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Using neurophysiological tools to investigate marketing communication elements in digital and extended reality contexts

DOCTORAL DISSERTATION

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Content

Preface

This research thesis has been submitted as a compendium of three published articles in internationally indexed journals, as follows:

1. *How visual attention to social media cues impacts visit intention and liking expectation for restaurants*, published in the International Journal of Contemporary Hospitality Management (2022). Journal metrics in the Journal Citation Reports (2021): IF: 9.32; Q1 in Hospitality, Leisure, Sport & Tourism, and Q1 in Management.
2. *EEG theta and N400 responses to congruent versus incongruent brand logos*, published in Scientific Reports (2022). Journal metrics in the Journal Citation Reports (2021): IF: 5.00; Q2 in Multidisciplinary Sciences. (Shared authorship.)
3. *Does banner advertising still capture attention? An eye tracking study*, accepted for publication in the Spanish Journal of Marketing (2023). Journal metrics in the Scopus database (2021): H-index: 18; Q2 in Marketing.

Another four complementary studies are discussed, as follows:

1. Congruence of third-party adverting with the social media content. This study is part of the article *How online advertising competes with user-generated content in TripAdvisor. A neuroscientific approach*, published in the Journal of Business Research (2021). Journal metrics in the Journal Citation Reports (2021): IF: 10.97; Q1 in Business.
2. Conscious and non-conscious responses to branded narrative advertising with different narrativity levels (Simonetti, A., Dini, H., Bruni, L. E. & Bigne, E.). Part of this study is published in the article *Higher levels of narrativity lead to similar patterns of posterior EEG activity across individuals* accepted by Frontiers in Human Neuroscience (2023). Journal metrics in the Journal Citation Reports (2021): IF: 3.47; Q2 in Psychology and Q3 in Neurosciences.
3. Effectiveness of augmented reality advertising (Simonetti, A., Schreiber, R. & Bigne, E.)
4. Brand choice in the metaverse and its relationship with personal and social factors (Simonetti, A., Bigne, E. & Navas L. F. R.)

Abstract

Not so many years ago, marketing communications—particularly advertising—were restricted to few mediums. These mediums themselves restricted marketing communications to pre-defined spaces and times. Now, digital mediums—including extended reality—removed those space and time barriers, allowing brands to interact with consumers virtually from anywhere and at any time. The digital medium also transformed consumers' role in marketing communication: from mere passive spectators to active opinion- and input-givers. The understanding of the effects of these changes on consumers' perceptions of the brands and communication itself is still incomplete. The challenges derive from the dynamic nature of digital technology combined with the limited answers that traditional marketing research tools provide. Therefore, the use of knowledge and tools from the psychology and neuroscience fields appear as a useful contribution to marketing research investigating communication elements in digital and extended reality contexts.

Under this context, this thesis presents several studies using neurophysiological tools to provide a more complete assessment of different formats of marketing communication. We investigated user- and firm-generated content in social media, brand elements and brand choice, and advertising: static ads, video ads, augmented-reality-based ads, and online banner ads. Our data came from laboratory and online studies, always employing a quantitative approach. We analyzed signals generated by the brain, eyes, and physiological signals, either alone or in combination with self-reported and behavioral metrics. Each study provides a unique contribution to marketing communication research. Together, they reveal the value of obtaining neurophysiological signals to uncover responses that could not be otherwise attained solely by more traditional measurements. Therefore, this thesis supports the move toward consumer neuroscience research, commonly known as neuromarketing.

CHAPTER 1
INTRODUCTION

The research topic

The topic of this thesis is the investigation of marketing communication elements in digital and extended reality contexts using neurophysiological tools. The studies presented here approached two forms of marketing communication, namely advertising and, to a lesser extent, social media, and intrinsic elements of marketing communication: brand products/services, brand logos, and packaging. We separate social media from advertising in the specific case where the brand appearing on a social media platform did not pay for it, for example, a free business profile in Trip Advisor. Thus, when a brand pays for having its ad on a social media platform, this is considered under the umbrella of advertising. The studies reported here focused on digital contexts or the combination of digital and extended reality contexts (i.e., augmented and virtual reality). Although extended reality pertains to the digital domain, we purposely state it separately to emphasize that this new digital set of tools should receive special attention in marketing research due to its unique characteristics, such as increased interactivity. Moreover, we employed in the studies some neurophysiological tools either alone or alongside traditional measurement tools to investigate the research questions and hypotheses proposed. This doctoral thesis received the financial support of the Rhumbo project (European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie Grant Agreement No 813234). The project proposed "using measures of subconscious brain processes through the use of mixed reality technologies and advanced biometric signals processing as a new paradigm to improve the knowledge that implicit brain processes have in human decision-making" (Rhumbo, 2018).

The remainder of this chapter provides a general, synthesized, but a sufficient background for understanding the areas covered and the tools used in the studies. An in-depth and specific background for each topic is described in the chapters covering the studies.

Marketing communication in the digital and extended reality contexts

Global spending in digital advertising is forecasted to reach over US$ 700 billion in 2023, with video advertising representing 30% of this amount and banner advertising, 25% (Statista, 2022c). The digital context implies that brands can deliver their message without constrains of time and space, as consumers can access content at anytime and anywhere (Lee & Cho, 2020). From the total global ad spending in advertising in 2022, more than 60% went to digital promotions, turning the Internet the medium with the highest investment. In comparison, TV ads represented only 23% of the total ad spending (Guttmann, 2022). There are different definitions for digital advertising, here we adopted the one proposed by Lee and Cho (2020):

> We therefore propose that digital advertising refers to a message of persuasion (regarding products, services, and ideas) that interacts with consumers through digital media. We also posit that digital media should include not only traditional online media (e.g., Internet) but also all interactive media—including offline channels—to broaden the comprehensive meaning of digital advertising [e.g. digital signage, IPTV, over-the-top services, smart TV, tablet PC, smart phone, SNS, VR/AR platforms, in-game advertising, advergame, digital PPL, multi-channel networks (MCNs), and AI speakers]

Digital and extended reality mediums allow brands to create interactive advertisements. Interaction can be achieved in different ways, from simply allowing consumers to pause a video ad to having them be part of the ad using augmented reality, for example. Augmented reality is the technology that merges the digital and physical worlds, and its use is being fostered by the ubiquitous presence of mobile devices in everyday life. In fact, the number of mobile AR users is expected to reach over 1.7 billion in 2024 (Alsop, 2021). Moreover, social media platforms have introduced augmented reality tools for promotional tools, meaning that brands can create augmented reality ads on Instagram, for example. In addition to being a medium for testing new technologies, social media platforms have gained increased attention from marketing scholars due to their widespread adoption by the public. Indeed, in 2022, the number of users engaged with some social media platforms reached 4.59 billion (Dixon, 2023), representing more than 50% of the total population of 2022 (United Nations, 2022). A recent study analyzed academic research on the evolution of digital consumers (Sağkaya Güngör & Ozansoy Çadırcı, 2022). They found that the highest number of publications refer to advertising effectiveness, followed by media engagement, aligned with what was mentioned previously.

The statistics presented here suggest that advertising in digital and extended reality contexts cannot be disregarded by any company type and size and that the future points to the continued growth of digital advertising.

Neurophysiological data

The assessment of whether and how marketing communications impact consumers' decisions is not trivial. Consumers are not aware or fully aware of this impact, which implies they are not able to describe all factors that influence their choices. Even though many researchers and marketers are mindful of these issues, for long marketing research has been employing self-reported metrics, usually in the form of questionnaires, seeking to understand underlying reasons for consumers' attitudes and preferences toward some form of marketing communication and ultimate behaviors (e.g., purchase). Although self-reported metrics have their value in providing answers to marketing questions in some situations, they capture only consumers' conscious responses. Moreover, these metrics can be—and usually are—subjective to common human biases and limitations, such as a late appraisal of an emotion, lack/distortion of memory, or a need to comply with others' expectancies.

The recognition of problems derived by only using self-reported metrics by marketing scholars and practitioners gave rise to the field of consumer neuroscience. As consumer information processing includes conscious and unconscious processes, emotions and moods, memory, and attitudes (MacInnis & Folkes, 2010), the application of neurophysiological metrics, often in combination with traditional methods, gives a more comprehensive understanding of the reasons behind consumers' behaviors. This knowledge potentially leads to better marketing communication strategies through data-driven marketing (Lee & Cho, 2020). Neurophysiological tools can capture what consumers do not want to reveal or simply cannot reveal (Shaw & Bagozzi, 2018) because these tools target unconscious, implicit, and automatic processes (Karmarkar & Plassmann, 2019). In the neurocognition domain, electroencephalography and functional magnetic resonance imaging are the most common brain imaging methods used in marketing research (Karmarkar & Plassmann, 2019; Shaw & Bagozzi, 2018). But a set of other neurophysiological tools are also employed. They include, among others, eye-tracking, galvanic skin response, heart-related metrics, and reaction time tests.

Marketing communications research mainly focuses on attention, memory, affect, and desirability as core constructs (Venkatraman et al., 2015). These constructs can be particularly useful for investigating advertising effectiveness. It is, therefore, not surprising that among scientific publications in consumer neuroscience, “advertising” is the second most cited term (Oliveira et al., 2022). But not all neurophysiological tools can provide direct or indirect measurements of all constructs, rather there is some specificity on what each tool best measures. Thus, a combination of metrics should be preferred depending on the type of question to be answered. Following, we provide a basic explanation of the neurophysiological tools used in the studies included in this thesis, namely: eye-tracking (Chapters 2, 4, and 5: studies 1 and 3), electroencephalography (Chapter 3 and 5: study 2), galvanic skin response (Chapter 5: studies 2 and 3), heart rate (Chapter 5: study 3), and reaction time (Chapter 5: study 4).

Eye-tracking. Eye-tracking is considered one of the best tools to measure visual attention to some piece of marketing communication (Karmarkar & Plassmann, 2019). Although gazing at something does not directly imply an attentional process is involved, it is accepted that in most situations there is a direct connection between the visual area and higher-order cognitive areas. This allows the inference that where the eyes look, the brain is directing attention toward the stimulus gazed (Just & Carpenter, 1975). In eye-tracking, the movement of the eyes is recorded by an eye-tracker device. The device can be stationary (screen-based) or portable. A stationary eye-tracker is usually placed under the device that is being used for stimulus presentation (e.g., a computer screen), whereas a portable eye-tracker resembles eyeglasses, and is worn by the person as normal eyeglasses. For research using immersive virtual reality headsets (head-mounted displays), some virtual reality devices have an eye-tracking system embedded in them. Regardless of the type of eye-tracker, all of them (except webcam-based eye-tracking) work based on the same principle: an infrared light emitted by the device passes the eye pupil, to then be reflected by both the pupil and the cornea. These reflections are the indicators of the direction and movement of the eye in a certain time frame (the sampling rate is different across eye trackers). By knowing the eyes' movements and directions, it is possible to identify with high precision where the person is looking, as well as the gaze pattern. Additional metrics that are often used in marketing research are the total time fixating a stimulus, how many times a stimulus was fixated, and the time that the stimulus was first fixated.

Electroencephalography. Electroencephalography detects electrical signals emitted by neurons when they are involved in synapses, which are called action potentials (i.e., when neurons are "communicating" with each other). An electroencephalogram device consists of electrodes that are placed over the person's scalp. The number of electrodes and their positions can largely vary; however, the common acting principle is to record brain activity derived from neuronal electrical impulses. When time-locked to a stimulus, the information provided by the electroencephalogram allows inferences of brain activity involved in processing the given stimulus. This brain activity can then be compared with the brain activity evoked by a different kind of stimulus or with baseline activity, for example. The main advantage of electroencephalography is its high temporal resolution, which means that brain activity can be recorded almost instantaneously, with a precision of milliseconds or less. However, electroencephalography has poor spatial resolution, meaning that only cortical activity can be recorded, making it complicated to infer activity in subcortical areas. Nevertheless, the metrics provided by an electroencephalogram, both in the time and frequency domains, can indicate both cognitive and affective processes.

Galvanic skin response. Emotional arousal, either positive or negative, triggers physiological responses in the skin that can be captured by electrodes placed on the skin. This skin response consists of the production of sweat by eccrine sweat glands, where palms and soles have the higher density of these glands. The production of sweat in response to an arousing stimulus is a process carried out by the autonomous nervous system, and therefore, not consciously controlled and often not consciously perceived. Electrodes placed on the body, usually on the fingers or palms, can capture the differences in skin conductivity generated by sweat production over time. Although slow changes in conductivity naturally occur even in absence of an emotional trigger (this stable response is usually referred to as the tonic component of the galvanic skin response signal), a faster and pronounced change often reflects sympathetic activity to an external stimulus (this fast response is usually referred as the phasic component of the galvanic skin response). Several metrics can be derived from the response produced by the skin. Most often, research in marketing is interested in whether a stimulus-evoked galvanic skin response peaks (i.e., a response that crossed a pre-defined threshold), the total number of peaks, and the amplitude of the peak or the overall response.

Heart rate. The heart is sensitive to both cognitive and affective processes, and it is controlled by the autonomous nervous system. The shape of a heart signal is better known by its QRS complex, where the R-waves represent the most pronounced peaks in the signal. These R-waves are the ones used to calculate the heart rate. To obtain information from the heart, electrocardiogram devices can be used. They require the placement of electrodes preferably on the participants' chest to record the heart signal. With this signal, several hear-related metrics can be derived, such as heart rate and heart rate variability, as well as frequency information. However, to avoid electrode placement on the participants' chest and speed up the setup phase of an experiment, photoplethysmography can be used. This technique records heartbeats indirectly through optical measurement of blood volume changes. A sensor with a light source and a photodetector are placed usually on the participants' fingers or wrists. The data obtained is then pre-processed and processed to estimate the R waves of the heart signal.

Reaction time tests. There are several types of reaction time tests. Common examples are implicit association tests, semantic priming tests, Stroop tests, and flanker tasks. The last two are not applied to marketing studies. The first publication with an implicit association test was back in 1998 (Greenwald et al., 1998) and since then the test and its variations (Mauri et al., 2021) have been used in consumer-related studies to uncover hidden associations between different concepts (see Maison et al., 2001). In general, reaction time tests assume that if there is either a positive or negative strong association between two concepts (e.g., an attribute and a brand), the response will be faster (i.e., lower reaction time) than if this association is weak (i.e., higher reaction time) (Maison et al., 2001). Therefore, in marketing, the tests aim to capture unbiased associations between the concepts under study, that is, associations that consumers may not be aware of.

Studies part of this thesis

This thesis is organized by study; each of the official studies for this thesis is reported as a separate chapter. The complementary studies are discussed in a chapter dedicated to them. The intent is to provide additional information for a more in-depth understanding of the application of neurophysiological tools to investigate marketing communication elements in digital and extended reality contexts.

In Chapter 2, we used TripAdvisor to investigate how social media content derived from user- and firm-generated content influences consumers’ judgments of a restaurant. Specifically, we explored how visual attention—measured through eye-tracking—given to pre-selected webpage elements affects the probability of visiting the restaurant and consumers’ expected liking of that restaurant, and whether the overall valence of the ratings given by other consumers affects viewing patterns. This study was published in 2022, in the International Journal of Contemporary Hospitality Management (Simonetti & Bigne, 2022). A complementary study derived from the same experiment is included in Chapter 5 (refer to Study 3 of the article). There, we explored whether visual attention to a third-party ad embedded into the TripAdvisor webpage differs depending on the congruence of the ad with the restaurant being announced on the TripAdvisor page. That study was published in 2021 as part of a bigger study, in the Journal of Business Research (Bigne et al., 2021).

In Chapter 3, we investigated congruence effects in the brand domain. We used electroencephalography to understand how the brain reacts to incongruence between brand communication elements (i.e., a brand logo) to products or services representing a brand. This study was published in 2022, in Scientific Reports (Dini et al., 2022).

In Chapter 4, we investigated online banner advertising on third-party websites. We used eye-tracking to investigate how visual attention paid to banner ads embedded in the webpage content could depend on the type of task the user is performing. We also evaluated memory effects over time and the correlation between attention, banner ad clicking, and banner ad position. This study was accepted for publication in 2023, in the Spanish Journal of Marketing (Simonetti & Bigne, 2023).

In addition to these just mentioned three experiments, we conducted other three experiments on the topic of this thesis. These experiments are reported in Chapter 5. Now we provide an overview of them. In the first experiment, we used video advertising as stimuli to investigate whether different levels of narrativity in video ads influence ad and brand perceptions. We combined self-reported and neurophysiological metrics (galvanic skin response and electroencephalography) to obtain more comprehensive results. In the second experiment, we used augmented reality applied to advertising to investigate how an ad featuring augmented reality elements performs in terms of ad and brand perceptions, as well as in product recognition at the point-of-sale and product purchase compared to an animated ad. For this, we combined self-reported, behavioral, and neurophysiological metrics (i.e., eye-tracking, galvanic skin response, and heart rate). In the third experiment, we explored choices in the metaverse. Specifically, we were interested in whether consumers are willing to pay for branded virtual products when there is a default, free option available as a substitute. In addition, we investigated the similarity between virtual and real-life choices and the psychological drivers behind those choices. For this, we combined self-reported data and a reaction time task.

The rest of the thesis is organized as follows: Chapters 2, 3, and 4 present the studies that are officially part of this thesis, Chapter 5 presents the complementary studies discussed in this thesis, and Chapter 6 summarizes the main results of each study and a general conclusion based on the findings of the studies presented for this thesis. Appendices 1–3 refer to the published version of the studies reported in Chapters 2–4.

CHAPTER 2

HOW VISUAL ATTENTION TO SOCIAL MEDIA CUES IMPACTS VISIT INTENTION AND LIKING EXPECTATION FOR RESTAURANTS

Simonetti, A., & Bigne, E. (2022). How visual attention to social media cues impacts visit intention and liking expectation for restaurants. *International Journal of Contemporary Hospitality Management*, 34(6), 2049–2070.

Introduction

Social media platforms contain online reviews from users as well as communicative content from the companies themselves (F. Li et al., 2021). Academic research, including meta-analyses, has shown that online reviews influence consumer choices (Babić Rosario et al., 2016, 2020; Pourfakhimi et al., 2020), including sales (Chu et al., 2020). Furthermore, a TripAdvisor survey of restaurateurs in five markets revealed that social media marketing channels generate greater return on investment than other media (TripAdvisor LLC, 2017). Notwithstanding, the effect of restaurant reviews in social media remains understudied (for a review, see Rodríguez-López *et al.*, 2019).

Social media content features three distinct characteristics. First, it contains both user-generated content (UGC) and firm-generated content (FGC). Second, it displays different formats: mainly text and pictures. Third, its content can be positive or negative—typically termed as valence. Therefore, social media content differs in origin, format type, and valence. Lang's (2000) limited capacity model suggests that people have limited mental resources with which to process all available information. Thus, in tension with the principle of least effort, processing social media content can be cognitively demanding. Furthermore, the assumption that consumers pay attention to all cues, in the same order, and with the same intensity, contradicts such existing postulations as signaling theory, information processing theory (Kirmani, 1997), and selective attention. Extending such theoretical bases to social media, we expected consumers to view each social media cue in varying ways, ultimately affecting their choices.

Relevant literature reviews have examined a variety of research directions for studies on the role of social media in hospitality, tourism and travel (see Chu et al., 2020). Further, extensive research has used surveys, and to a lesser extent, crawled data (Chu et al., 2020; Nusair, 2020) to investigate how consumers process online reviews (Risselada et al., 2018); but virtually no studies have used eye-tracking measurements to investigate “whether and how consumers use different elements of reviews in the decision-making process" (Maslowska et al., 2020, p. 283). Recent studies have called for "research to employ eye-tracking methodology to advance understanding of consumers' processing of eWOM [electronic word-of-mouth]" (Babić Rosario et al., 2020, p. 439). Eye-tracking research has proven that consumers' attention drives decisions (Orquin & Mueller Loose, 2013). Indeed, very few previous studies have examined social media viewing patterns (Bigne et al., 2020, 2021; Muñoz-Leiva et al., 2019) and, to the best of our knowledge, ours is the first to explore the relationship between social media visual attention and the intention to visit and expected liking of the service under different valence conditions. We thus seek to fill the research gap concerning how attention paid to heuristic cues in social media shapes consumer decision-making. To achieve this, we investigated how consumers view social media content (both UGC and FCG) in different formats (text and pictures), and with different valence, as well as how these heuristic cues influence consumers' intention to visit and their liking expectations in the context of restaurants.

