cognitive Load Theory. In *Educational Psychology Review* (Vol. 31, Issue 2, pp. 339–359). Springer New York LLC. https://doi.org/10.1007/s10648-019-09473-5

Poels, K., & Dewitte, S. (2006). How to Capture the Heart? Reviewing 20 Years of Emotion Measurement in Advertising. *Journal of Advertising Research*, *46*(1), 18–37. https://doi.org/10.2501/S0021849906060041

Prithul, A., Adhanom, I. B., & Folmer, E. (2021). Teleportation in Virtual Reality; A Mini-Review. *Frontiers in*

Virtual Reality, *2*(October), 1–7. https://doi.org/10.3389/frvir.2021.730792

Purnawirawan, N., De Pelsmacker, P., & Dens, N. (2012). Balance and Sequence in Online Reviews: How Perceived Usefulness Affects Attitudes and Intentions. *Journal of Interactive Marketing*. https://doi.org/10.1016/j.intmar.2012.04.002

Purnawirawan, N., Eisend, M., De Pelsmacker, P., & Dens, N. (2015). A Meta-analytic Investigation of the Role of Valence in Online Reviews. *Journal of Interactive Marketing*, *31*, 17–27. https://doi.org/10.1016/j.intmar.2015.05.001

Rauschnabel, P. A., Felix, R., Hinsch, C., Shahab, H., & Alt, F. (2022). What is XR? Towards a Framework for Augmented and Virtual Reality. *Computers in Human Behavior*, *133*, 107289. https://doi.org/10.1016/J.CHB.2022.107289

Redine, A., Deshpande, S., Jebarajakirthy, C., & Surachartkumtonkun, J. (2023). Impulse buying: A systematic literature review and future research directions. In *International Journal of Consumer Studies* (Vol. 47, Issue 1, pp. 3–41). John Wiley & Sons, Ltd. https://doi.org/10.1111/ijcs.12862

Richardson, P. S., Dick, A. S., & Jain, A. K. (1994). Extrinsic and Intrinsic Cue Effects on Perceptions of Store Brand Quality. *Journal of Marketing*, *58*(4), 28. https://doi.org/10.2307/1251914

Rodero, E., & Potter, R. F. (2021). Do not sound like an announcer. The emphasis strategy in commercials. *Psychology and Marketing*, *38*(9), 1417–1425. https://doi.org/10.1002/mar.21525

Rook, D. W., & Fisher, R. J. (1995). Normative Influences on Impulsive Buying Behavior. *Journal of Consumer Research*, *22*(3), 305–313. https://doi.org/10.1086/209452

Rook, D. W., & Hoch, S. J. (1985). Consuming Impulses. *ACR North American Advances*, *NA-12*. https://www.acrwebsite.org/volumes/6351/volumes/v12/NA-12/full

Rosario, A. B., Sotgiu, F., De Valck, K., & Bijmolt, T. H. A. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297–318. https://doi.org/10.1509/jmr.14.0380

Roschk, H., Loureiro, S. M. C., & Breitsohl, J. (2017). Calibrating 30 Years of Experimental Research: A Meta-Analysis of the Atmospheric Effects of Music, Scent, and Color. *Journal of Retailing*, *93*(2), 228–240. https://doi.org/10.1016/j.jretai.2016.10.001

Rossi, P. E., & Allenby, G. M. (2003). Bayesian Statistics and Marketing. *Https://Doi.Org/10.1287/Mksc.22.3.304.17739*, *22*(3). https://doi.org/10.1287/MKSC.22.3.304.17739

Roy, S., & Attri, R. (2022). Physimorphic vs. Typographic logos in destination marketing: Integrating destination familiarity and consumer characteristics. *Tourism Management*, *92*, 104544. https://doi.org/10.1016/J.TOURMAN.2022.104544

Royo-Vela, M., & Varga, Á. (2022). Unveiling Neuromarketing and Its Research Methodology. *Encyclopedia*, *2*(2), 729–751. https://doi.org/10.3390/encyclopedia2020051