Online reviews can be deconstructed into several distinct cues, thereby enabling our investigation into which are the most impactful on consumer decision-making. We sought to identify which elements of information consumers consider when viewing business social media pages. On social media platforms, many elements are classified as heuristic cues (Chung et al., 2017; Hlee et al., 2018). Heuristic processing is associated with decisions based on cues featuring limited information (e.g., heuristic cues). For example, overall restaurant ratings posted on TripAdvisor are evaluated by consumers heuristically (Yoon et al., 2019), for instance, by their using the "consensus implies correctness" heuristic. These star ratings have become highly important; firms are witnessing firsthand the significant sales impact of well-managed star ratings (Yoon et al., 2019).

The valence of social media content remains a challenging research topic. In general, positive content elicits purchases. However, research suggests that negative content can more strongly impact purchase decisions and can even benefit the brand (Luan et al., 2021). We argue that these inconsistent findings could be explained by the filters that consumers apply when sorting and choosing between positive or negative content (Tata et al., 2020), as filtering leads to different visual attention patterns. Therefore, how consumers view social media content containing multiple UGC/FGC information cues, particularly with varied valences, requires further research.

Therefore, this study has three aims: (i) to understand how UGC valence affects consumers' social media content viewing; (ii) to examine the influence of the content viewed from a TripAdvisor page on visit intention and liking expectations; and (iii) to evaluate how consumers respond to the content, particularly in terms of which elements capture their initial attention. To achieve these aims, we conducted an empirical study based on explicit self-reporting measures and implicit eye-tracking measures. This research contributes to the relevant literature through its analysis of viewing behavior. It demonstrates how consumers process specific content cues based on review valence. It also provides evidence on how consumer intentions and expectations relate to the information processing of restaurant content. Moreover, we offer managerial insights into comprehensively understanding the role that content plays in consumer behavior and the ways in which attention is allocated to different social media elements. Our results may help managers delineate their strategies for social media communication, particularly when the valence of a comment is negative.

The remainder of the work is structured as follows. Section 2 introduces the main theoretical background and poses our research questions (RQs). Section 3 outlines the methodology and measures. Section 4 provides the results and discusses them. Section 5 addresses the general conclusions of our findings, provides the theoretical and managerial implications, and examines the study's limitations in addition to potential avenues for future research.

Theoretical background

Social media valence

Although the findings of previous studies are inconclusive, it is generally recognized that valence can affect consumers' perceptions of a review's usefulness (Z. Liu & Park, 2015; S. Park & Nicolau, 2015). Whereas some studies have posited that negative electronic word-of-mouth (eWOM) has a greater influence on sales than positive eWOM (Chevalier & Mayzlin, 2006), others have demonstrated the reverse (Babić Rosario et al., 2016), including eye-tracking studies analyzing online comments (Shi et al., 2020). Surprisingly, little attention has been paid to what—and how—social media content is viewed. Research has shown that consumers may filter information cues and thus may view either the entirety of the content or only parts of it (Bigne et al., 2020; Varga & Albuquerque, 2019). However, while many previous studies have analyzed the effects of social media content's elements (Hlee et al., 2018), they have neglected to offer an integrative perspective in examining the effects of both its types (i.e., UGC and FGC).

The literature demonstrates that trust in UGC generates expectations about destinations, that is, positive UGC creates positive expectations, and vice versa (Narangajavana et al., 2017). However, for online booking of hotels, negative online reviews negatively influence the number of bookings whereas positive reviews have no impact on it (Zhao et al., 2015). For restaurants, ratings regarding the service, environment, and especially the food have all been found to correlate positively with online popularity (Z. Zhang et al., 2010). Daugherty and Hoffman (2014) manipulated message valence (positive, neutral, negative) of two product categories, cars and restaurants, and found that eWOM valence had a main effect on fixation duration, with participants viewing negative stimuli for the longest periods of time, followed by positive, then neutral. The same experiment was conducted to include the structural elements (text and images) as independent variables and restaurants as the product (Hoffman & Daugherty, 2013), with attention measured as the total number of fixations on pre-defined areas of interest (AOI). The authors found that participants fixated most often on non-luxury restaurant pictures and on luxury restaurant text. Valence was found to have an interaction effect with element type for luxury restaurants.

As mentioned above, social media valence is key to consumer decision-making. Depending on UGC valence, consumers might attach different degrees of importance to UGC and FGC in decision-making and consequently follow different screening strategies. Thus, we assessed whether consumers view social media content differently based on the valence of the reviews they read. Because firms cannot interfere in TripAdvisor's metrics, we have instead focused upon the valence of user evaluations. Therefore, we pose the following research question:

RQ1: Does viewing behavior vary depending on UGC valence?

Viewing social media cues

Daugherty and Hoffman (2014, p. 95) stated that “consumer attention is a critical variable that should not be neglected in research, theory, and practice pertaining to eWOM communication within social media.” In fact, a bibliometric study on the hospitality and tourism field (2002– 2016 period) showed a steep growth on consumer behavior research (2011–2016 period), particularly related to eWOM topics (Nusair et al., 2019). So far, research has established that consumers’ viewing of social media UGC is a “complex phenomenon” that should be examined in order to understand the effects of eWOM, and that message elements are impactful only if viewers notice them (Hoffman & Daugherty, 2013). A product’s social media page usually contains UGC and other product-related FGC (e.g., pictures and technical information). These elements may well vary in importance to the consumer. Indeed, the literature contains inconclusive findings concerning how review elements affect consumer behavior (Baek et al., 2012; Chung et al., 2017; S.-B. Yang et al., 2017). Furthermore, the literature has tended to ignore how users’ social media viewing affects visit intention and liking expectations.

Visual attention has been described as a proxy for preference (Wedel & Pieters, 2014); in other words, an effective indicator of the viewer’s focus is to identify what is being looked at. Just and Carpenter (1975) revealed a direct link between visual attention and mental processing when the visual stimulus is important in a task’s encoding and processing. Filtering content viewing is the result of selective attention, which itself is driven by the principle of least effort. To reduce cognitive effort, people use heuristic mechanisms in which they apply previously formed schemas, rules of thumb, in viewing stimuli instead of carefully analyzing each piece of information presented. Social media elements tend to differ in how they capture attention (bottom-up or top-down) (Maslowska et al., 2020). For example, in social media settings, consumers’ attention follows a top-down mechanism when only text is present, yet this changes to a bottom-up process when pictures are included (Bigne et al., 2020).

Consumers may examine some or all of social media content’s multiple UGC and FGC cues. In addition, the visual attention paid to each cue may differ, thereby influencing the cue’s ability to impact consumers’ judgments. Since the overall rating condenses the assessment of the service provided, one could argue that, in accordance with the principle of least effort, consumers will tend to view this cue first. Furthermore, Bigne et al. (2020) have shown that the online rating is viewed the most. Therefore, we posit that, because of the nature of social media content, consumers may form impressions about services based on the overall ratings provided by other consumers, and that these impressions ultimately drive visit intention and liking expectations for restaurants. When presented with less informative cues (i.e., heuristic cues) compared to message content cues, consumers might pay varying levels of attention to them and may consider all—or only some—in order to reach a decision. Therefore, we pose the following research question:

RQ2: Which social media content cues (overall rating, pictures, detailed ratings, and opinions) affect (a) intention to visit and (b) liking expectations?

Following the attention capture and transfer (AC_TEA) model (Pieters and Wedel, 2004) proposed in printed advertisements, we acknowledge that stimuli can engage bottom-up or top-down visual mechanisms. The former occurs involuntarily by diverting attention to a stimulus's salient features, whereas the latter involves cognitive strategies and is goal-oriented. For example, Pieters and Wedel (2004) found that pictures capture attention more effectively (e.g., they attract higher initial attention) than text.

Social media content consists of multiple cues, but is the first the most important? The "first impression" aspect has been previously addressed in advertising research (Lindgaard et al., 2006; Pieters & Wedel, 2012). Pieters and Wedel (2012) suggested that readers can understand the essence of a printed advertisement within 100 milliseconds or less, typically during the first eye fixation. Using self-reported measures, Lindgaard et al. (2006) found that a website's visual appeal is gauged in the first 500 milliseconds. These rapid judgments are recognized as cognitive confirmation bias effects (Nisbett & Ross, 1980) that lead viewers to search for confirmatory evidence of what they first saw. In a Facebook-based study in which the participants viewed a series of posts (social, news, political), the eye-tracking data revealed that posts containing richer content, such as pictures and links, attracted more attention (Vraga et al., 2016). To the best of our knowledge, no previous study has explicitly addressed the question of what users initially view in social media content, with some exceptions (e.g., Bigne et al., 2021). Therefore, we address the following question:

RQ3: Do different content types (i.e., picture vs. text) capture different levels of initial and subsequent attention?

Methodology

This study relies on the eye-tracking data and self-reported data that we obtained from our experimental design. We created TripAdvisor-type online review pages for four types of specialty restaurants: pasta, pizza, paella, and steak. We chose these categories for being the most representative in the study context and for their popularity on TripAdvisor. More generally, we chose restaurants due to their economic importance and the influence of online restaurant reviews on consumer choices. The global full-service restaurant (i.e., table-service restaurants) market in 2020 was estimated at USD 1.2 trillion and has been projected to reach USD 1.7 trillion by 2027 (Lock, 2021). Thus, it is notable that, despite the steep increase in food delivery demands due to the COVID-19 pandemic, the full-service restaurant format continues to experience positive growth. We chose to use TripAdvisor as the model for our online review pages because it is among the largest restaurant review platforms and claims to be more influential than Google, Facebook, and Yelp in consumers' choices of eateries (TripAdvisor LLC, 2017, 2018).

Experimental design

We applied a 2-within-subjects (WS) design, with rating valence (positive = 4.5 stars vs. negative = 1.5 stars) as the independent variable, and (a) the probability of visiting the restaurant and (b) the expected liking of the restaurant as the explicit dependent variables. We treated the eye-tracking metrics as independent or dependent variables, depending on the analysis. We mimicked the same upper-page layout as TripAdvisor's desktop display. Written comments were excluded due to their subjective interpretation. The experiment featured four restaurant types and two conditions, namely positive and negative valence. We used two groups of participants to cover both conditions for all restaurants, and all participants viewed four stimuli (two restaurants per condition; see Table I). We counterbalanced the presentation order across the participants.

Table I. Groups and experimental conditions.

	Restaurant 1	**Restaurant 2**	**Restaurant 3**	**Restaurant 4**
Group 1	PV	NV	PV	NV
Group 2	NV	PV	NV	PV

P: positive; N: negative; V: valence

Participants

Our sample comprised 128 Spanish residents representative of the area's population, of whom 100 were recruited by an external agency and 28 internally to account for possible data loss. We recorded the following demographic information: 51.6% female; M_{age} = 32.97, SD_{age} = 10.14, age range: 18–56; 68.5% employed, 26% students, 5.5% unemployed; 83% users of the TripAdvisor restaurant platform; and 98% restaurant patrons. The participants recruited by the external agency were financially compensated. The internal recruitment was conducted by two researchers, who approached staff and students enrolled at the university where the study took place. All participants were fully informed as to the nature of the study and their participation. We selected Spain due to its representative size and increasing potential in the restaurant market (TripAdvisor LLC, 2019). Following the analysis of the raw data, we excluded four participants and included only partial data from another five due to poor eye-tracking data quality (recordings below the 70% threshold).

Procedure and task

The participants signed informed consent forms. The eye-tracking system, the Tobii X2-30 Compact, was calibrated. The stimuli were viewed through a 23-inch 1920 x 1080-pixel monitor, and the data were recorded through iMotions software (iMotions 8.1, https://imotions.com). We collected the data in February 2020.

The first screen showed the experiment's instructions; then the TripAdvisor stimuli were displayed. To standardize viewing time, each restaurant page was shown for 30 seconds. Due to the participants' familiarity with TripAdvisor, we expected them to reproduce their actual viewing patterns. After being exposed to each restaurant for 30 seconds, participants were redirected to a survey showing the same stimulus to aid recall and were asked to rate the probability of visiting the restaurant on a slider bar (range 0 to 100%). Next, participants were asked how much they believed they would like the restaurant (i.e., whether they should visit it) by using a slider bar ranging from "I would dislike it a lot" to "I would like it a lot." The process was repeated for each restaurant, and the presentation order of the restaurants was counterbalanced among the participants. Finally, the sample answered demographic questions.

Measures and analyses

We used a questionnaire and eye-tracking as our measurements. The questionnaire captured participants' intention to visit and liking expectations for the restaurant. Eye-tracking studies (see Wedel & Pieters, 2006) tend to use the following metrics: time to first fixation (TTFF; ms), time spent in fixations (sec), number of visits (revisits), and fixation count (i.e., the number of total fixations) by AOIs. TTFF is valuable in identifying which element first captures the participant's attention and facilitates mapping the initial viewing pattern of the entire stimulus. Time spent in fixations measures the attention focused on an element. High attention could indicate either the element's importance or its greater cognitive processing demand. Revisits identify how often participants look at elements, while fixation count reveals how many fixations each element receives.

To analyze the eye-tracking data, we divided each TripAdvisor page into seven AOIs reflecting both UGC and FGC (Figure 1) as follows. AOI_1: overall restaurant rating (top-left corner); AOI_2: pictures posted by company (top); AOI_3: detailed ratings of services, such as food, quality, and price (center-left); AOI_4: details of restaurant type (center-center); AOI_5: location and contact details (center-right); AOI_6: distribution of opinions, from excellent to terrible (bottom-left center); and AOI_7: third-party online advertisement (bottom-right).

Regarding the analyses performed, we describe here the main approach utilized for each RQ. Further and post-hoc analyses can be seen in the Results and Discussion section.

To answer RQ1, we performed a repeated-measures (WS) ANOVA for each dependent variable. The four above-mentioned eye-tracking variables for each AOI served as the dependent variables. We set valence as the independent variable. The four trials were condensed into two by aggregating the two positive, and the two negative, valence trials.

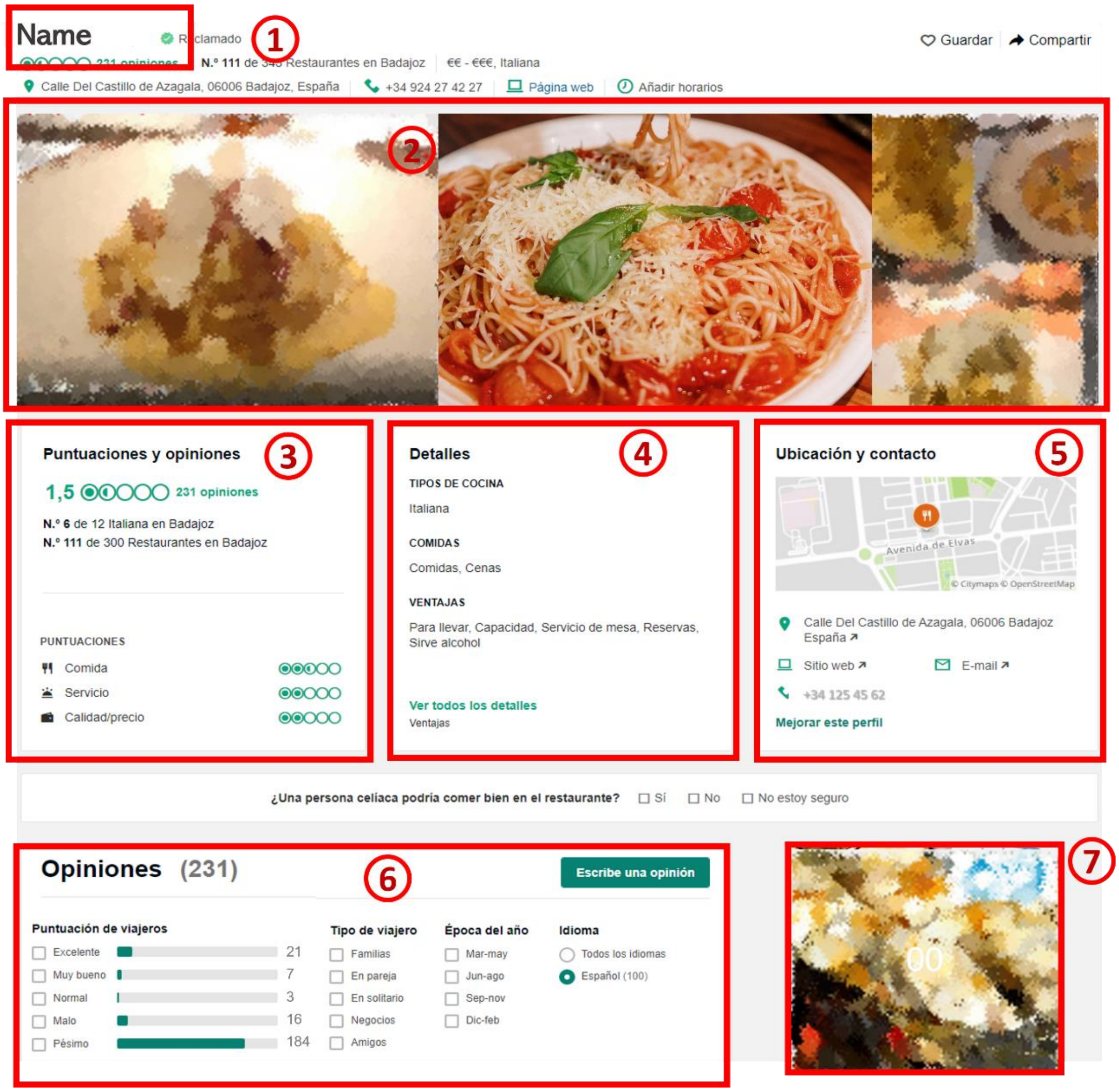

Figure 1. TripAdvisor AOI content. Name of the restaurant was removed, and images were blurred for reproduction. The original name was a generic restaurant name indicating the type of the food. The photo not blurred is an example of the original type of images used. Credits: photo by Cottonbro from Pexels (pasta), TripAdvisor/Google Maps (location map).

To answer RQ2, we performed four generalized linear models: a WS regression (GLM-WS) with a robust estimation procedure for each dependent variable (i.e., the questionnaire metrics). The independent variables were valence and the time spent in fixations for AOIs 1, 2, 3, and 6. We excluded AOI_4 (details), AOI_5 (location and contact details, which was identical for all restaurants) and AOI_7 (third-party advertisement) due to their low relevance for the dependent variables. We included restaurant type in order to control for it. Following the GLM-WS formula with the fixed factors (Formula 1), *Y* = dependent variable, β_i = regression coefficients, A_i = time spent in fixations for each AOI (*i* = 1, 2, 3, 6), *V* = valence, R_i = dummy variable for restaurant type, and ε = residual term.

$$Y = \beta_0 + \beta 1A_1 + \beta_2A_2 + \beta_3A_3 + \beta_4A_6 + \beta_5V + \beta_6A_1V + \beta_7A_2V + \beta_8A_3V + \beta_9A_6V + \beta_{10}R_1 + \beta_{11}R_2 + \beta_{12}R_3 + \varepsilon \text{ (Formula 1)}$$

We combined all four trials and conducted descriptive analyses in order to answer RQ3.

Results and discussion

Manipulation check

As stated previously, we expected valence to affect the dependent variables of RQ2. Accordingly, we first conducted a repeated-measures ANOVA to compare valence's effects on visit intention (VisInt) and expected liking (ExpLik) as the dependent variables in both the positive and negative conditions. The results revealed that valence had a statistically significant effect on VisInt ($F(1, 127) = 168.98$, $p = .000$, $\eta^2 = .57$), where positive (negative) valence increases (decreases) VisInt ($M_{pos} = 72.37$, $SD = 17.69$; $M_{neg} = 34.67$, $SD = 24.61$), and ExpLik ($F(1, 127) = 155.22$, $p = .000$, $\eta^2 = .55$), where positive (negative) valence increases (decreases) ExpLik ($M_{pos} = 72.67$, $SD = 17.00$; $M_{neg} = 40.57$, $SD = 23.04$). Therefore, the valence manipulation significantly affected behavior.

Does viewing behavior vary depending on UGC valence?

To address RQ1, we set the following eye-tracking metrics as the dependent variables: TTFF, time spent in fixations, revisits, and fixation count across the valence conditions. Our first step involved plotting each metric by valence condition to visually observe the participants' viewing behaviors (Figure 2). The visual inspection of the plots showed no valence influence on stimuli viewing patterns.

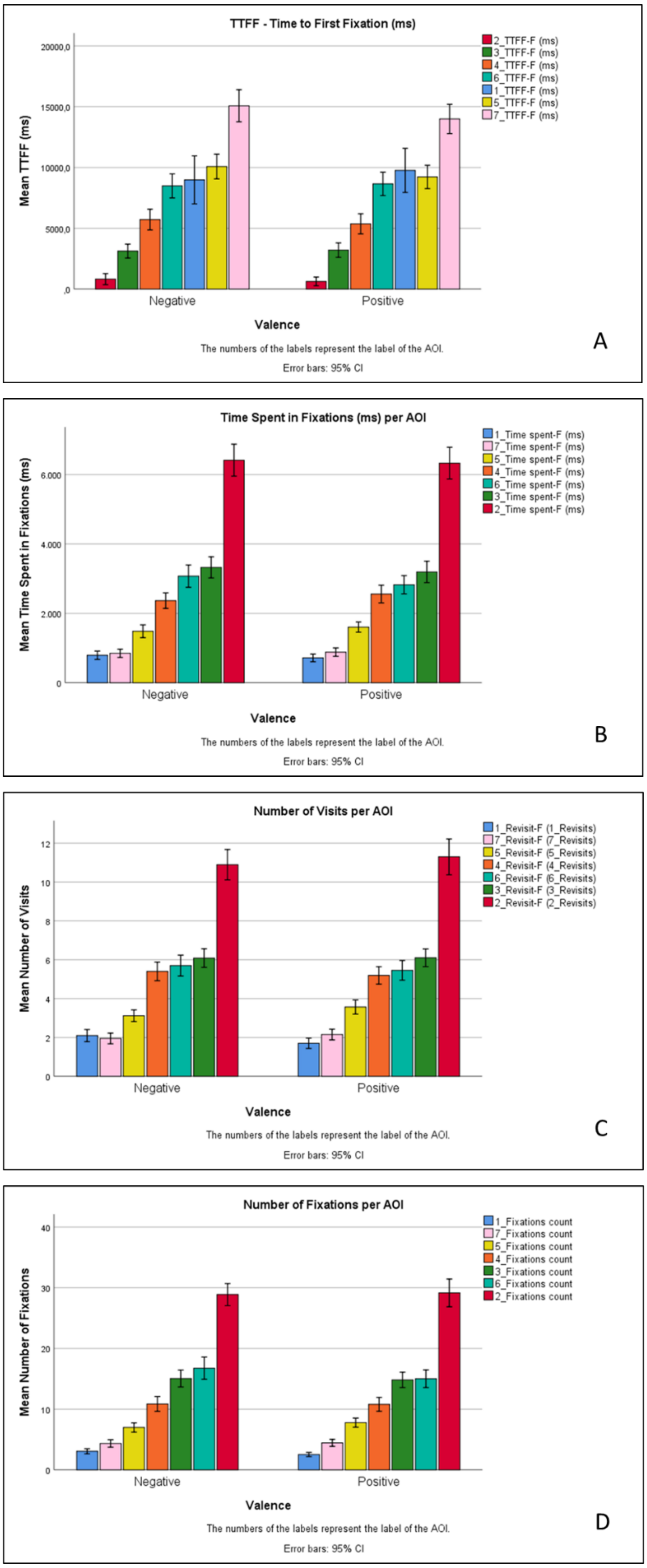

Figure 2. Visualization pattern across valence conditions. A: TTFF; B: time spent in fixations; C: revisits; D: fixations count.

The second step involved the statistical analysis using a WS-ANOVA (see subsection 3.4). The significant results are shown in Table II. The TTFF results showed no difference across valence for any of the AOIs, meaning that the TTFF of each was the same for each valence condition. The analysis revealed that time spent in fixations on AOI_5 and AOI_6 differed across the valence conditions. The time spent in fixations was longer in AOI_5 in the positive condition and longer in AOI_6 for the negative condition. The revisits results showed that AOI_1 and AOI_5 differed across the valence conditions. AOI_1 was revisited more times in the negative condition, and AOI_5 more often in the positive condition. The results for fixation count mimicked the revisit results.

Table II. Statistically significant ($p < .10$) tests of each AOI on valence effects.

Metric	**AOI (source)**	***F(1,123)***	***p-value***	**Positive valence**	**Negative valence**
				M (SD)	***M (SD)***
Time spent in fixations (sec)	5 (FGC)	3.62	.059	1.60 (0.82)	1.48 (1.03)
	6 (UGC)	3.72	.056	2.83 (1.48)	3.07 (1.80)
Revisits	1 (UGC)	6.51	.012	1.70 (1.50)	2.10 (1.75)
	5 (FGC)	5.82	.017	3.57 (2.05)	3.12 (1.69)
Fixation count	1 (UGC)	7.54	.007	2.54 (1.91)	3.08 (2.32)
	5 (FGC)	5.16	.025	7.79 (4.22)	6.99 (4.30)

Note: p-values were not corrected for multiple testing.

In summary, participants followed the same viewing patterns across stimuli regardless of UGC valence. This is consistent with Bigne et al. (2021), who also found a common viewing pattern independent of valence while using positive and neutral TripAdvisor ratings. However, we found some variations for certain AOIs. For the time spent on fixations, AOI_5 (location and contact) had more viewing time in the positive than in the negative valence condition, whereas the opposite was true for AOI_6 (reviews). In line with Shi et al. (2020), we found that participants fixated longer on the opinions element of written comments (AOI_6) in the negative valence condition than in the positive condition. Regarding AOI_5, we would propose that the higher attention paid to this element in the positive valence condition might be due to searching for practical information (i.e., address) derived from a positive, but unconscious, attitude (i.e., intention to visit). The number of visits and fixations were higher for AOI_1 (overall rating) in the negative rather than in the positive valence condition, whereas the reverse was true for AOI_5.

Although some neurological studies have demonstrated that negative stimuli evoke more attention than positive or neutral stimuli (e.g., Smith et al., 2003), and that negative reviews generally receive higher and longer-lasting fixation counts than positive ones (Daugherty & Hoffman, 2014; Moriuchi, 2021), we found no substantial differences between the two valence conditions. This could have been due to how we presented the stimuli to the participants: both conditions were shown for the same amount of time. This might have masked a possible difference in time spent fixating on the stimuli across conditions compared to if the task had been self-paced. However, we did find that parts of the UGC received more attention when negatively (rather than positively) valenced, corroborating the importance of well-managed star ratings (Yoon et al., 2019).

The effect of visual attention of social media content on intention to visit and liking expectations

RQ2 aimed to address which FGC (AOI_2 [picture]) and UGC areas—overall rating (AOI_1), detailed rating (AOI_3), and opinions (AOI_6)—affect intention to visit (VisInt) and liking expectations (ExpLik). We used the time spent in fixations to measure visual attention. As mentioned earlier (see subsection 3.4), we performed a GLM-WS.

For VisInt and ExpLik, the interactions terms of valence with time spent in fixations were significant. To analyze the simple effects, we conducted two further GLM-WS, one for each valence condition (see Table III for the results). The data for the positive valence condition revealed that, for AOI_2, an increase of one second in fixation time decreased VisInt by 1.01%, but that this same addition increased VisInt by 1.69% for AOI_6. In the negative valence condition, a one-second increase in fixation time on AOI_2 led to an increase of 1.29% in VisInt, and 2.00% and 1.98% decreases for AOI_3 and AOI_6, respectively. For ExpLik, the data for the positive valence condition revealed that, for AOI_6, a one-second increase in fixation time increased ExpLik by 1.38%. In the negative valence condition, for AOI_1 and AOI_2, a one-second increase in fixation time led to increases of 4.17% and 0.97% in ExpLik, respectively. For AOI_6, this same increase led to a 2.11% decrease in ExpLik.

Table III. Statistically significant (p < .10) tests of each AOI on intention to visit and expected liking of the restaurant.

Independent variable: time spent in fixations									
Metric	**AOI (source)**	**Interaction valence x time spent in fixations**		**Simple effects**					
				Positive valence			**Negative valence**		
		F(1, 476)	*p-value*	*F(1, 237)*	*p-value*	*Beta coef.*	*F(1, 236)*	*p-value*	*Beta coef.*
Intention to	3 (UGC)	4.77	.029			-	3.96	.048	-2.005
	6 (UGC)	7.73	.006	4.09	.044	1.685	4.43	.036	-1.975
	2 (FGC)	6.53	.011	3.10	.080	-1.012	4.03	.046	1.291
Expected liking	1 (UGC)	-	-	-	-	-	4.01	.046*	4.171
	3 (UGC)	4.26	.039	-	-	-	-	-	-
	6 (UGC)	9.35	.002	3.40	.066	1.381	6.25	.013	-2.106
	2 (FGC)	5.10	.024	-	-	-	3.40	.066	0.968

Note: p-values were not corrected for multiple testing. *This result might reflect a type I error

The time spent in fixations indicated that the four AOIs differed in their effects on VisInt and ExpLik, and that these differences depended on UGC valence. The pictures (AOI_2) and the opinions section (AOI_6) affected VisInt scores. However, the effect went in opposite directions depending on UGC valence. With positive UGC, the greater the fixation on pictures, the lower the VisInt; but the more the participants fixated on opinions, the higher their VisInt. Conversely, with negative UGC, longer fixations on AOI_2 led to higher VisInt, whereas longer fixations on AOI_6 led to lower VisInt. Moreover, for the negative valence stimuli, AOI_3 (detailed ratings) also negatively influenced VisInt (i.e., increased fixation time on AOI_3 decreased VisInt).

These direction effects were the same for ExpLik, although the participants relied on a slightly different set of cues. Only AOI_6 influenced ExpLik in the positive valence condition. For the negative condition, the participants considered pictures and opinions (AOI_2 and AOI_6) in their ExpLik ratings. Moreover, for the negative valence condition, the participants also took AOI_1 into account, although somewhat unexpectedly the effect's direction was opposite of that found for AOI_6. Given that both AOIs conveyed ratings information, it seems implausible that a longer fixation duration on the overall negative rating (AOI_1) would increase their VisInt. Accordingly, as this result may be based on a type I error, it should be treated with caution.

Therefore, the answer to RQ2 is that FGC pictures of a restaurant (AOI_2) and the UGC opinions regarding it (AOI_6) are the cues that affect VisInt and ExpLik (for the positive valence, only AOI_6 was significant). In the negative rating condition, participants also considered AOI_3 as an additional UGC cue in assessing their VisInt. These findings appear to suggest that UGC functions as an "indicator of information credibility" impacting consumers' behaviors and attitudes (Flanagin & Metzger, 2013). Moreover, negative UGC had a stronger impact on intention and expectation than positive UCG (see beta coefficient values). This supports previous findings that negative (vs. positive) reviews tend to be more influential (e.g., Chevalier & Mayzlin, 2006), especially for experience goods (C. Park & Lee, 2009).

Surprisingly, we found that the direction of firm-posted pictures' influence was opposite that of its UGC counterpart. To the best of our knowledge, no study has previously evaluated the interplay between the attention paid to a firm-posted picture and the ratings provided by consumers on purchase or visit intentions. However, it should be noted that previous FGC studies have reported mixed results. Indeed, prior research has found FGC (including highly visual elements, such as Instagram posts) to positively influence visit (Ballester et al., 2021) and purchase intentions (Poulis et al., 2019) but to negatively impact the purchase intentions of new clients (Santiago et al., 2022).

In our case, one might conclude that an FGC picture is perceived as less credible than a UGC photo because of the restaurant's motives for posting it. However, this would not explain the results for the negative valence, in which pictures increased self-reported VisInt. One possible explanation is that the picture did not sufficiently "match" the positive and the negative valence scores. For example, the positively evaluated restaurants had an overall rating of 4.5 stars; thus, the picture might have been perceived as not sufficiently "good" or "attractive" for such a high rating. Moreover, the reverse may be the case for the negative valence, in which the overall rating was 1.5 stars; in this case, the pictures might have been perceived as more attractive or of a higher quality than might be expected for such a low rating, and they may even have triggered a biological desire to eat the food.

We found that participants did not use all the information available to make their judgments. Chaiken (1980) found that information processing is more exhaustive for high, rather than low, levels of involvement with the message's topic. Given that our participants were passively receiving restaurant information and were not organically motivated to find a place to eat, their use of few cues to reach a decision is consistent with the principle of least effort. Nonetheless, it is noteworthy that those simple cues still shaped intentions and expectations, possibly by activating the "consensus implies correctness" heuristic, as can be inferred from the analysis of the explicit data (see subsection 4.1) More interesting still is that, with a positive UGC valence, the participants relied on two cues to form opinions, but needed an additional cue when the UGC valence was negative. This supports Varga and Albuquerque's (2019) finding that exposure to negative content motivates additional information-seeking, even if this implies the use of more cognitive resources.

The effect of initial attention to social media cues on subsequent attention

Because UGC valence did not affect the participants' viewing patterns, to address RQ3, we combined all four trials to gain insights into their viewing patterns during the social media stimuli. This involved three complementary analyses: (i) the order of initial fixations on the AOIs to determine which first captured viewers' attention; (ii) the percentage of participants who looked at each AOI in every possible viewing order; and (iii) the time spent in fixations on each AOI based on the total fixation and stimulus presentation times (30s).

Based on the averaged data, the ranking order is clear for the three first-viewed AOIs and the last position. As shown in Figure 3, the FGC pictures (AOI_2) were the first to be viewed, followed by detailed ratings (AOI_3) and restaurant type (AOI_4). The participants next viewed either overall rating (AOI_1) or opinions (AOI_6). The TTFF of overall star rating (AOI_1) did not differ significantly from AOI_5 (location or contact details) or AOI_6, whereas AOI_5 did differ from AOI_6 ($F(1, 123) = 5.32$, $p = .023$). Thus, from AOI_1 or AOI_6, they looked at either AOI_5, AOI_1, or AOI_6, depending on which AOI was previously viewed. The third-party advertisement (AOI_7) was the last to be viewed.

This pattern of viewing order was similar to that found by Bigne et al. (2021), who used a TripAdvisor-like layout excluding the picture at the top (our AOI_2). They found that the areas on the top-left and top-center (comparable to our AOI_3 and AOI_4) attracted the fastest initial attention. In contrast to our findings, their third-party advertisement (our AOI_7) captured attention faster than UGC elements (our AOI_6). However, important layout variations may explain these differences. We presented two pictorial elements: the top picture (AOI_2) and the small advertisement (AOI_7). However, in Bigne et al. (2021), the advertisement was the only pictorial content and was of a larger size. These differences might have generated increased and quicker attention.

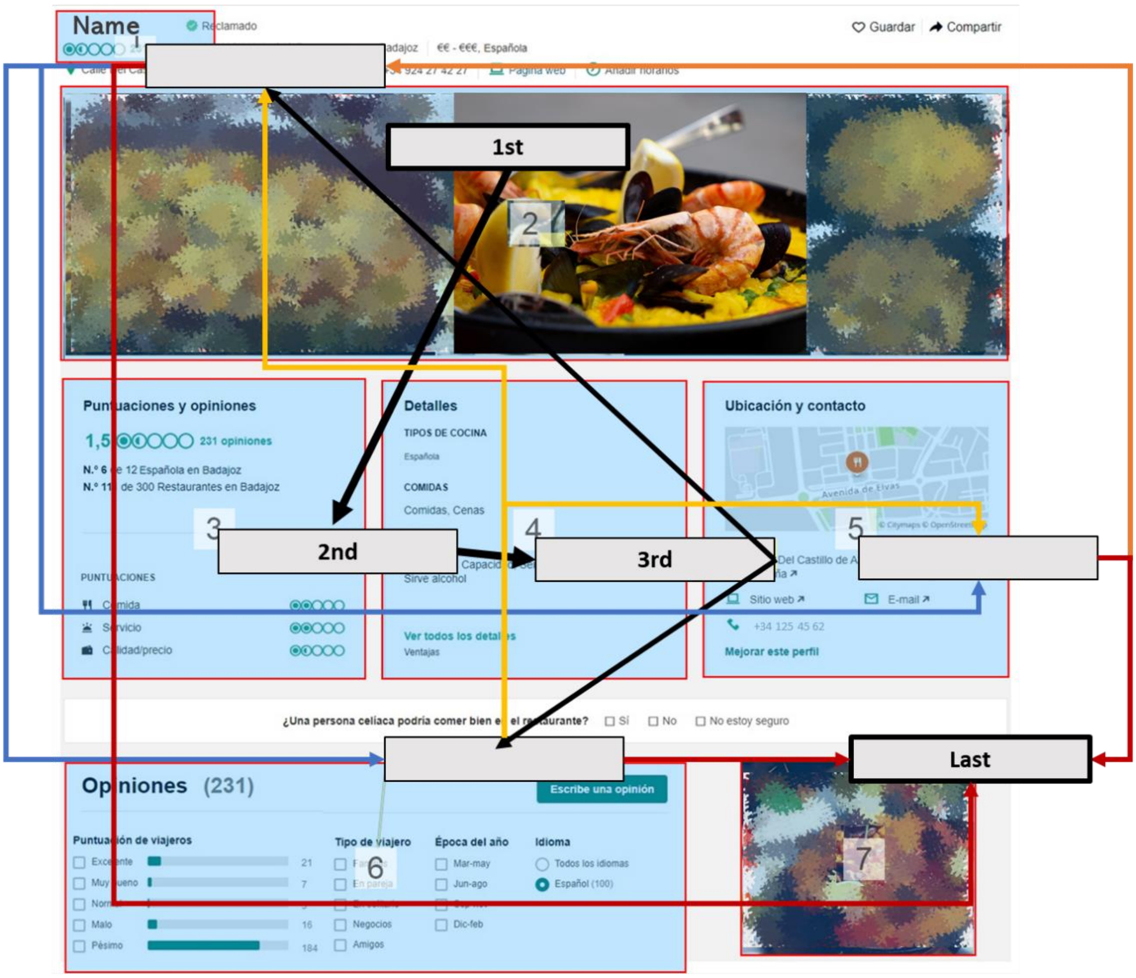

Figure 3. Order of TTFF of each AOI for one of the four types of restaurants. Each light blue box represents a different AOI. The gray numbers inside the small squares represent the AOIs' labels. The arrows represent the pattern of the first fixation across AOIs. Name of the restaurant was removed, and images were blurred for reproduction. The original name was a generic restaurant name indicating the type of the food. The photo not blurred is an example of the original type of images used. Credits: photo by Boris Hamer from Pexels (pasta), TripAdvisor/Google Maps (location map).

A viewer's initial attention can be a signal of either (i) motivation to look, that is, a goal-oriented, top-down mechanism; or (ii) an involuntary response to a random stimulus, that is, a bottom-up mechanism. Therefore, to more comprehensively understand the variation of the TTFFs across AOIs, we computed the percentage of participants that looked at each AOI in every possible viewing order (see Table IV).