Ruiz-Mafe, C., Bigné-Alcañiz, E., & Currás-Pérez, R. (2020). The effect of emotions, eWOM quality and online review sequence on consumer intention to follow advice obtained from digital services. *Journal of Service Management*. https://doi.org/10.1108/JOSM-11-2018-0349

Saffari, F., Kakaria, S., Bigné, E., Bruni, L. E., Zarei, S., & Ramsøy, T. Z. (2023). Motivation in the metaverse: A dual-process approach to consumer choices in a virtual reality supermarket. *Frontiers in Neuroscience*, *17*, 170. https://doi.org/10.3389/fnins.2023.1062980

Santini, F. D. O., Ladeira, W. J., Vieira, V. A., Araujo, C. F., & Sampaio, C. H. (2019). Antecedents and consequences of impulse buying: a meta-analytic study. *RAUSP Management Journal*, *54*(2), 178–204. https://doi.org/10.1108/RAUSP-07-2018-0037/FULL/PDF

Scarfe, P., & Glennerster, A. (2019). The Science behind Virtual Reality Displays. *Annual Review of Vision Science*, *5*, 529–547. https://doi.org/10.1146/annurev-vision-091718-014942

Schapkin, S. A., Raggatz, J., Hillmert, M., & Böckelmann, I. (2020). EEG correlates of cognitive load in a multiple choice reaction task. *Acta Neurobiologiae Experimentalis*, *80*(1), 76–89. https://doi.org/10.21307/ANE-2020-008

Schmutz, P., Heinz, S., Métrailler, Y., & Opwis, K. (2009). Cognitive Load in eCommerce Applications—Measurement and Effects on User Satisfaction. *Advances in Human-Computer Interaction*, *2009*, 1–9. https://doi.org/10.1155/2009/121494

Schnack, A., Wright, M. J., & Elms, J. (2021). Investigating the impact of shopper personality on behaviour in immersive Virtual Reality store environments. *Journal of Retailing and Consumer Services*, *61*, 102581. https://doi.org/10.1016/j.jretconser.2021.102581

Schnack, A., Wright, M. J., & Holdershaw, J. L. (2019). Immersive virtual reality technology in a three-dimensional virtual simulated store: Investigating telepresence and usability. *Food Research International*, *117*, 40–49. https://doi.org/10.1016/J.FOODRES.2018.01.028

Schnack, A., Wright, M. J., & Holdershaw, J. L. (2020). An exploratory investigation of shopper behaviour in an immersive virtual reality store. *Journal of Consumer Behaviour*, *19*(2), 182–195. https://doi.org/10.1002/cb.1803

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. *Frontiers in Public Health*, *5*, 258. https://doi.org/10.3389/fpubh.2017.00258

Shen, B., Tan, W., Guo, J., Zhao, L., & Qin, P. (2021). How to Promote User Purchase in Metaverse? A Systematic Literature Review on Consumer Behavior Research and Virtual Commerce Application Design. *Applied Sciences*, *11*(23), 11087. https://doi.org/10.3390/app112311087

Silvani, A., Calandra-Buonaura, G., Dampney, R. A. L., & Cortelli, P. (2016). Brainheart interactions: physiology and clinical implications. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2067). https://doi.org/10.1098/RSTA.2015.0181

Simmonds, L., Bogomolova, S., Kennedy, R., Nenycz-Thiel, M., & Bellman, S. (2020). A dual-process model of how incorporating audio-visual sensory cues in video advertising promotes active attention. *Psychology and Marketing*, *37*(8), 1057–1067. https://doi.org/10.1002/mar.21357

Singh, B., Bharti, N., & Engineering, C. (2015). Software Tools for Heart Rate Variability Analysis. *International Journal of Recent Scientific Research*, *6*.