Table IV. Percentage of participants for each ranking position of time to first fixation of the AOIs.

Order TTFF	AOI 1 (UGC)	AOI 2 (FGC)	AOI 3 (UGC)	AOI 4 (FGC)	AOI 5 (FGC)	AOI 6 (UGC)	AOI 7 (FGC)
1st	4.03%	**81.45%**	8.87%	5.65%	0.00%	0.00%	0.00%
2nd	27.42%	16.94%	**37.10%**	16.13%	0.81%	1.61%	0.00%
3rd	16.13%	1.61%	34.68%	25.81%	7.26%	13.71%	0.81%
4th	8.87%	0.00%	12.90%	**28.23%**	15.32%	25.00%	9.68%
5th	5.65%	0.00%	5.65%	14.52%	**34.68%**	**30.65%**	8.87%
6th	9.68%	0.00%	0.00%	6.45%	32.26%	22.58%	29.03%
7th	28.23%	0.00%	0.81%	3.23%	9.68%	6.45%	**51.61%**

Note: The first row contains the table of each AOI, and the first column represents the ranking order fixation.

Table IV shows that AOI_2, a pictorial element, captured the initial attention of most participants (81.4%), a result consistent with Pieters and Wedel (2004). The opposite was the case with the third-party advertisement (AOI_7), which tended to be the last area viewed. The superior performance of the picture (AOI_2) in grabbing initial attention may reflect a bottom-up mechanism, especially due to this AOI's comparative salience. Although the third-party advertisement also had salient features (colors and images), it was much smaller than AOI_2 and was positioned in a low-attention area. Moreover, we observed an interplay between salience effects (bottom-up mechanism) and top-down mechanisms. The fact that the third-party advertisement was the last-viewed AOI was potentially indicative of a strong top-down influence on initial attention, such as a deliberate lack of interest in the advertisement (see Kowler, 2011, for an explanation on the notion of a saliency map and how it relates to top-down processes). Due to the participants' familiarity with the TripAdvisor layout, they would have been aware that the bottom-right area is dedicated to advertising. Hence, they might have employed a selective attention process, at least regarding initial attention.

Furthermore, our results showed a transfer effect from pictorial to text content in a social media setting, which is in line with Pieters and Wedel's (2004) model of attention capture and transfer (AC_TEA model). In addition, we observed that behavior varied depending on the AOI. Whereas AOI_2 and AOI_7 had a clear, common response across the participants, the behavior in relation to AOI_1 was diverse. AOI_1 captured the immediate attention of a representative percentage of the participants, as evidenced by the large percentage in the second and third positions, whereas another representative portion of the participants were unattracted to it (see the percentages in the sixth and seventh positions). Many participants also looked at AOI_3 in the second or third positions. The remaining AOIs (4, 5, and 6) occupied the intermediary positions. A study using an Amazon.com-like stimulus found that consumers initially examined product information (product title, image, and descriptions) before turning to ratings (Moriuchi, 2021). We observed this general behavior in our participants in that they glanced at product-related pictures before the ratings. However, we saw that participants focused on ratings (AOI_3) before product-related information (AOI_4), perhaps because in the context of food, pictures are sufficiently informative, and for experiential products (e.g., restaurants), the quality assessment is initially more important than further product-related information.

To analyze the time spent fixating on each AOI, we calculated the percentage of time spent looking at all AOIs (*M* = 18.21s, *SD* = 3.11) by measuring the total time spent viewing the stimulus (30s). The results are depicted in Figure 4, which also contains a heat map for one of the stimuli. Although only one such map is provided, the remaining stimuli showed similar distributions. The percentages shown in Figure 4 depict the average value of all 16 stimuli used in the different scenarios.

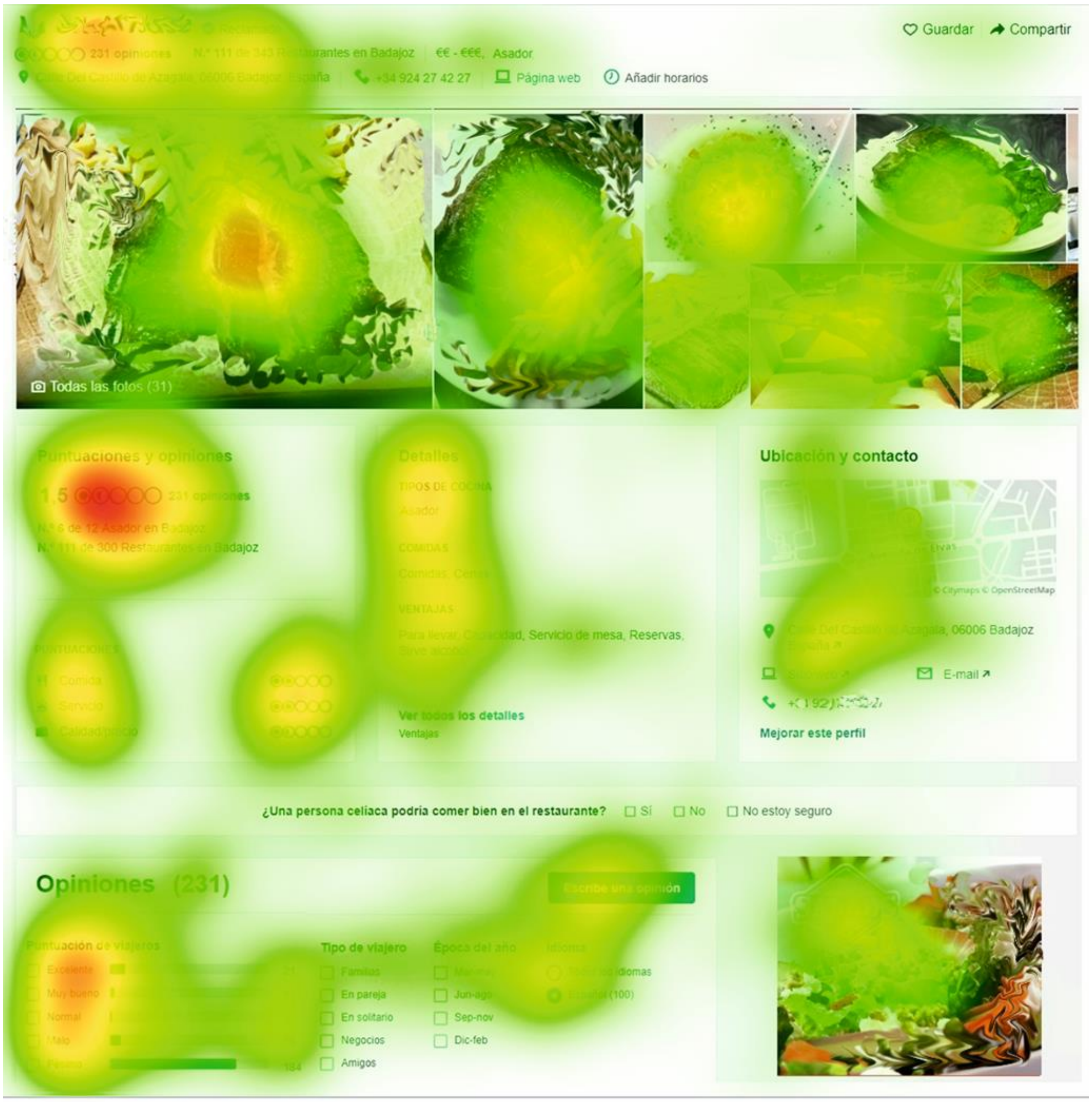

Figure 4. Heat map of one of the stimuli (Restaurant 4 NV) and time spent in fixation metric. The name and photos were distorted for reproduction. Credits: TripAdvisor/Google Maps (location map).

Conclusions

This study analyzed viewing behavior and the influence of cues in firms' and users' social media posts on consumers' intentions to visit a restaurant and their expected liking of the experience. Participants viewed four restaurants in a mock-up TripAdvisor social media page, two of which were rated positively and two negatively. We measured visual attention through eye-tracking and subsequently used a questionnaire to ask the participants about their intention to visit and their expectations of liking the four restaurants.

The analyses showed that social media elements had different impacts on consumers' intentions and expectations toward restaurants depending on the UGC valence (RQ2). A closer inspection of viewing behavior revealed that the patterns for social media content were identical, regardless of UGC valence, although with certain particularities (RQ1). Moreover, we noted that, in general, although relevant and salient pictures captured consumers' initial attention, text sustained their attention for longer intervals of time (when controlled for area size; RQ3).

Two main ideas can be generalized for the hospitality industry that will impact users and commercial practices alike. Social media is changing the communication field and appears to be increasingly influential in decision-making in the hospitality industry (Litvin et al., 2018). Users' influence through UGC is ubiquitous. However, social media also allows for the influence of FGC, thereby preserving the need for focused research to improve it (Santiago et al., 2022). Accordingly, both UGC and FGC coexist and compete for consumers' attention. However, how consumers examine the social media content of users and firms alike is the essence of their influence. Our study provides insights into how visual attention influences two outcome variables: visit intention and liking expectations in both positive and negative valence settings.

Previous studies have established a positive relationship between review quantity and restaurant performance rating (D. Kim et al., 2015). However, the massive amount of content delivered by social media is forcing potential consumers to focus their instant gaze on salient and attractive pictures. Therefore, the visual content is significant in two directions. First, as proposed by Litvin et al., (2018), social media and the deep selection of pictures should be included in overall marketing and communications strategies. Second, because UGC and FGC compete in the same setting, the weighted influences of both demand targeted research. As such, the actual value of social media is driven by how potential consumers view social media content and how firms strategize in selecting appropriate content.

Theoretical implications

In a recent review of studies related to social media in tourism and hospitality journals, Lin et al. (2020) have identified UGC as one of the five main lines of research employed. Moreover, the field of tourism and hospitality has demonstrated a steep interest in social media since 2006, and TripAdvisor was identified as a trend in the field, mainly in the hotel industry (Nusair, 2020). Our study therefore contributes to this area by investigating both UGC and FGC in a social media context (i.e., TripAdvisor) for restaurants.

The main theoretical implications of our study concern the influence of social media elements on consumers' viewing behavior and judgments (i.e., their visiting intentions and liking expectations). This is especially pertinent to the tourism, hospitality, and travel sector as it was suggested that economic and social factors would determine consumers' use of social media platforms related to this sector (Chu et al., 2020). Our results revealed that, although our participants viewed all relevant elements, they did not use all to reach a decision. This might be because participants' motivation to assess the reliability of the information and their confidence in the decision-making outcome were not strong enough to overcome the tendency to save cognitive resources (the principle of least effort). Consequently, participants relied on few heuristic cues during their decision-making processes. However, by measuring attention via eye-tracking, we found neurological evidence that consumers employ greater levels of cognitive effort to form opinions when faced with negatively valenced reviews compared to positive ones. This suggests that negatively valenced reviews increase uncertainty about product/service quality, which requires consideration of additional cues to remedy. This could explain, for example, why consumers search more extensively for competing items when faced with negative reviews (Varga & Albuquerque, 2019).

As to the social media cues that first attract visual attention (RQ3), we found that the participants were initially attracted to the picture, possibly due to its saliency (e.g., colors, content, size) and its location, indicating a bottom-up visualization process. Furthermore, we noted an indication that this initial attention was transferred to the text. However, normalizing for the size of the area of elements, it seems likely that the participants used a top-down process to evaluate the UGC elements, as the time and number of those fixations were especially significant. The social media page also contained a third-party advertisement (AOI_7). Because AOI_7 was the last element to be seen, our participants tended to engage in a top-down process and to employ selective attention related to the third-party advertisement. This is a relevant finding to better understand the intersection area of tourism and hospitality with social media and advertising, and warrants further research (Chu et al., 2020). Finally, we also contributed to the theory by providing findings which expand the current models of social media influence based on measurements of actual attention given to the cues. Such an approach has not been addressed to the hospitality domain (Chu et al., 2020).

Practical implications

To managers, we would stress the importance of the pictorial element, which tends to attract initial attention, possibly via a bottom-up mechanism. This is especially important as the features of visual content tend to influence several consumer-company behavioral responses (Ballester et al., 2021). Moreover, the restaurant would be in complete control of the pictorial element. We emphasize this element's importance because of the intriguing finding that the picture influenced judgments in opposite directions depending on the UGC's valence. Whereas UGC increases (decreases) intention to visit and expected liking with positive (negative) valence, pictures evoked the opposite behavior. We interpreted this to mean that the participants perceived the picture as incongruent with the star rating valence. Therefore, our advice is to always pre-test the attractiveness levels of pictures to be posted on social media pages.

UGC also appears to significantly impact consumers' decisions. Our results showed that participants based their judgments on the opinions of others expressed via star ratings, possibly by activating the "consensus implies correctness" heuristic. Importantly, with positive valence reviews, the participants considered only how many others voted on each rating score (i.e., the breakdown of star ratings, AOI_6) to reach a decision. However, when review valence was negative, participants displayed a need for further restaurant-related data—such as food, service, and value-for-money information—to form their judgments. Knowing that these factors (mainly food) correlate positively with restaurant popularity (Z. Zhang et al., 2010), it is imperative for restaurants to deliver high-quality service in these areas.

Another implication of our study regards the different AOIs. When correcting for area size, we found that UGC elements attracted a significant proportion of the participants' attention. This supports behavioral findings on the importance of considering UGC in marketing strategies (Babić Rosario et al., 2016, 2020; Pourfakhimi et al., 2020).

Furthermore, it is crucial that companies using social media for their advertising be fully aware of the selective manner in which their (potential) customers respond to content. We found that the third-party advertisement is the last area viewed, suggesting a deliberate effort by site visitors to ignore advertising. Therefore, companies should diversify their marketing investments across different media and social media platforms and seek innovative advertising formats (e.g., augmented reality) to most effectively capture consumers' attention.

Although we set restaurants as our context, we argue that the implications of this study can be generalized to other sectors of the hospitality industry, such as hotels and other touristic services (trip packages, attractions). Indeed, the layout of social media platforms for these sectors also includes UGC and FGC, text, and images. Furthermore, the metrics we employed would suitably apply to these sectors as well.

Limitations and future research

This study has limitations that must be considered when examining its findings. However, they present opportunities for future research. First, participants viewed the stimuli for a fixed period of time, which would not be the case in real settings due to individual differences in total time spent looking at stimuli. We fixed the time to control for this variable and to obtain consistent eye-tracking data across conditions and participants. However, in so doing, we may have masked some potential differences in viewing behavior between the positive and negative valence conditions and may have influenced information processing. A follow-up study could remove this time constraint in order to assess the reliability of our findings. Second, the participants faced a hypothetical situation, thereby possibly removing any true motivation to perform the task. This could have led them to follow the principle of least effort and form heuristics-based judgments. Future studies might use incentive-compatible tasks to test the reproducibility of our findings. Third, our stimuli did not include written reviews, which, due to their subjective nature, may have been differently interpreted among the participants. Written reviews could potentially moderate the effect of the other page elements on visit intention and liking expectations. A future study might consider testing their potential influence. Fourth, we considered only one platform, TripAdvisor; our findings may not apply to other social media platforms. Moreover, future research could explore attentional patterns of the content elements with different elements and layout configurations. For example, in a TripAdvisor restaurant-based study, Bigne et al. (2020) manipulated review comments with or without pictures and showed that the attention participants paid to the review text (identified via gaze patterns) differed depending on the inclusion of a picture. In this vein, other types of social media platforms that are heavily based on pictures (e.g., Instagram) could be used for further research. Fifth, our statistical analyses were not corrected for multiple testing, which are known to increase type I errors.

CHAPTER 3

EEG THETA AND N400 RESPONSES TO CONGRUENT VERSUS INCONGRUENT BRAND LOGOS

Dini, H., Simonetti, A., Bigne, E., & Bruni, L. E. (2022). EEG theta and N400 responses to congruent versus incongruent brand logos. *Scientific Reports*, 12(1), 4490.

Introduction

The world's 100 most valuable brands reached a record value of 7.1 trillion U.S. dollars in 2021 (Statista Research Department, 2021). It is widely accepted that brands often represent the most important asset of a company and can influence purchasing decisions (Cobb-Walgren et al., 1995; Laroche et al., 1996). Neuroimaging and behavioral studies have shown that brands convey meaning to consumers (McClure et al., 2004; Reimann et al., 2012). However, how the brain connects brand elements (e.g., products) with brand representations (i.e., brand logo) is poorly understood. Thus, the immediate reaction of the brain to brand logos that are followed by congruent or incongruent pictorial brand cues can deepen our understanding of the semantic processing of brands.

Incongruence can be understood as a form of violation of pre-encoded rules or previous knowledge at the syntactic, semantic, or pragmatic levels, including contextual and background knowledge (Posner, 1992; Van Berkum, 2009). Because incongruences are most often unexpected, a violation of expectations may happen when they occur. Previous studies, mainly in the linguistic field, have found different brain responses to congruent and incongruent stimuli (see Baggio & Hagoort, 2011, for a review of this topic). A specific electrophysiological marker related to congruence is the N400 event-related potential (ERP), a negative deflection in the electroencephalogram (EEG) signals that peaks around 400 ms after stimulus presentation. This marker was first found by Kutas and Hillyard, in 1980, who defined it as "an electrophysiological sign of the 'reprocessing' of semantically anomalous information" (p.1). After this initial work, several studies investigated the N400 effect on conflicting tasks (e.g., Stroop and flanker tasks) (Appelbaum et al., 2014; Ergen et al., 2014; Hanslmayr et al., 2008; McKay et al., 2017; Shitova et al., 2016; D. Tang et al., 2013), affective influences (X. Chen et al., 2013; Q. Zhang et al., 2006), gesture representations (Ousterhout, 2015; Wu & Coulson, 2005), sentences/words (Bentin et al., 1993; Ghosh Hajra et al., 2018; Hald et al., 2006; Marta Kutas & Hillyard, 1984; Mongelli et al., 2019; L. Wang et al., 2012; Weimer et al., 2019), text and image (Coco et al., 2017; M. Tang et al., 2021), and pictures (Barrett & Rugg, 1990) (see Kutas & Federmeier, 2011, for an extensive review of N400 studies.)

Brand logos are symbolic visual elements, consisting of image and/or text cues that aim to represent a brand in order to differentiate it from its competitors. They are so important that early definitions of "brand" could be summarized as "brand as a logo" (de Chernatony & Dall'Olmo Riley, 1998). In fact, competitive brands imitate features of leading brands, including brand logo, to benefit from brand equity of these leading brands (Van Horen & Pieters, 2012). Thus, it is crucial for companies that consumers associate a brand logo with the brand products and features. The N400 effect could indicate whether this link exists. Previous literature investigating semantic violations in sentence processing shows larger N400 amplitude, usually centro-parietally distributed, for words that are incongruent with a context, are infrequent, or have low cloze probability compared with congruent, frequent, or high cloze probability words (Bentin et al., 1993; Ghosh Hajra et al., 2018; Hald et al., 2006; Marta Kutas & Hillyard, 1980, 1984; Mongelli et al., 2019; L. Wang et al., 2012; Weimer et al., 2019). However, studies using pictorial content as stimuli may be more relevant to this study as the brain could react differently to sentences as against images. Those studies provide evidence of the sensitivity of the N400 ERP to the semantic relationships between pictures (Barrett & Rugg, 1990; Wu & Coulson, 2005). Participants presented with pairs of either matched or mismatched pictures (e.g., knife-fork or cup-leaf respectively) had larger N400 amplitude (centering around 450 ms) broadly distributed over the scalp after a second mismatched picture, compared to a second matched picture (Barrett & Rugg, 1990). Another study presented participants with words that were related or unrelated to succeeding pictures, regarding categorical or specific levels (Hamm et al., 2002). The N400 effect was found in the centro-parietal electrodes for all the manipulations, reflecting semantic mismatches in general. Gestural representations were investigated by presenting a short cartoon segment, followed by a short video with an actor reproducing the cartoon non-verbally (with spontaneous gestures) (Wu & Coulson, 2005). The video was either paired with the corresponding cartoon or with another cartoon segment. The results showed a wide, spatially distributed N400 effect, though more pronounced over the frontal and frontal-central midline sites, where a larger amplitude was found for incongruent than congruent gestures.

Overall, a violation of expectations seems to trigger the N400 response. It can be argued, however, that expectations exist because of previous knowledge of the world and of structures. It is therefore plausible to assume that memory is actively involved in stimulus processing. The findings of several studies suggest that the N400 effect reflects both the activation of working memory (e.g., immediate stimulus-context relationships) and also accessibility to long-term memory (e.g., context-independent relationships) (Kutas & Federmeier, 2000). Hence, stored knowledge related to a stimulus has to exist in the person's mind in order to judge whether some piece of information is expected or not (Kutas & Federmeier, 2000; Wu & Coulson, 2005). Indeed, the magnitude of the N400 effect is sensitive to the ease of retrieval of this previous knowledge, which can be interpreted as proportional to the cognitive load needed to process the stimuli (Ousterhout, 2015). Though such a time-domain EEG feature (i.e., N400) already indicates that memory plays a role in semantic processing—with implications for cognitive load—information from the EEG frequency-domain can confirm and extend the role of memory.

Neural oscillations pertain to the EEG frequency-domain analysis. The theta band—an oscillation in the frequency of 4-7Hz—has been shown to differ in power depending on stimulus congruity level, where stimuli perceived as incongruent increase theta power compared to congruent stimuli (Beatty et al., 2020; Brunetti et al., 2019; X. Chen et al., 2013; Ergen et al., 2014; Hald et al., 2006; Hanslmayr et al., 2008; D. Tang et al., 2013; M. Tang et al., 2021; L. Wang et al., 2012). Past studies suggest that the location of the theta activity indicates the type of process involved. For example, an increase in theta power over the posterior region (found for semantically incongruent words, though not for semantically congruent but unpredictable words) could simply reflect the detection of semantic incongruences (L. Wang et al., 2012); whereas an increase in theta power over the midfrontal regions (found after presenting an incongruent word), possibly reflects an error-monitoring process (Hald et al., 2006). Moreover, there is a relationship between theta power and memory (Herweg et al., 2020), including working and long-term memory (X. Chen et al., 2013; M. Tang et al., 2021). In addition, the strength of the theta power is positively related to working memory demand (Luo et al., 2010; M. Tang et al., 2021). The investigation of the semantic processing of emojis (pictorial representations of emotions or ideas) revealed that incongruent emojis—those emojis inconsistent with a sentential context—generated higher theta power at midfrontal, temporal, and occipital brain regions, compared with congruent emojis (M. Tang et al., 2021). This was attributed to an increase in working memory load for error monitoring—represented by the midfrontal theta, and the activation of the long-term memory for emoji recognition and concept retrieval—represented by the occipital and temporal theta. However, theta increase in anterior parts (frontal) was also associated with retrieval of lexical information from long-term memory (X. Chen et al., 2013).

Most of the aforementioned ERP and brain-oscillation studies of congruence effects focus on language (in verbal and non-verbal forms). Because brand logos can influence consumers' brand perceptions (Morgan et al., 2021), investigation of the processing of brands by the brain can expand our understanding of how brands are represented in consumers' minds. We therefore use real brands to explore how the brain reacts to brand-logos, representing brands that are congruently associated with brand cues (e.g., products, store layout), compared to logos that are incongruently associated with such cues. If brand logos are clearly represented in the minds of consumers, this knowledge should be accessible for retrieval when consumers encounter cues related to the brand. Thus, based on previous findings from other fields, we postulate that an increase in both N400 and theta power will occur in response to incongruent as against congruent logos. We propose that the N400 ERP and theta power features could be valuable for understanding how consolidated brands are encoded in the minds of consumers. Given our study design and stimulus, we expect to find a theta increase that represents an error-monitoring process, which is linked to working memory, as well as an activation of long-term memory. If this occurs, it could be argued that brand logos induce semantic processing that is similar to other representations, such as those encoded deeply in language.

Methodology

Participants

Thirty-two right-handed participants (13 female) living in Copenhagen of 16 nationalities. Demographics were as follows. Age: M = 26.84, SD = 4.33, Age range: 20-37. Occupation: 69% students, 16% workers, 15% both. Highest educational level (completed or ongoing): 12% bachelor, 88% masters. The sample size was determined by a power analysis for the ERP and theta band effect with alpha = 0.05 and power = 80%. The highest sample size required by this analysis was chosen for the study (in this case, N = 32).

All participants signed an informed consent, were debriefed at the end of the experiment, and were paid for their time and effort. 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.

Design and stimuli

A within-subsects design with one independent variable called level of congruence (hereafter, “condition”)—congruent as against incongruent—was conducted. There were 80 image sets in total (40 per condition), where each set was related to a well-known brand. Each image size was 1000x1000 px with a white background placed on a black background screen. The presentation order of the sets was randomized across participants. The task was divided into two blocks with 40 image sets each (50% incongruent).

Data collection and task procedure

Thirty-two channel EEG active electrodes were placed on the scalp of the participant according to the 10-20 system, based on the participant’s head perimeter. The signals were recorded by Brain Products EEG system, using 500 Hz sampling rate. Conductive gel was applied to the electrodes to keep the impedance between the electrodes and the scalp below 25 KΩ (as required by the hardware). A virtual reality (VR) headset (HTC

Vive Pro) was placed on top of the EEG cap. The VR headset was used for stimulus presentation because this study was part of a larger study.

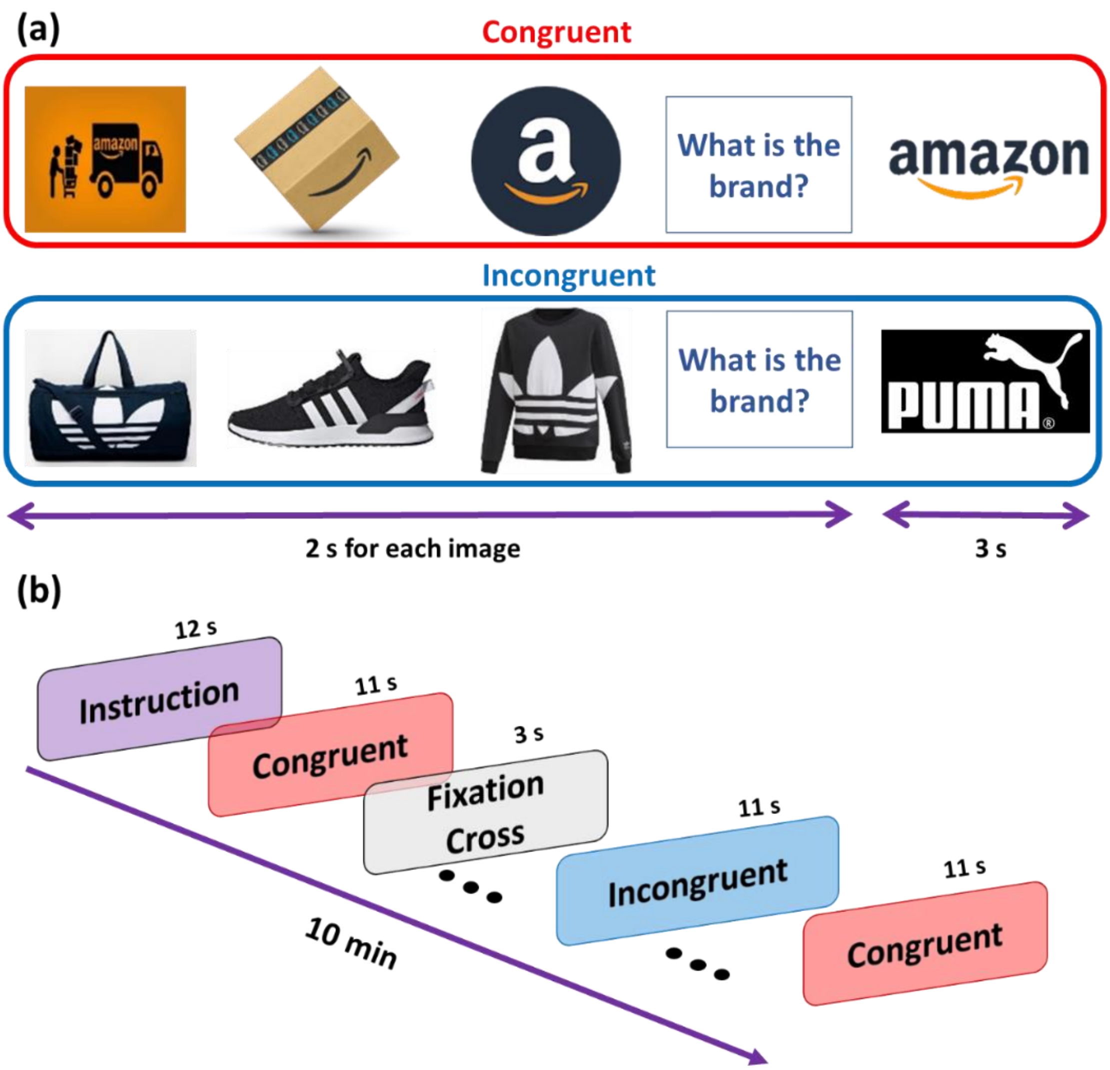

Figure 4: Example for stimuli and the task procedure. Panel (a) upper part shows an example for congruent set, where the last image (brand logo) matches the brand of the first three images. Panel (a) bottom part is an example for incongruent set where the last image and first three images do not match. Panel (b) shows the task procedure, which started with 12 s of instruction followed by congruent and incongruent image sets (randomized through the experiment). After each image set, there was a 3-s fixation cross.

The task comprised 80 image sets (40 incongruent sets). Before the task, participants were informed that they would see a sequence of three images related to a brand and subsequently would be asked to guess the brand. However, they were instructed to think of the answer but not say it aloud. Therefore, each set started by displaying a sequence of three images of a product or service from a specific brand for 2 s each.

These three images could include explicit cues (e.g., name of the brand) or only implicit cues (e.g., products or store layout). After the third image, the question "What is the brand?" was displayed for another 2 s. Following this question, the logo was shown for 3 s (this is the target image of our analysis). The logo was either from the brand of the previous images (congruent) or from another brand (incongruent). All logos included a linguistic component (i.e., letters/words) in order to control for possible differences in information processing (Ehri, 2005; Morgan et al., 2021). In the incongruent condition, the mismatched logos were randomized to be either from a competitor brand (20%) or an unrelated brand (80%). Thus, the mismatched logos would violate pre-encoded rules or previous knowledge at the semantic and/or pragmatic levels. Figure 4-a shows an example for congruent and incongruent image sets, respectively. Next, a fixation cross appeared for 3 s, and the next image set started. Each block with 40 image sets lasted for almost 10 min (Figure 4-b shows the procedure of each block). The order of congruent and incongruent images was randomized across the participants in each block. The task was presented in the VR environment, using the desktop option of *Steam VR*. The images were therefore seen in 2D, but in a curved, big screen and with the "home" background of the software.

Data Analysis

This section is divided into three sub-sections: (i) pre-processing, (ii) ERP analysis, and (iii) relative power calculation. The analyses were performed using Matlab R2020b (The Math Works, Inc) with in-house codes and tools from EEGLAB 2021.0 (https://eeglab.org/) and FieldTrip 20210128 (http://fieldtriptoolbox.org) toolboxes.

Pre-processing. The signals were filtered using a third order IIR Butterworth filter with 1 to 40 Hz cut-off frequencies to remove high and low frequency noises. Afterward, bad channels were detected using automated rejection procedure with voltage threshold of $\pm$500 µV, confirmed by an expert, and rejected from the channel list. All rejected channels were interpolated by spherical spline method using the information from six surrounding channels in FieldTrip toolbox. The average number of rejected channels per participant was 1.43 $\pm$ 1.42. One participant was excluded due to having more than four bad channels. Subsequently, considering the stationary assumption, the filtered data was segmented to 4s epochs: 1s before (pre-stimuli) and 3s after (post stimuli) from the start of the stimulus for each condition (Figure 5-a). Noisy epochs were detected by a strict automatic rejection procedure with a voltage threshold of $\pm$120 µV, confirmed by an expert, and rejected from the data. The average number of rejected epochs per subject was 1.46 $\pm$ 2.2. Afterwards, the epochs were concatenated and fed into independent component analysis (ICA) to remove remaining artifacts. The Second-order Blind Identification (SOBI) method was used to estimate source activities. EOG (eye-related artifacts) and other artifact sources were detected by an expert and removed from the source list. For further ERP calculations, the same Butterworth filter, but with low cut-off frequency of 0.1 Hz, was applied to a copy of the raw data, and ERP-filtered data was obtained. The calculated coefficients of ICA part were then applied on the ERP-filtered data to estimate the sources, and the rest of the abovementioned procedure was identical for the ERP analysis. Finally, the de-noised data was re-referenced to the average activity of the electrodes. The preprocessing steps can be seen in Figure 5-b. For the following analyses, we divided the electrodes in four different regions: mid-frontal (Fz, F3, FC1, FC2, and F4), central (C3, CP1, CP2, Cz, and C4), parietal (CP5, CP1, Pz, P3, and P7), and occipital (O1, Oz, and O2).

ERP analysis. The ERP-filtered and de-noised data were used to calculate the ERPs. First, the baseline of all epochs was corrected by subtracting, from the entire signal, the signal average across a 200 ms pre-stimulus portion. Then, the epochs of the corresponding conditions (i.e., congruent and incongruent) of specific regions were averaged separately to obtain ERPs per condition and region. The steps are shown in Figure 5-c and c-1. Figure 1 (a-d) shows grand ERP average (obtained from averaging all participants' ERPs) in different regions. For the purpose of this study, the N400 activity of each individual's ERP was calculated by averaging from 400 to 600 ms, and these values were then used for statistical analysis.

Relative power calculation. The relative power was calculated using the de-noised data. The TF information for each channel was estimated using the Welch method, including a Hanning window with 50% overlap. Then, the baseline-TFs (i.e., the TFs calculated from the one sec pre-stimulus portion of the signal) of all channels from a participant were averaged to obtain the averaged baseline-TF. This obtained average was used to calculate the relative power activity of each epoch as follows:

$$relative\ power\ = \frac{TF\ - averaged\ baselineTF}{averaged\ baselineTF} \qquad \text{Eq.1}$$

The calculation steps for relative power are shown in Figures 5-d and 5-d-1. Finally, the relative powers of each condition and each region, for a participant, were obtained by averaging the corresponding TFs separately, and the values were used for statistical analysis. Figure 2 shows the overall TF activity for each condition in the central region.

To select the time window for further statistical analysis, we used a separate permutation test procedure for exploratory searching of power changes; this procedure was an adapted version of a method in the literature (Hald et al., 2006; Maris, 2004). To do this, all subjects' TF in each condition were concatenated separately. Then, the resulting matrices were averaged across subjects. The difference between the two conditions was calculated by subtracting the average TF of the incongruent condition from that of the congruent condition (congruent − incongruent), this is the observed difference. Next, to generate the null distribution, the TFs of the two conditions were scrambled 1000 times, and the difference between the two conditions was calculated for each iteration. Finally, the observed difference was compared to the generated null distribution in order to calculate the p-value for each pixel of TF difference (Song et al., 2021). Then, the pixels that had a p-value lower than 0.01 were considered to show a significant difference between the two conditions. The result of this procedure in the central and mid-frontal region revealed that TF difference showed a significant pattern within the 700–1200 ms time window. Therefore, this interval was used for further statistical analysis.

Statistical analysis. The dependent variables are the N400 feature from ERP and the TFs, which are the averaged TF for each individual in the theta band (4 Hz to 7 Hz) and from 700 to 1200 ms. We used a permutation test to evaluate the significant differences between the conditions. As shown in Figure 5-e, the actual difference (M_main) between extracted features for each condition was calculated. Then, the features corresponding to each condition were shuffled 10000 times, and in each shuffled trial, the difference (m_s1 to m_s10000) between two newly generated groups was calculated. These differences were used to generate a random distribution, and the actual difference was tested on this distribution using significance level of 0.05.

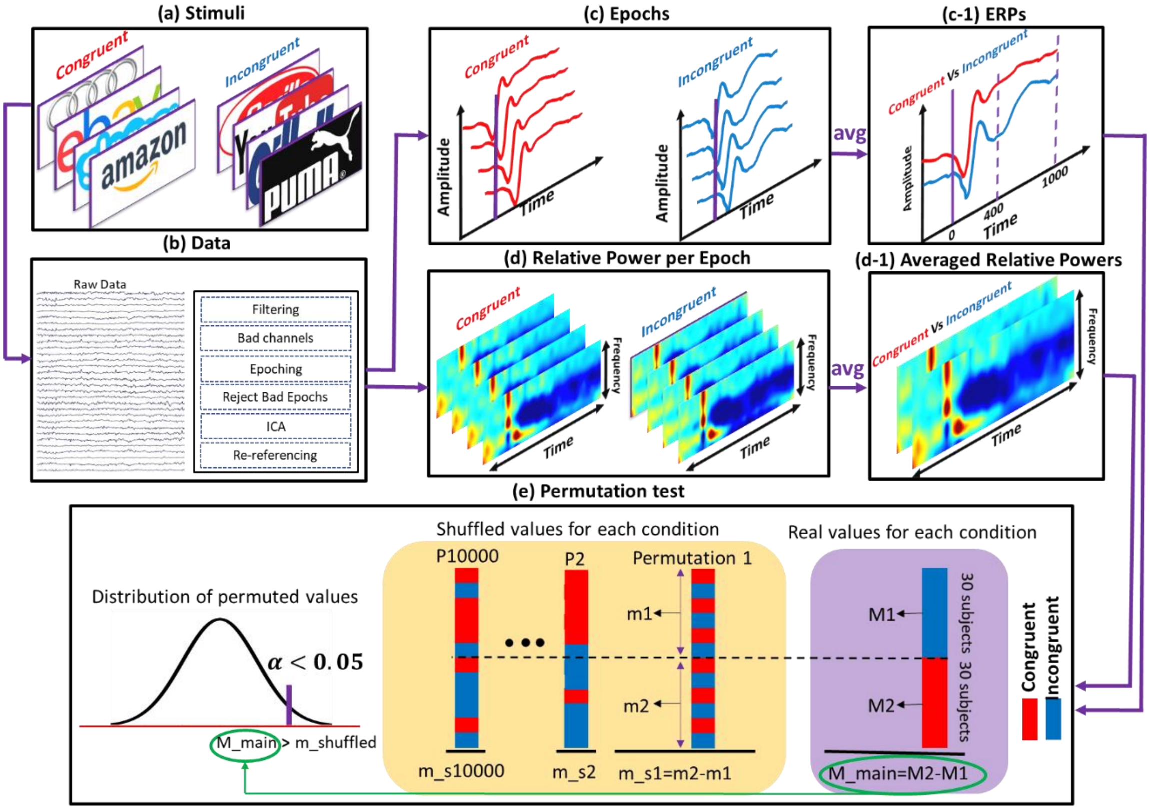

Figure 5: shows the steps in our methodology. The plots related to congruent condition are indicated by red color, and incongruent condition by blue color. Panel (a) shows congruent and incongruent target brands (the last image of each set). Panel (b) shows an example of the EEG data followed by pre-processing steps. Panel (c) relates to pre-processed epochs corresponding to each condition. By averaging the epochs of each condition we reached panel (c-1), showing the ERP activity for each condition. Panel (d) shows the time-frequency activity of each epoch for two conditions separately (in each TF, hot colors indicate positive relative power and cold colors indicate negative relative power). By averaging of TF of each condition, panel (d-1) is obtained, showing the actual time-frequency activity of each condition. Panel (e) shows the statistical analysis using the permutation test—starting with actual difference calculation, then shuffling the extracted feature 10000 times and calculating the difference in each iteration, and finally building up the random distribution and comparing it with the actual difference.