Skarbez, R., Brooks, F. P., & Whitton, M. C. (2017). A survey of presence and related concepts. *ACM Computing Surveys*, *50*(6). https://doi.org/10.1145/3134301

So, T. Y., Li, M. Y. E., & Lau, H. (2021). Between-subject correlation of heart rate variability predicts movie preferences. *PLoS ONE*, *16*(2 February). https://doi.org/10.1371/journal.pone.0247625

Sohn, Y. S., & Ko, M. T. (2021). The impact of planned vs. unplanned purchases on subsequent purchase decision making in sequential buying situations. *Journal of Retailing and Consumer Services*, *59*, 102419. https://doi.org/10.1016/j.jretconser.2020.102419

Solhjoo, S., Haigney, M. C., McBee, E., van Merrienboer, J. J. G., Schuwirth, L., Artino, A. R., Battista, A., Ratcliffe, T. A., Lee, H. D., & Durning, S. J. (2019). Heart Rate and Heart Rate Variability Correlate with Clinical Reasoning Performance and Self-Reported Measures of Cognitive Load. *Scientific Reports*, *9*(1), 1–9. https://doi.org/10.1038/s41598-019-50280-3

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323. https://doi.org/10.1016/J.TOURMAN.2010.12.011

Spivack, S. (2019, June 28). *Report: The Impact of Reviews On Consumer Purchase Decisions | Bizrate Insights*. How Many Reviews Are Shoppers Reading? https://bizrateinsights.com/resources/shopper-survey-report-the-impact-reviews-have-on-consumers-purchase-decisions/

Srivastava, V., & Kalro, A. D. (2019). Enhancing the Helpfulness of Online Consumer Reviews: The Role of Latent (Content) Factors. *Journal of Interactive Marketing*, *48*, 33–50.

https://doi.org/10.1016/j.intmar.2018.12.003

Stewart, K. J. (2003). Trust transfer on the World Wide Web. *Organization Science*, *14*(1), 5–17. https://doi.org/10.1287/ORSC.14.1.5.12810

Stilley, K. M., Inman, J. J., & Wakefield, K. L. (2010). Planning to make unplanned purchases? The role of in-store slack in budget deviation. *Journal of Consumer Research*, *37*(2), 264–278. https://doi.org/10.1086/651567

Stokols, D. (1972). On the distinction between density and crowding: Some implications for future research. *Psychological Review*, *79*(3), 275–277. https://doi.org/10.1037/H0032706

Streicher, M. C., Estes, Z., & Büttner, O. B. (2021). Exploratory Shopping: Attention Affects In-Store Exploration and Unplanned Purchasing. *Journal of Consumer Research*, *48*(1), 51–76. https://doi.org/10.1093/jcr/ucaa054

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

Suher, J., Huang, S. chi, & Lee, L. (2019). Planning for Multiple Shopping Goals in the Marketplace. *Journal of Consumer Psychology*, *29*(4), 642–651. https://doi.org/10.1002/JCPY.1130

Sun, J., Nazlan, N. H., Leung, X. Y., & Bai, B. (2020). "A cute surprise": Examining the influence of meeting giveaways on word-of-mouth intention. *Journal of Hospitality and Tourism Management*, *45*, 456–463. https://doi.org/10.1016/J.JHTM.2020.10.003

Sunagawa, K., Kawada, T., & Nakahara, T. (1998). Dynamic nonlinear vago-sympathetic interaction in regulating heart rate. *Heart and Vessels 1998 13:4*, *13*(4), 157–174. https://doi.org/10.1007/BF01745040

Sung, B., Phau, I., & Duong, V. C. C. (2021). Opening the 'black box' of luxury consumers: An application of psychophysiological method. *Journal of Marketing Communications*, *27*(3), 250–268. https://doi.org/10.1080/13527266.2019.1657484

Sung, Billy, Hartley, N., Vanman, E., & Phau, I. (2016). How can the word "NEW" evoke consumers' experiences of novelty and interest? *Journal of Retailing and Consumer Services*, *31*, 166–173. https://doi.org/10.1016/j.jretconser.2016.02.010