Results

This section describes the results of the ERP analysis focusing on the N400 component, followed by the results of the time-frequency (TF) analysis comparing congruent as against incongruent conditions in the theta band (4 to 7 Hz).

Event-Related Potential

ERPs for each condition (congruent and incongruent) were obtained by averaging the corresponding pre-processed trials, in each specific brain region (mid-frontal, central, parietal, and occipital). Figure 1 (a-d) shows the grand ERPs, which were obtained from the ERP average for all subjects in each condition.

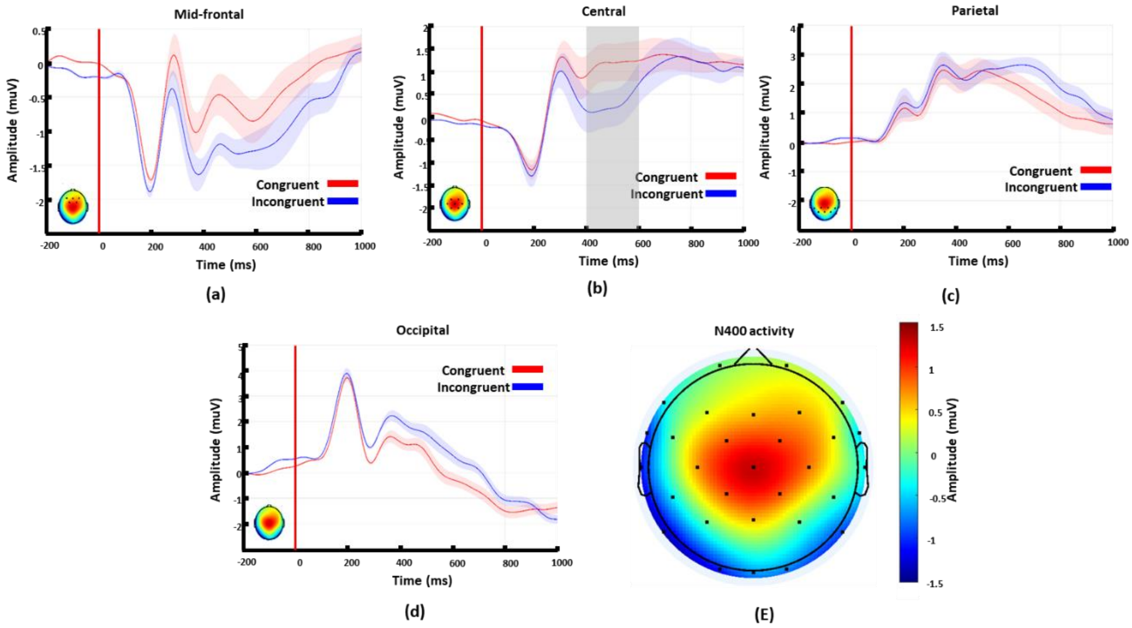

Figure 1: ERP obtained from average on trials of each condition and specific regions, and topo-map of N400 activity. Panels (a) to (e) show ERP activity for frontal, central, parietal, and occipital regions respectively. In all panels from (a) to (d), red curves show the ERP of congruent condition, and blue curve shows ERP of incongruent condition. The shaded area around each line indicates standard deviation of signals divided by square root of number of channels. In the same panels, the vertical red line in 0 ms indicates the start of the stimuli. The small topo-map at the bottom-left of each panel shows N400 activity and indicates the selected electrodes of each region. In panel (c), for the central region, the area highlighted in gray shows the significant difference between congruent and incongruent conditions (p= 0.04, effect size=0.54), that occurs in N400. Panel (e) shows the difference of brain activity in two conditions (congruent-incongruent) in N400 (averaged from 400 ms to 600 ms). The hot colors show positive activity (i.e., congruent>incongruent) and the cold colors indicate negative activity (i.e., congruent<incongruent).

In the mid-frontal region (Figure 1-a), and the range of 400 to 600 ms, there is a pronounced difference between conditions, where the incongruent condition has greater negative activity than the congruent condition. However, a permutation test on the averaged data for the 400 to 600 ms time window revealed that this difference is not statistically significant (*p*= 0.19, effect size= 0.34). In the central region (Figure 1-b), there is a difference between the conditions in the range of the 400 to 600 ms time window, where the oscillations in the incongruent condition have greater negativity than in the congruent condition, which is statistically significant (*p*= 0.04, effect size=

0.54). In the parietal (Figure 1-c) and occipital regions (Figure 1-d), there was no significant difference in the 400 to 600 ms range between the two conditions (parietal: *p*= 0.84, effect size= -0.05, and occipital: *p*= 0.27, effect size= -0.29). Finally, Figure 1-e shows the averaged ERP amplitude differences (congruent minus incongruent) of each electrode in the 400 to 600 ms time window. The main difference occurred in the central region, which is consistent with a significant difference between the conditions occurring only in the central region.

Time-Frequency

Figures 2-a and 2-c show the TF activity of congruent and incongruent conditions in the central region respectively.

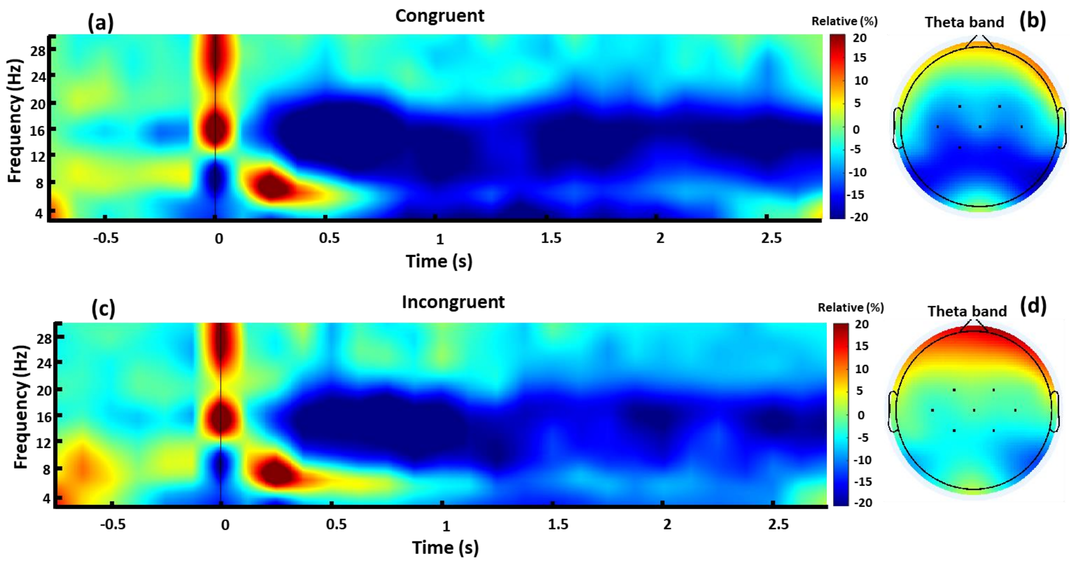

Figure 2: Time-Frequency and topo-map (of theta band in central region) for congruent and incongruent conditions, calculated from brain activity of central region. Hot colors show positive relative power and cold colors show negative relative power. Panels (a) and (c) show time-frequency of congruent and incongruent conditions respectively. Both panels are plotted from -0.75 to 2.75 s. The y-axis indicates frequency and the x-axis indicates time. The vertical black line in 0 s indicates the start of the stimuli. Panels (b) and (d) show topo-maps of brain activity in theta band of congruent and incongruent conditions respectively. The activity is averaged over theta (4 to 7 Hz) and time (0 to 2 s), and plotted as topo-maps.

As shown, in the theta band frequency, and from 700 to 2300 ms, there is a negative relative power in both conditions, where the congruent condition is more negative. In addition, there is a negative relative power in alpha and beta frequencies for both conditions, starting from around 200 ms and lasting until the end of the stimulus. Figures

2-b and 2-d show the scalp power spectrum activity for the congruent and incongruent conditions respectively. There is negative relative power activity in the central region in both conditions, but the strength of this negativity is higher in the congruent condition. Moreover, there is positive relative power activity in the mid-frontal region only in the incongruent condition.

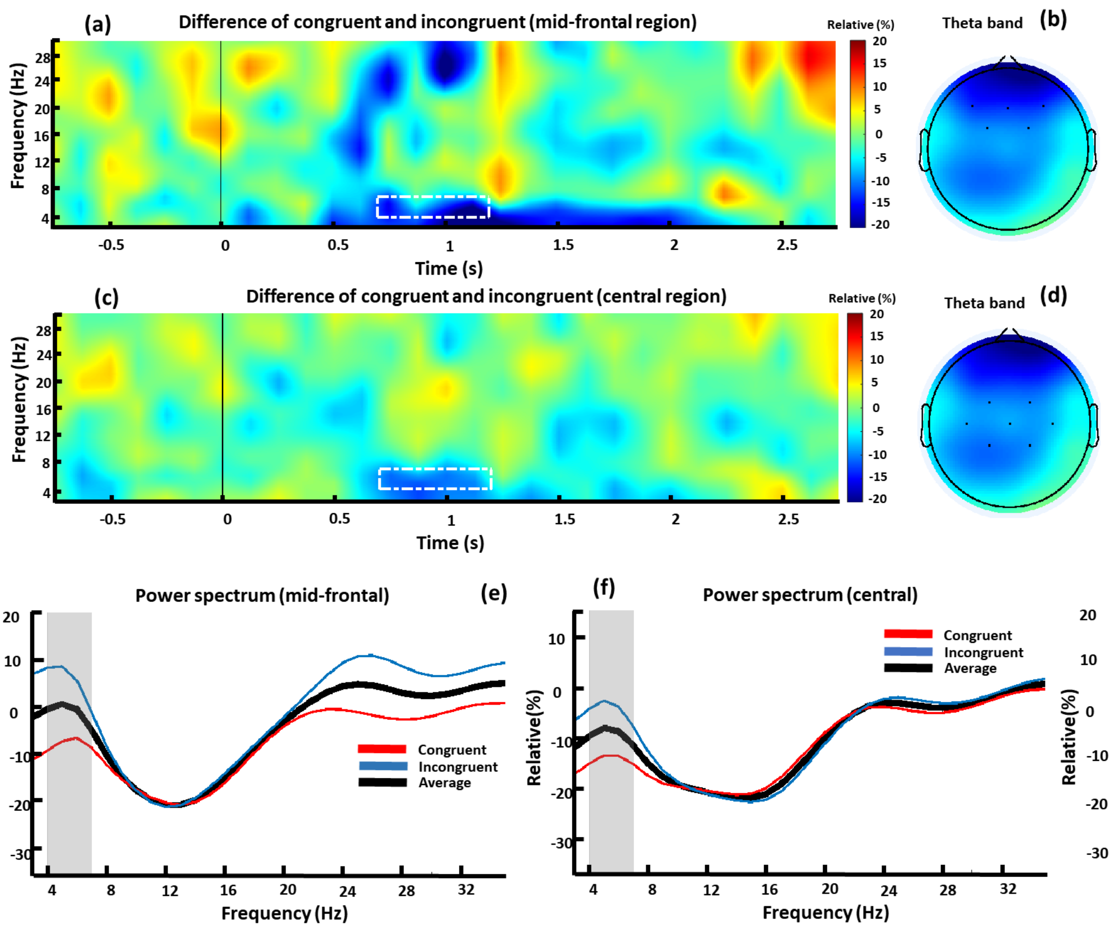

Figure 3: Time-Frequency differences (congruent-incongruent), topo-maps (of theta band), and power spectrums. Hot colors show positive relative power and cold colors show negative relative power. Panels (a) and (c) show the subtracted TF of incongruent condition from congruent condition (congruent-incongruent). The white rectangle shows the region of theta frequency (4 to 7 Hz) and time (700 to 1200 ms), where the difference is maximum. The statistics, topo-maps, and power spectrum of this figure are all focused on this region. Panel (a) shows the TF difference in mid-frontal region and panel (c) shows the TF difference in central region. Panels (b) and (d) show topo-maps for mid-frontal and central regions respectively. They show brain activity averaged on the theta frequency and 700 to 1200 ms (the area of white rectangular). Panels (e) and (f) show the power spectrum activity of mid-frontal and central regions respectively. They show power spectrum of all frequencies averaged over time. The gray regions in both panels indicate the theta band, and there is significant difference between congruent and incongruent conditions both in mid-frontal (p=0.03, effect size=-0.54)

and central (p=0.01, effect size=-0.69) regions. In both panels, the yellow curve shows the power spectrum of congruent, the red curve shows the power spectrum of incongruent, and the black curve shows the average power spectrum of congruent and incongruent conditions.

Figures 3-a and 3-c show the TF differences between the conditions (congruent minus incongruent) in the mid-frontal and central regions respectively. There is negative relative power in the theta band, and the 700 to 1200 ms time window (demarcated by the white rectangle), which occurs in both regions. We tested the statistical significance using a permutation test. The results showed that, in the mid-frontal region, activity is significantly higher for the incongruent condition compared with the congruent condition (p=0.03, effect size= -0.54), as well as in the central region (p= 0.01, effect size= -0.69). Figures 3-b and 3-d show the differences in activity of the conditions in the mid-frontal and central regions respectively, obtained from averaging the same abovementioned frequencies and periods. The difference between conditions in the central and mid-frontal regions is noticeable. Finally, Figures 3-e and 3-f show the power spectrum density of the mid-frontal and central regions respectively, which is the TF averaged over time. A significant difference occurs in the theta band, and it is specified by the gray area in the figures, where theta activity in the incongruent condition (blue line) is significantly higher than in the congruent condition (red line). Statistical analysis showed no significant difference between the two conditions in any other specified regions.

Discussion

In this study, we evaluated the ongoing, neuronal, semantic processing of brand logos, using ERP and Welch-based relative power analysis. Participants were exposed to 80 image sets, where the last image of each set included a brand logo preceded by a set of three images including brand-related cues (e.g., products or services). The last image (i.e., the logo) could either be congruent or incongruent with the previous cues. We aimed to identify both time (ERP) and frequency (EEG power) changes that were anticipated as emerging because of semantic violation between brand cues and logos (hereafter, brand cues-logo). We therefore focused on N400 ERP activity and theta-band (4 to 7 Hz) power. In time-domain analysis, the results showed significantly larger negative N400 amplitude in the central electrode locations when incongruent logos were presented to participants, compared with congruent logos. In the frequency domain, incongruent logos led to significantly higher relative theta activity in the mid-frontal and central electrode locations compared with congruent logos, which can be further related to cognitive demands. The results suggest a neural distinction for semantic processing, between the congruent and incongruent semantic processing of brand logos. In the following paragraphs, we will first discuss the ERP and then the time frequency results.

Regarding the ERP, we found a significantly higher N400 peak in the central electrode locations for semantically incongruent brand cues-logo representations than semantically congruent ones. It is widely accepted that violations in semantic expectations result in larger higher N400 peaks in a wide variety of fields and tasks (Barrett & Rugg, 1990; M Kutas & Van Petten, 1988; Marta Kutas & Hillyard, 1980, 1984). A review paper in the linguistic field suggested that the N400 reflects two main brain processes, unification and pre-activation, which are related to meaning integration. The authors declared that this activation is widely spread across brain electrode locations, but mostly focused in the frontal and temporal cortexes (Baggio & Hagoort, 2011). Studies using pictures as stimuli, which relate better to the present study, have also found a higher N400 for the incongruent than congruent condition. For example, Hamm et al. investigated brain responses to semantically congruent and incongruent images of different objects during an object-identification procedure (Hamm et al., 2002). Their results showed a greater N400 effect in the central-parietal electrode locations, and they concluded that N400 is responsible for semantic mismatch processing. In another study, Wu et al. showed a video-clip of a cartoon followed by an image of either a congruent or incongruent gesture (Wu & Coulson, 2005). They reported that the N400 is greater for the incongruent condition in the frontal electrodes, and claimed this is connected to semantic processing of gesture images. Moreover, many other image-based studies using picture series, line drawings, and videos as stimuli, reported greater N400 peaks in the frontal electrode locations (Barrett & Rugg, 1990; McPherson & Holcomb, 1999; Sitnikova et al., 2003; West & Holcomb, 2002). Our results prove that, in line with previous studies, the N400 peak reflects the semantic processing of brand cues-logo associations. We argue that incongruence between brand logos and other brand cues represents a semantic violation that requires greater mental processing effort, to adjust to the violation, which is reflected by a high N400 peak. Although most previous image-based studies have reported frontal N400 (except Wu & Coulson, 2005, that reported the effect in the central-frontal electrode locations), our results showed the N400 effect in the central electrode locations. This could be because of our type of stimulus (i.e., brand logos), whereas most other studies used ordinary objects, gestures, or images, shown within a context of sentences. Contrary to most forms of visual representation, such as those used in previous studies (mostly iconic), brand logos are not so open to interpretation due to their symbolic nature (note that we are not referring to the creative elements of a logo, instead to what they intrinsically represent). They provide a direct, unique, and unambiguous connection with a particular brand, while most other visual elements can have multiple associations. It is therefore reasonable to expect differences in the N400 effect compared with other types of stimuli. Finally, it is worth mentioning that studies including conflict tasks (such as the Stroop or flanker tasks) have consistently found greater N400 in the frontal-central electrode locations for incongruent as against congruent conditions (Appelbaum et al., 2014; Ergen et al., 2014; Hanslmayr et al., 2008; McKay et al., 2017; Shitova et al., 2016). Even though they emphasize more the response in the frontal than the central electrode locations, these studies provide evidence of the role of the central electrode locations in tasks concerning conflict (incongruence). The present study does not have a conflict-oriented task, therefore, the role of the central electrode locations in semantic violation processing needs further investigation.

Regarding the time frequency analysis, consistent with previous studies showing a theta power increase in the frontal/mid-frontal areas with higher cognitive processing, incongruence between brand cues and brand logo representations in the present study led to an increase in the theta band. Previous studies, which mainly focused on linguistic information, found that the theta band is connected to improved cognitive processing of language-related tasks (Bastiaansen et al., 2005; Davidson & Indefrey, 2007; Hagoort et al., 2004; Hald et al., 2006), working memory demand (Luo et al., 2010; M. Tang et al., 2021), long-term memory (X. Chen et al., 2013; M. Tang et al., 2021), detection of semantic incongruences (L. Wang et al., 2012), increased task difficulty, and higher attention demands (Summerfield & Mangels, 2005; Zion-Golumbic et al., 2010). In a study of the pictorial aspects of cognitive processing, Tang et al. declared that cognitive processing of "paralanguage information", which is a category differentiated from linguistic processing, is also connected to theta oscillations (D. Tang et al., 2013). Despite the fact that brand-related stimuli are neither linguistic nor emoji-based, the present findings showed that their cognitive processing is connected to theta oscillation. This suggests that theta oscillation indicates the neural activities occurring behind the detection of semantic violations.

In this study, we mitigated the influence of brand and picture (design differences) on brain responses by subtracting the responses to incongruent as against congruent brand logos. Semantic violations in incongruent brand cues-logo led to an increase in theta power in the mid-frontal electrode locations. Previous literature has declared that a theta power increase in the frontal and mid-frontal electrode locations is associated with difficulties in meaning integration, such as lexicon context and higher processing effort (M. Tang et al., 2021). Moreover, mid-frontal theta increase possibly reflects an error-monitoring process (Hald et al., 2006), and theta power increase could indicate higher working memory load in error monitoring (M. Tang et al., 2021). Considering our current results concerning theta power increase, and previous studies, we argue that the processing of violations between brand cues and brand logos needs greater effort in integrating mismatched brand representations (i.e., logos) with previous knowledge about the brand. Consequently, there is high working memory load in monitoring the manifested error during prediction, and this cognitive load is reflected in higher theta activity in the mid-frontal electrode locations.

The findings also showed a significant theta power increase in the central electrode locations caused by semantic violation of incongruent brand cues-logo. To the best of our knowledge, there are not many studies investigating theta power responses to semantically incongruent image stimuli. Past results are mainly related to flanker and Stroop tasks, concluding that theta power increase is caused by conflict-related processing. Fernández et al. investigated theta activity in incongruent-vs-congruent trials in a Stroop task followed by a speech task (Morís Fernández et al., 2018). They reported that the conflict caused by both tasks (especially the speech task), induced a theta power increase in the mid-central electrode locations. Using a flanker-type task, Pan et al. (2020), reported an increase of theta power for positive targets after incongruent rather than congruent primes in the central electrode locations. They suggested that this theta increase was due to the integration of positive emotions with conflict resolution. Using an emotional conflict task, Ma et al. (2015), concluded that greater central theta activity in the incongruent (as against congruent) condition was due to a greater need for control in conflicting conditions. Our results showed a significant increase in central theta. Because our task does not contain conflicting situations, it seems that this central theta increase reflects other kinds of processes. We found no previous EEG studies investigating brand logos or using related image stimuli. Therefore, further studies need to be done to have a better understanding of central theta increases in response to incongruent brand cues-logo.

Our data did not show a significant theta increase with incongruent processing, either in the occipital or the temporal electrode locations. Regarding the occipital electrode locations, a linguistic study stated that left-occipital theta power increase might be associated with visual form processing where longer and more complex words showed higher theta than shorter and simpler words (Bastiaansen et al., 2005). Another study reported a theta power increase in the occipital lobe with emoji-processing compared to word-processing, which is possibly due to the complexity of the visual forms of emojis, which can be vague and difficult to retrieve (M. Tang et al., 2021). One reason for dissimilar results might be because of our stimulus type. The abovementioned studies compared either two linguistic related stimuli together or a word/sentence stimulus with emoji, while we compared two different conditions for brand logos as stimuli. Therefore, we cannot expect to have differences in visual form retrieval. Another reason for this dissimilarity could be the fact that, in addition to visual form, language- or emoji-processing contains extra information such as phonetical, morphological, and lexical, potentially affecting visual form retrieval. Moreover, previous studies found significant theta increase in the temporal lobe with incongruent stimuli. They associate this increase with lexical retrieval (Bastiaansen et al., 2005; Klimesch, 1999) or the retrieval of pre-constructed concepts (M. Tang et al., 2021). In our case, it could be that brand logos do not have actual lexical form. Although some brands use words (i.e., dictionary words) or letters in their logo, these elements are not necessarily related lexically to what the brand represents.

This is the first study using time and frequency domain EEG features to investigate how the brain reacts to a mismatch between brand-related cues and the expected brand, represented by its brand logo. In summary, two neuronal markers for semantic violation, the N400 effect and a pronounced theta oscillation, were found. The difference in theta oscillation occurred in the time window of 700-1200 ms, while the ERP difference occurred in the N400 component (i.e., approximately 400 ms). This finding suggests that these two methods capture different aspects of brain activity. Overall, our results were consistent with previous studies investigating semantic violations in other fields. However, specific to our study is the N400 effect present only in the central electrode locations, and pronounced theta in the frontal and central electrode locations. The presence of both markers, associated with the corresponding brain electrode locations, provide strong support for the view that brand logos are not only represented in consumers' minds but also that this representation differs from other forms of ordinary visual representations (e.g., objects, gestures, emojis). Regarding cognitive processes, we assume a working memory involvement during task performance, because information provided by the brand cues needs to be stored to confront it further with the brand logo information. Though our data did not show theta activation in regions related to long-term memory, as found in previous studies (M. Tang et al., 2021), we infer that this could be because of our stimulus type. We argue that long-term memory must have been present as well. As the task required inferring brand name from brand-related cues, when assessing those cues, participants had to retrieve previous formed associations with those cues from their long-term memory, especially which brand they represented. The same applies for the brand logo. When presented with the logos, it was again necessary to retrieve from memory brand-logo associations. Finally, some form of integration process must have taken place to link those elements (cues, logo, predicted brand name) and reach a decision (the name of the brand). Furthermore, the findings suggest that an error-monitoring process took place during task performance. We presume that the brand cues were in the working memory, together with the brand name information, and when an erroneous (i.e., incongruent) brand logo was shown, the brain engaged in a searching process, trying to find links between the cues and the mismatched brand logo, increasing cognitive load. In summary, our results suggest that brands and their representations (e.g., products and logos) can be deeply encoded in consumers' minds. Moreover, the data suggests that incongruence between brand cues and brand logos increases consumers' cognitive load due to the activation of an error-monitoring process.

Limitations and future studies

In this section, we consider this study's limitations and discuss suggestions for further research.

i) Our study design required the participants to think about the brand of the products or services that were going to be shown to them. The reminder of this requirement occurred just before the appearance of the target stimuli (and its silent answer) and was intended to reinforce the expectative state, which presupposes a semantic association at the precise moment before the incongruence/congruence appeared. This step was intended to ensure that the participant associated the target with the preceding images. The necessity of this reminder could itself be tested using a control group; this could validate our assumption that the question was implicit at the outset and that a reminder was necessary. In future studies, a comparison could be established between a group that is prompted by the reminder of the "silent question" and a group that is not. Nevertheless, if there were a difference between the two groups, it would remain a challenge to elucidate whether the difference was due to the presence or absence of the reminder question or to other confounding factors (e.g., if the task were unintelligible or lacked a clear goal).

ii) In the incongruent condition, the target brand logo was either a competitor of previously shown brand cues (i.e., from a related product category) or unrelated to the brand cues (i.e., from another product category). In the present study, we did not compare these two conditions due to the limited number of trials of each category. An interesting approach for future research would be to balance these two conditions in a 50-50 proportion in order to investigate this relationship.

iii) Our logos had a linguistic component (i.e., letters/words). To mitigate the possible influence of a reading process in the results, further studies could use either exclusively image-only logos or equally balance the logo types (linguistic and image-only).

CHAPTER 4

DOES BANNER ADVERTISING STILL CAPTURE ATTENTION?

AN EYE TRACKING STUDY

Simonetti, A. & Bigne, E. (2023). Does Banner Advertising Still Capture Attention? An Eye-Tracking Study. *Spanish Journal of Marketing* (forthcoming).

Introduction

It has been almost 30 years since the first online banner ad appeared on websites. Currently, the presence of banner ads on the internet is ubiquitous, and monetary investment in this ad format continues to grow, with projections of reaching $226.80 billion by 2027 (Statista, 2022b). However, marketers fear and acknowledge an increase in ad avoidance over the years (Çelik et al., 2022). In fact, only four years after the first online banner ad appeared, the term "banner blindness" was created (Benway, 1998).

One explanation for banner blindness could be related to selective attention (Wedel & Pieters, 2008). When navigating websites, consumers often are goal oriented. Whether they are making a search, buying a product, or merely reading news, cognitive resources are allocated to the task being performed. In this sense, banner ads are considered distractors (Cho & Cheon, 2004; Seyedghorban et al., 2016), and mental resources would not be directed to them. Moreover, consumers already associate traditional spots (i.e., the top and lateral of a webpage) with advertisements that do not align with their search oriented-goal tasks, leading to banner blindness (Sapronov & Gorbunova, 2022). Hence, hoping to cancel out this conscious avoidance of ads, companies embed banners in the website content. This way, to view all page content, consumers need to scroll through a banner ad. But there are few studies observing whether placing banner ads in between the main webpage content in fact directs consumer attention to ads (Schmidt & Maier, 2022). To our knowledge, no previous study has investigated how task-goal affects attention paid to banner ads embedded into the content.

Looking at something may indicate an active attentional process, but it does not necessarily mean that the acquired information will remain stored and accessible for a long time according to the limited capacity model of motivated mediated message processing (LC4MP) (Lang, 2000). Therefore, simply measuring visual attention toward a banner ad may not lead to accurate conclusions regarding consumers' memory of ads. Thus, several studies have measured brand and banner recognition and recall (Burke et al., 2005; Drèze & Hussherr, 2003; Guitart et al., 2019; Hamborg et al., 2012; J. Lee &

Ahn, 2012; K. Li et al., 2016; W. Liu et al., 2019; Muñoz-Leiva et al., 2019, 2021; Schmidt & Maier, 2022) as support metrics to infer banner ad effectiveness. However, most of the studies assessed these memory effects soon after consumers were exposed to the banners. Considering that individuals are exposed to a myriad of stimuli every day, it is also valuable to verify whether ad recognition lasts longer than a few minutes or one day.

Therefore, this study seeks to fill in the gap in the literature on the relationship between task goal and visual attention to banner ads embedded in webpage content. Moreover, it approaches banner ad performance through ad clicking and lasting memory. Our theoretical approach is based on processes of selective attention and its relationship with task-goal, and memory formation. In addition, we consider previous empirical findings on how banner position affects visual attention to it. With this theoretical and empirical background, we aim:

(1) To investigate whether attention to online banner ads differs depending on the goal of the task (e.g., reading news or finding what to see next). This is the goal effect.
(2) To assess the position effect of online banner ad clicking depending on (a) the attention paid to the banner and (b) the position of the banner on the website.
(3) To explore the decay effect of advertising (Havlena & Graham, 2004): that is, if consumers recognize online banner ads from a website after (a) one day and (b) one week of exposure

The contribution of this study is threefold. First, it expands the knowledge on internet ad avoidance related to task-goal (Cho & Cheon, 2004; Seyedghorban et al., 2016) to recent marketing strategies, that is, embedding banner ads into the content. Second, it provides objective (i.e., eye-tracking) measures of visual attention to this type of banner and its relationship with selective attention and ad clicking. Third, it demonstrates the effectiveness of this type of banner through ad recognition over time.

Theoretical and Empirical Background

Traditionally, banner ads were horizontally placed on the top of a webpage. Later, a vertical format called the “skyscraper banner” was created, and together with the traditional horizontal format, they still have represented the most common formats and locations even until today (Pernice, 2018). Indeed, several studies have addressed these and similar types of banners (Drèze & Hussherr, 2003; Hamborg et al., 2012; Im et al., 2021; Köster et al., 2015; Kuisma et al., 2010; K. Li et al., 2016; W. Liu et al., 2019; Resnick & Albert, 2014). Over time, consumers learned to associate these traditional locations with advertising spots; this association contributes to banner blindness (Sapronov & Gorbunova, 2022). Consequently, in an effort to bring back consumers' attention to banner ads, marketers moved the ads from their rather isolated places to the main content webpage area. Similar practices such as native advertising have been shown to have a better performance than normal banner ads (Sussman et al., 2022). However, as consumers are hardly interested in banner ads when navigating on the internet, attention is often and purposely given to other webpage elements, which may affect banner effectiveness.

Therefore, we aim to test how banner ads embedded into the content perform in terms of visual attention depending on task orientation, and its relationship with ad clicking and recognition. Figure 1 depicts our conceptual framework.

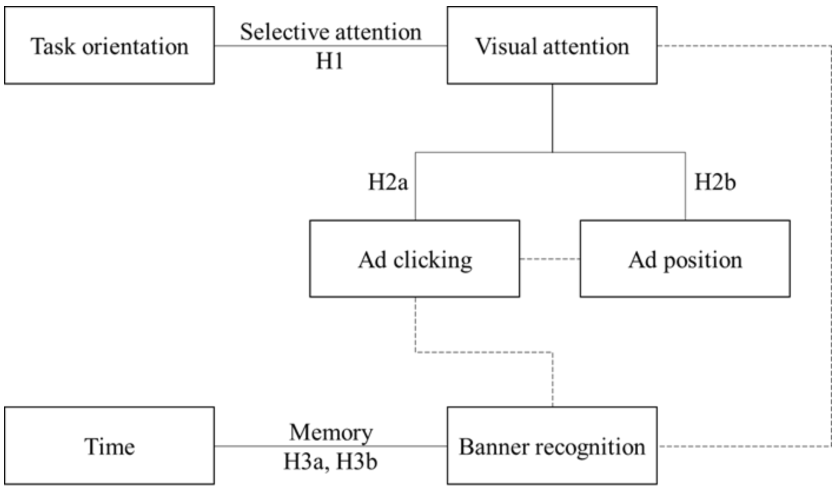

Figure 1. Schematic representation of the study hypotheses (solid lines) and further relationships explored (dashed lines).

Selective Attention

Whenever a task demands attention to specific elements, and not all elements present in the environment are relevant for performing the task, a selection process might occur (Dayan et al., 2000). This process is regulated by top-down signals modulating the activity in sensory regions by prioritizing reactions to task-relevant elements (Gazzaley & Nobre, 2012). Nonetheless, selective attention rarely implies that the irrelevant stimuli are completely neglected; instead, they receive relative reduced attention in relation to task-relevant elements (Dayan et al., 2000; Driver, 2001). Moreover, the level of distractor processing is conditioned to the type and level of load required to process task-relevant information, with high perceptual load leading to complete elimination of distractor processing in certain cases (Lavie, 2005).

In third-party website settings, ad avoidance is mostly explained by perceived goal impediment (Cho & Cheon, 2004; Seyedghorban et al., 2016). In fact, the internet is assumed to be a more goal-oriented medium compared to other mediums (Cho & Cheon, 2004). When navigating a news website, users mostly encounter textual information. Text processing requires the engagement of cognitive processes, which implies top-down attention in the case of news reading (Sapronov & Gorbunova, 2022). Because banner ads differ from textual news, they tend to be unnoticed by users engaged in news reading (Sapronov & Gorbunova, 2022). Similarly, in devices with larger screens compared to mobile screens, users can easily avoid viewing ads (Schmidt & Maier, 2022) by directing attention to goal-relevant content (Duff & Faber, 2011), which refers to cognitive avoidance (Cho & Cheon, 2004).

A recent study found that cognitive load negatively impacts the attention paid to banner ads (Theodorakioglou et al., 2023). Though higher perceived goal impediment leads to higher ad avoidance, this avoidance is more pronounced if users are in a serious mindset (e.g., searching on the internet) compared to a playful mindset (e.g., surfing on the internet) (Seyedghorban et al., 2016). However, in the absence of a high perceptual load, distractors can interfere with individuals even if they are instructed to pay attention to a given task (Lavie, 2005). Strategies such as personalized banners or highly creative banner ads perform differently depending on whether users are freely browsing or involved in some task (Abedi & Koslow, 2022). Goal-direct looking (i.e., top-down attention) indicates active avoidance of distractors, whereas passive exposure to web content (e.g., freely navigating a news website) suggests a bottom-up attentional process (Duff & Faber, 2011). Indeed, when the goal is not reading a piece of news, individuals have a higher chance of noticing banner ads (Sapronov & Gorbunova, 2022).

Following the principle of least effort (Zipf, 2016), the brain directs attention to what is relevant at the moment and filters out distractor stimuli. Furthermore, LC4MP says that individuals are information processors, but their capacity to process information is limited (Lang, 2000). Therefore, we expect that:

H1: Attention paid to the banner ads is inversely proportional to the cognitive demand of the task being performed.

Attentional Patterns and Behavior

One metric brands use to evaluate banner ad effectiveness is click-through rate (Namin et al., 2020). Ad clicking can only occur if users look at the banner; hence, banner ads must first grab users' attention (Drèze & Hussherr, 2003). Increased degree of forced exposure to banner ads was found to positively correlate with perception of the banner ad (i.e., awareness) and the click-through rate (Cho et al., 2001). Furthermore, clicks on a banner ad have been used as a proxy for the attention paid to the banner (Goodrich, 2010, 2011), as visual attention patterns highly correlate with clicking patterns (Egner et al., 2018).

Therefore, based on previous literature showing a positive correlation between the attention given to an element and clicks on the element, we expect:

H2a: There is a positive relationship between attention paid to a banner ad and clicks on the ad.

Position Effect

Visual attention to webpage content is not evenly distributed across the entire page. Instead, different locations attract different attentional levels (e.g., Bigne *et al.*, 2021; Drèze and Hussherr, 2003; Simonetti and Bigne, 2022). Moreover, the same digital element displayed in distinct locations across a webpage receives a different amount of visual attention (Muñoz-Leiva et al., 2021). The location of an element also influences its click-through probability. For example, hyperlinks placed at the top of a list tend to be the most clicked ones (Murphy et al., 2006).

In the banner ad context, most studies investigate the two most common locations: the top and lateral parts of the page. Some studies have shown that skyscraper banners, which are usually placed on the right side of a webpage, attract higher attention levels than horizontal banners at the top (Kuisma et al., 2010), but others have shown that lateral banners receive less attention than top banners (K. Li et al., 2016; Resnick & Albert, 2014). However, when banners are embedded in the content of interest, it is preferable to examine top, middle, and bottom webpage locations. In search websites, top-located results receive around 65% of total dwell time, whereas middle- and bottom-located results receive around 15% and 5% dwell time, respectively (Navalpakkam et al., 2013). Banners located at the top of the page receive less attention than banners embedded into the page content (Burke et al., 2005; Goodrich, 2010). On news websites, banners located at the top and left side attract more attention than those placed at the bottom or right side (Outing, 2004). As most webpages require users to scroll down the page to access the full content, banners located toward the bottom are less likely to be noticed, as users might not scroll down.

Therefore, based on previous literature concerning attentional patterns, we expect:

H2b: The bottom position leads to less attention than the middle and top positions, hence leading to decreased ad clicking.

Decay Effect

Selective attention suggests active engagement in avoiding distractor processing. However, complete disregard for a non-task-relevant stimulus is rare; rather some attention is directed to it (Dayan et al., 2000). Although superficial information encoding may not be enough for generating explicit long-term recognition (Lavie, 2005), deep information processing to a certain degree could also occur for unattended elements (Driver, 2001).

Memory is classified into three major types: sensory memory, short-term memory—which is related to working memory—and long-term memory (Camina & Güell, 2017). The mechanism for new memory formation comprises the transferring of sensory information to short-term memory, and from short-term memory to long-term memory through a consolidation process (Benfenati, 2007). Without a consolidation process, information stored in the short-term memory fades quickly, leading to forgetfulness (Benfenati, 2007). However, even consolidated memories—particularly those considered useless—can fade and change with time (Silva & Josselyn, 2002). Thus, one way to assess memory for a piece of information could be through information recall or recognition over a period of time.

Recent studies in the banner ad context found that the valence of a banner, but not the arousal it elicits, can affect banner recognition (Sapronov & Gorbunova, 2022). Moreover, hedonic banner ads, compared to utilitarian banner ads, increase the probability of banner recall (Casado-Aranda et al., 2022). Regardless of banner ad features, previous studies measuring memory for banner ads in general found that around 20–65% of banner ads are recognized. One study presented several hyperlinks on a screen and included two banner ads (Burke et al., 2005). After performing a task, ad recognition was evaluated by presenting previously shown and new banner ads to the participants. Their results revealed that 20% of the ads were correctly recognized, which was the hit rate, while 20% of the new ads were classified as present in the task, which was the false positive rate. Another study using a search portal and a banner ad located at the top of the webpage found 23% of hits and 18% of false positives, and 30% of hits in a second experiment (Drèze & Hussherr, 2003). In the context of a news website featuring short news articles and banner ads, the participants recognized 42% of the banner ads, with this percentage increasing to 64% with a three-times exposure repetition (J. Lee et al., 2015). A recent study had participants using either a mobile phone or a computer to browse news articles with embedded banner ads in the news context (Schmidt & Maier, 2022). They were then tested for aided and unaided banner ad recall. For unaided recall, participants remembered 21% of the mobile ads and 28% of the computer ads, whereas for aided recall, it increased to remembering 61% mobile and 67% computer ads. In social media and blogs featuring banner ads, around 60% of visitors recalled having seen an ad (Muñoz-Leiva et al., 2019).