Sweller, J. (2011). Cognitive Load Theory. *Psychology of Learning and Motivation - Advances in Research and Theory*, *55*, 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Szybillo, G. J., & Jacoby, J. (1974). Intrinsic versus extrinsic cues as determinants of perceived product quality. *Journal of Applied Psychology*, *59*(1), 74–78. https://doi.org/10.1037/h0035796

Tata, S. V., Prashar, S., & Gupta, S. (2020). An examination of the role of review valence and review source in varying consumption contexts on purchase decision. *Journal of Retailing and Consumer Services*, *52*(January 2019), 101734. https://doi.org/10.1016/j.jretconser.2019.01.003

Thaler, R. H. (2018). From cashews to nudges: The evolution of behavioral economics. *American Economic Review*, *108*(6), 1265–1287.

Thomas, B. L., Claassen, N., Becker, P., & Viljoen, M. (2019). Validity of Commonly Used Heart Rate Variability Markers of Autonomic Nervous System Function. *Neuropsychobiology*, *78*(1), 14–26. https://doi.org/10.1159/000495519

Thompson, D. V., Hamilton, R. W., & Rust, R. T. (2005). Feature fatigue: When product capabilities become too much of a good thing. *Journal of Marketing Research*, *42*(4), 431–442. https://doi.org/10.1509/JMKR.2005.42.4.431/ASSET/IMAGES/LARGE/10.1509_JMKR.2005.42.4.431-FIG2.JPEG

Tozman, T., Magdas, E. S., MacDougall, H. G., & Vollmeyer, R. (2015). Understanding the psychophysiology of flow: A driving simulator experiment to investigate the relationship between flow and heart rate variability. *Computers in Human Behavior*, *52*, 408–418. https://doi.org/10.1016/j.chb.2015.06.023

Tremmel, C., Herff, C., Sato, T., Rechowicz, K., Yamani, Y., & Krusienski, D. J. (2019). Estimating Cognitive Workload in an Interactive Virtual Reality Environment Using EEG. *Frontiers in Human Neuroscience*, *13*, 401. https://doi.org/10.3389/fnhum.2019.00401

Tsao, W.-C., & Tsao, W.-C. (2014). Which type of online review is more persuasive? The influence of consumer reviews and critic ratings on moviegoers. *Electron Commer Res*, *14*(9), 559–583. https://doi.org/10.1007/s10660-014-9160-5

Valenza, G., Sclocco, R., Duggento, A., Passamonti, L., Napadow, V., Barbieri, R., & Toschi, N. (2019). The central autonomic network at rest: Uncovering functional MRI correlates of time-varying autonomic outflow. *NeuroImage*, *197*, 383–390. https://doi.org/10.1016/J.NEUROIMAGE.2019.04.075

Valenza, Gaetano, Citi, L., Lanatá, A., Scilingo, E. P., & Barbieri, R. (2014). Revealing real-time emotional responses: A personalized assessment based on heartbeat dynamics. *Scientific Reports*, *4*(1), 1–13. https://doi.org/10.1038/srep04998

Valenza, Gaetano, Citi, L., Saul, J. P., & Barbieri, R. (2018). Measures of sympathetic and parasympathetic autonomic outflow from heartbeat dynamics. *Journal of Applied Physiology*, *125*(1), 19–39. https://doi.org/10.1152/JAPPLPHYSIOL.00842.2017/ASSET/IMAGES/LARGE/ZDG004182587A006.JPEG

van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/S11192-009-0146-3/FIGURES/7

van Herpen, E., van den Broek, E., van Trijp, H. C. M., & Yu, T. (2016). Can a virtual supermarket bring realism into the lab? Comparing shopping behavior using virtual and pictorial store representations to behavior in a physical store. *Appetite*, *107*, 196–207. https://doi.org/10.1016/j.appet.2016.07.033

van Waterschoot, W., & Van den Bulte, C. (1992). The 4P Classification of the Marketing Mix Revisited. *Journal of Marketing*, *56*(4), 83–93. https://doi.org/10.1177/002224299205600407

Varga, M., & Albuquerque, P. (2019). Measuring the Impact of a Single Negative Customer Review on Online Search and Purchase Decisions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3483429

Veloutsou, C., & Ruiz Mafe, C. (2020). Brands as relationship builders in the virtual world: A bibliometric analysis. *Electronic Commerce Research and Applications*, *39*(November 2019), 100901. https://doi.org/10.1016/j.elerap.2019.100901

Venkatraman, V., Dimoka, A., Pavlou, P. A. P. A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H. E. 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. https://doi.org/10.1509/jmr.13.0593

Verhulst, N., De Keyser, A., Gustafsson, A., Shams, P., & Van Vaerenbergh, Y. (2019). Neuroscience in service research: an overview and discussion of its possibilities. *Journal of Service Management*. https://doi.org/10.1108/JOSM-05-2019-0135

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127. https://doi.org/10.1016/j.tourman.2008.04.008

Verplanken, B., & Sato, A. (2011). The Psychology of Impulse Buying: An Integrative Self-Regulation Approach. *Journal of Consumer Policy*, *34*(2), 197–210. https://doi.org/10.1007/s10603-011-9158-5

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

Viglia, G., & Dolnicar, S. (2020). A review of experiments in tourism and hospitality. *Annals of Tourism Research*, *80*, 102858. https://doi.org/10.1016/j.annals.2020.102858

Viglia, G., Zaefarian, G., & Ulqinaku, A. (2021). How to design good experiments in marketing: Types, examples, and methods. *Industrial Marketing Management*, *98*, 193–206. https://doi.org/10.1016/j.indmarman.2021.08.007

Vrechopoulos, A., Apostolou, K., & Koutsiouris, V. (2010). Virtual reality retailing on the web: emerging consumer behavioural patterns. *Http://Dx.Doi.Org/10.1080/09593960903445194*, *19*(5), 469–482. https://doi.org/10.1080/09593960903445194

Wajid, A., Raziq, M. M., Ahmed, Q. M., & Ahmad, M. (2021). Observing viewers' self-reported and neurophysiological responses to message appeal in social media advertisements. *Journal of Retailing and Consumer Services*, *59*, 102373. https://doi.org/10.1016/j.jretconser.2020.102373

Wakefield, K. L., & Baker, J. (1998). Excitement at the mall: Determinants and effects on shopping response. *Journal of Retailing*, *74*(4), 515–539. https://doi.org/10.1016/S0022-4359(99)80106-7

Walla, P., Brenner, G., & Koller, M. (2011). Objective measures of emotion related to brand attitude: A new way to quantify emotion-related aspects relevant to marketing. *PLoS ONE*, *6*(11). https://doi.org/10.1371/journal.pone.0026782

Wang, L. C., & Hsiao, D. F. (2012). Antecedents of flow in retail store shopping. *Journal of Retailing and Consumer Services*, *19*(4), 381–389. https://doi.org/10.1016/J.JRETCONSER.2012.03.002

Wang, Q. J., Barbosa Escobar, F., Alves Da Mota, P., & Velasco, C. (2021). Getting started with virtual reality for sensory and consumer science: Current practices and future perspectives. *Food Research International*, *145*(May), 110410. https://doi.org/10.1016/j.foodres.2021.110410

Wedel, M., Bigné, E., & Zhang, J. (2020). Virtual and augmented reality: Advancing research in consumer marketing. *International Journal of Research in Marketing*, *37*(3), 443–465. https://doi.org/10.1016/j.ijresmar.2020.04.004

Witmer, B. G., & Singer, M. J. (1998). Measuring Presence in Virtual Environments: A Presence Questionnaire. *Presence: Teleoperators and Virtual Environments*, *7*(3), 225–240. https://doi.org/10.1162/105474698565686

Wu, Y., Ngai, E. W. T., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis, and directions for future research. *Decision Support Systems*, *132*. https://doi.org/10.1016/j.dss.2020.113280

Xi, N., Chen, J., Gama, F., Riar, M., & Hamari, J. (2022). The challenges of entering the metaverse: An experiment on the effect of extended reality on workload. *Information Systems Frontiers 2022*, *1*, 1–22. https://doi.org/10.1007/S10796-022-10244-X

Xi, N., & Hamari, J. (2021). Shopping in virtual reality: A literature review and future agenda. *Journal of Business Research*, *134*, 37–58. https://doi.org/10.1016/j.jbusres.2021.04.075

Xia, L., & Bechwati, N. N. (2008). Word of Mouse: The Role of Cognitive Personalization in Online Consumer Reviews. *Journal of Interactive Advertising*. https://doi.org/10.1080/15252019.2008.10722143

Xiong, J., & Zuo, M. (2020). What does existing NeuroIS research focus on? In *Information Systems* (Vol. 89, p. 101462). Pergamon. https://doi.org/10.1016/j.is.2019.101462

Xu, C., Demir-Kaymaz, Y., Hartmann, C., Menozzi, M., & Siegrist, M. (2021). The comparability of consumers' behavior in virtual reality and real life: A validation study of virtual reality based on a ranking task. *Food Quality and Preference*, *87*, 104071. https://doi.org/10.1016/J.FOODQUAL.2020.104071

Xu, Q. (2013). Social recommendation, source credibility, and recency: Effects of news cues in a social bookmarking website. *Journalism and Mass Communication Quarterly*, *90*(4), 757–775. https://doi.org/10.1177/1077699013503158

Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management*, *58*. https://doi.org/10.1016/J.IJINFOMGT.2021.102315

Yang, K., Kim, H. J. M., & Tanoff, L. (2020). Signaling trust: Cues from Instagram posts. *Electronic Commerce Research and Applications*, *43*. https://doi.org/10.1016/J.ELERAP.2020.100998

Yoo, K., Welden, R., Hewett, K., & Haenlein, M. (2023). The merchants of meta: A research agenda to understand the future of retailing in the metaverse. *Journal of Retailing*. https://doi.org/10.1016/J.JRETAI.2023.02.002

Yuan, C., Wang, S., Yu, X., Kim, K. H., & Moon, H. (2021). The influence of flow experience in the augmented reality context on psychological ownership. *International Journal of Advertising*, *40*(6), 922–944. https://doi.org/10.1080/02650487.2020.1869387

Yung, R., Khoo-Lattimore, C., & Potter, L. E. (2021). VR the world: Experimenting with emotion and presence for tourism marketing. *Journal of Hospitality and Tourism Management*, *46*(July 2020), 160–171. https://doi.org/10.1016/j.jhtm.2020.11.009

Zablocki, A., Schlegelmilch, B., & Houston, M. J. (2019). How valence, volume and variance of online reviews influence brand attitudes. *AMS Review*, *9*(1–2), 61–77. https://doi.org/10.1007/s13162-018-0123-1

Zhang, H., Zhao, L., & Gupta, S. (2018). The role of online product recommendations on customer decision making and loyalty in social shopping communities. *International Journal of Information Management*, *38*(1), 150–166. https://doi.org/10.1016/J.IJINFOMGT.2017.07.006

Zhang, Z., Wang, X., & Wu, R. (2021). Is the devil in the details? Construal-level effects on perceived usefulness of online reviews for experience services. *Electronic Commerce Research and Applications*, *46*, 101033. https://doi.org/10.1016/j.elerap.2021.101033

Zhao, H., Huang, F., Spence, C., & Wan, X. (2017). Visual search for wines with a triangle on the label in a virtual store. *Frontiers in Psychology*, *8*(DEC). https://doi.org/10.3389/FPSYG.2017.02173

Zheng, L. (2021). The classification of online consumer reviews: A systematic literature review and integrative framework. *Journal of Business Research*, *135*, 226–251. https://doi.org/10.1016/J.JBUSRES.2021.06.038

Zohar, A. H., Cloninger, C. R., & McCraty, R. (2013). Personality and Heart Rate Variability: Exploring Pathways from Personality to Cardiac Coherence and Health. *Open Journal of Social Sciences*, *01*(06), 32–39. https://doi.org/10.4236/jss.2013.16007