Therefore, based on previous studies and literature on memory, we expect:

H3a: To find similar results as those of previous studies for real (~20–65% of hits) and mock (~20% of false positives) banner ad recognition after one day of exposure.

H3b: A decay in ad recognition of both real and mock banner ad recognition after one week of exposure compared to after one day of exposure.

Methodology

Participants

One hundred participants living in Spain took part in the study (53 female; age range: 22–53 years old, *M* = 32.01, *SD* = 9.00; occupation: 49% workers, 16% students, and 32% both). We recruited participants via an external marketing agency (*n* = 81) and by internal means (convenience sample; *n* = 19). Participants recruited externally were monetarily compensated for their time and effort. The university ethics committee approved the study.

Design, Task, and Stimuli

We conducted a 2 (task: Read task x Click task) within-subjects design. First, the participants performed the Read task; they were instructed to read a pre-selected sports news article on a webpage that was a recreated version of an existing website. We told them they would answer some questions afterward to ensure that the participants read the news as they would normally read news of their own choice: that is, paying attention to the news. After reading it, the participants performed the Click task; an instructions screen informed them that they would see the same webpage once more, but this time, they could click only once on whichever hyperlink they wanted. This second part aimed to redirect the focus from the text to the other elements of the webpage. Our target stimuli were three banner ads embedded in the sports news webpage. One ad was positioned toward the top part, one in the middle, and one toward the bottom part of the webpage's news content (Figure 2). The three ads were different, and their positions were randomized among themselves in the six possible combinations across participants. The stimulus was presented in a 23-inch 1920 x 1080-pixel monitor, with a screen-based eye-tracking device (Tobii X2-30 Compact).

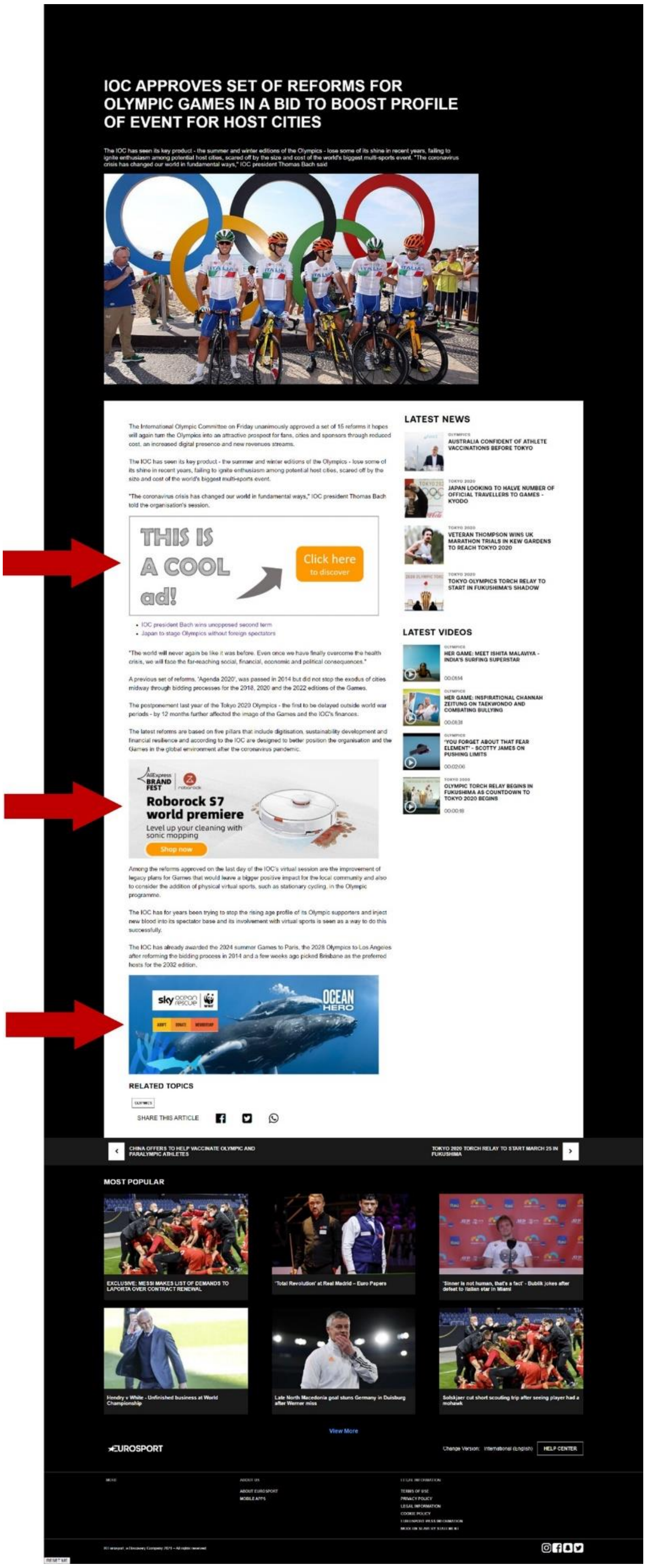

Figure 2. Layout of the sport news webpage. The three banner ads are indicated by the red arrow. The position of each ad was randomized among themselves across participants.

On the next day and next week of the lab experiment, the participants received an online survey to assess ad recognition. The survey contained six banner ads; three were the ads present on the webpage of the lab experiment, and another three were new but with similar features to the target ads (Figure 3). The participants were asked whether each banner ad was present or not on the webpage they saw. We presumed that memory effects would not represent a major problem in the results of the last measurement because the participants had a six-day interval between the two assessments where (i) they did not know the banner recognition task will also be asked six days later, (ii) they were exposed to thousands of different stimuli in their daily-life during this period, and (iii) the banners were presumably of low interest to them, which implies no need of storing any information about them.

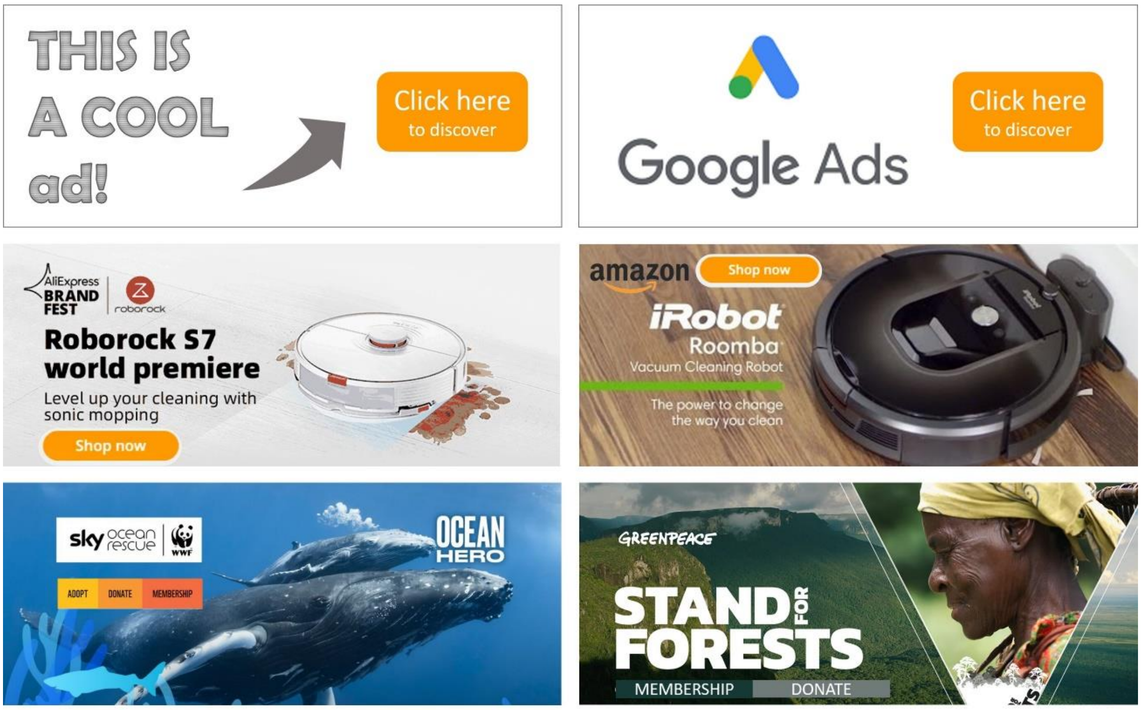

Figure 3. Layout of the banner ads used in the ad recognition task. The first column shows the three ads present in the sport news webpage (from top to bottom: banner_cool, banner_robot, banner_nature). The second column shows the three ads not present in the sport news webpage (from top to bottom: banner_cool_mock, banner_robot_mock, banner_nature_mock).

Metrics and Analysis

We gathered behavioral (i.e., clicks and ad recognition) and implicit (i.e., eye-tracking) data. We considered as independent variables: the task (Read Task × Click Task), the position (top, middle, bottom), and the time after exposure (one day × one week) depending on the type of the analysis. The data was analyzed in SPSS 26.

For eye tracking, we selected four metrics: (i) time spent in fixations, which is the sum of the total time in ms spent in fixations in a certain area of interest; (ii) fixation count, which is the total number of fixations within a certain area of interest; (iii) revisits, which is the number of times a certain area of interest is looked back; and (iv) time to the first fixation, which is the time in ms that a certain area of interest was first fixated since the starting of the stimulus presentation. To answer H1, we standardized the metric time spent in fixations by calculating the total time each participant looked at the three banner ads in relation to the total time each participant spent on the webpage. The eye-tracking data were recorded through iMotions software version 9.0 (iMotions.com). Two participants were excluded from the eye-tracking analysis due to low data quality.

For behavior, we computed the number of clicks on the banner ads or another webpage element. For ad recognition, we computed the number of correct answers: a “yes” answer to the ads shown and a “no” answer to the ads not shown on the webpage. In this analysis, seven participants were excluded because they either did not complete the survey or completed it at different points in time.

Results and Discussion

The Goal Effect

To investigate how attention to banner ads differs depending on the goal of the task—reading the news or deciding where to click—we compared both tasks. For this, we selected the eye-tracking metric of time spent in fixation as a proxy of attention paid to the ads (Pieters & Wedel, 2004). A paired-sample t-test showed that this time differed between the tasks ($t(89) = 6.62$, $p < .001$), where participants spent 11.9% of the time looking at the ads in the Click task, while only 5.5% of the time in the Read task, supporting H1. Our finding is consistent with a previous study employing a goal-oriented task (i.e., finding a piece of information) and a free viewing task (Resnick & Albert, 2014). The authors found increased visual attention to the banner ads located either at the top or lateral parts of the webpage in the free-viewing task (6.6% of the total dwell time) compared to the goal-oriented task (4.4% of the total dwell time). Therefore, our study confirms the effect of task-goal and expands it to the reading context..

In our experiment, the area covered by the three banner ads represented 10% of the website's content area. Thus, the 5.5% of total time spent looking at the banners in the Read task is roughly half of the expected viewing time if we consider the area comprising the ads. Time spent viewing an ad indicates the level of cognitive avoidance (H. Li et al., 2002). Thus, we attribute the lower time spent looking at the banner ads in the Read task to selective attention, which relates to cognitive avoidance and perceived goal impediment (Cho & Cheon, 2004). In that task, the participants were focused on processing the news information; hence, looking at the banner ads would be a source of distraction and increased cognitive load. In addition, reading news possibly evokes a serious mindset compared to a more playful mindset when browsing the webpage. Therefore, our results support previous findings on increased ad avoidance when users are in a serious compared to a playful mindset (Seyedghorban et al., 2016).

We also found that in the Read task, 93% of the participants looked at the three banners, while only 55% of participants did in the clicking task. This result might be due to the visual range covered by the participants in each task. In the Read task, the participants had to scroll through the entire webpage, but this was not required in the Click task.

The Position Effect

Clicking on banner ads was only possible in the Click task. A descriptive analysis showed that 29% of the participants clicked on one of the banner ads (banner_cool = 13%; banner_robot = 1%; banner_nature = 15%). However, attention paid to the webpage elements during the Read task could have influenced subsequent choice on where to click later. Thus, we analyzed the influence of attention paid to the ads on banner clicking for the two tasks.

According to H2a, we expect a positive relationship between attention paid and clicking. To investigate whether attention paid to the banners while engaged in reading the news during the Read task and ad position influenced ad clicking, we conducted a binary logistic regression for two out of the three ads. Only one participant clicked banner_robot, and it was therefore not analyzed here nor in the subsequent analyses.

The results showed no significant effects of any of the four eye-tracking variables nor position on further ad clicking for none of the ads, rejecting H2a for the Read task. We conducted the same analysis for the Click task. The results showed that for both ads, total fixation time was a significant predictor of ad clicking (banner_cool: *Wald* = 9.15, $p = .002$, *Exp(B)* = 1.31; banner_nature: *Wald* = 8.65, $p = .003$, *Exp(B)* = 1.22), where a longer time fixating on the ad increased the probability of clicking on the banner, supporting H2a in the case of the Click task. A previous study found that banner ads that induce attention through forced exposure receive more clicks compared to banner ads with a lower degree of forced exposure (Cho et al., 2001). The findings of our analyses imply that attention paid to the banner only matters when there is a need to consider them before making a decision: that is, a need to analyze all webpage elements to judge what is best to see next. The null effect of attention on clicking for the Read task might be attributed to the possible lack of interest in the advertised content.

To further investigate whether the time spent looking at the ads varied depending on the position of the ads, we assessed the differences between the two tasks, as well as within each task. Paired sample t-tests showed a significant difference in total time spent looking the ads depending on the task (all $p \leq .001$), where time spent in the Click task was higher than in the Read task in all positions. To evaluate how time spent in fixations on each position differed within each task, we conducted a repeated-measures ANOVA with position as a factor for each task. In the Read task, there was a significant difference among the positions ($F(2, 89) = 10.16$, $p < .001$). Pairwise comparisons (Bonferroni corrected) revealed this difference was between the top and middle positions ($p = .012$; $M_{top} = 1.78\%$; $M_{middle} = 2.48\%$), as well as the bottom and middle positions ($p < .001$; $M_{bottom} = 1.39\%$; $M_{middle} = 2.48\%$). Top versus bottom was only marginally significant ($p = .087$). In the Click task, there was no significant difference across the positions ($F(2, 50) = 1.54$, $p = .224$). We have predicted in H2b that the bottom location would lead to less attention. Our prediction was only partially correct. In the Read task, the bottom location indeed received less attention than the middle location, but no difference was found when comparing it to the top location. Some studies have also demonstrated low attention to bottom-located banners (Muñoz-Leiva et al., 2021; Outing, 2004), whereas other studies showed reduced attention to top-located banners compared to lateral or embedded banners (Burke et al., 2005; Goodrich, 2010; Kuisma et al., 2010). In the Click task, however, all locations did not have different attention levels among them. It is important to note that in the clicking task, only 55% of the participants looked at the three ads.

Regarding how ad position on the website relates to ad clicking, regardless of the banner ad creative, the percentage of total clicks for each position were: top = 34.5%, middle = 44.8%, bottom = 20.7%. Although the bottom ads received fewer clicks, there were no statistically significant differences in clicks among the ads $X^2(2, N = 100) = 2.55$, $p = .279$), which does not support the second part of H2b. This result aligned with the attention paid to the ads in the Click task, in which there was no difference in attention among the ads. However, ads in the middle position tended to receive a higher number of clicks, followed by the top and then the bottom ads. This pattern was the same for the attention paid to the ads in the Read task. The results of the logistic regression did not show any influence of attention on further ad click, but it is possible that we did not have enough power to detect an effect, as only 29% of the participants clicked on a banner ad.

The Decay Effect

H3 is related to memory of the ads over time. Thus, for each time point—one day after and one week after exposure—we have computed the percentage of participants that correctly recognized each banner ad. We have also computed the correct absence of recognitions for the banner ads that were not present on the webpage. We performed a McNemar test to assess whether there were differences between the time points. The results of all analyses are shown in Figure 4.

The analysis of Figure 4 reveals that almost all participants correctly answered when a banner ad was not present on the webpage the next day they participated in the experiment. In our experiment, the percentage of false positives was much lower than the ~20% reported in the literature (e.g., Drèze and Hussherr, 2003), not supporting H3a for the mock banners. However, in line with H3b for the mock banners, the percentage of false positives increased one week after exposure, reaching the benchmark levels.

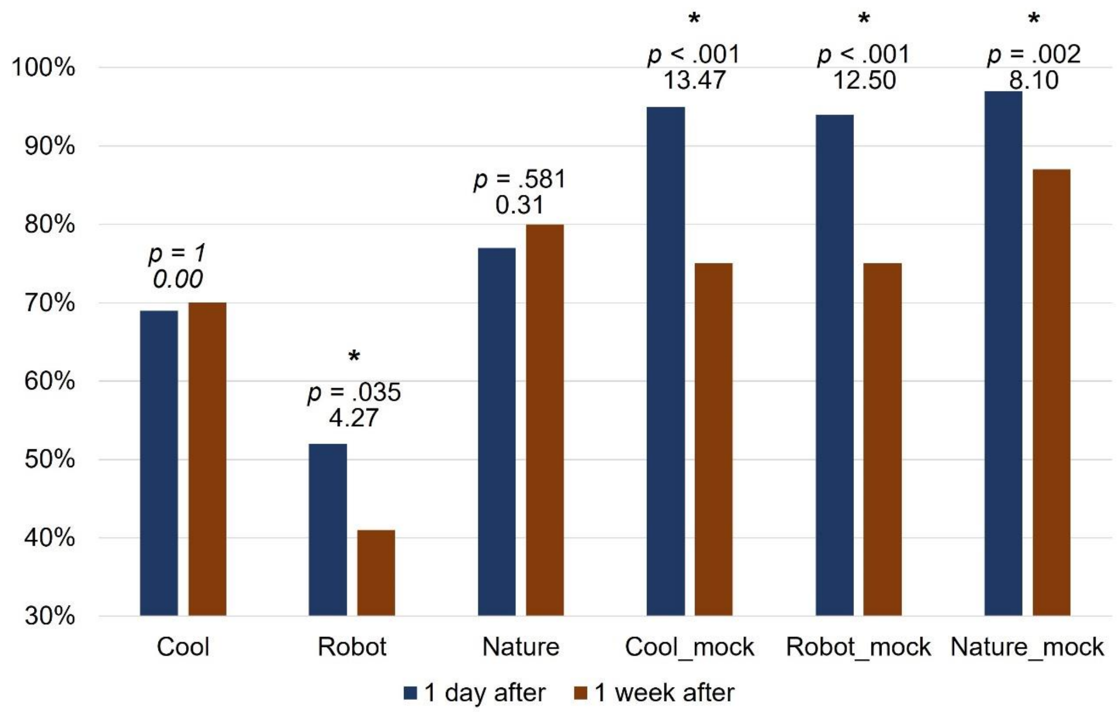

Figure 4. Results for ad recognition. Percentage of participants that correctly recognized each banner ad (a "yes" answer in the survey question) and a correct no recognition for the banner ads that were not present on the website (a "no" answer in the survey question) in each time point. * $p < .050$. The number below the p value refers to the McNemar statistical test: X^2 *(1, N = 93)*.

The results for the webpage banners showed a large percentage of banner ad recognition both one day and one week after exposure for two out of the three ads, much higher than benchmark levels (Burke et al., 2005; Drèze & Hussherr, 2003; J. Lee et al., 2015; Schmidt & Maier, 2022), which goes against H3a for these real banners. In fact, there was no statistical difference in ad recognition between the two time points for the two banners, contrary to our prediction in H3b for the real banners. In summary, the results demonstrate that aided memory for the banner ad was remarkably high and remained stable over time. However, for banner_robot, the percentages were not better than the chance level and were in the range found in previous literature. Considering that none of the three banner ads were related to the news participants read, and possibly none of them were relevant to the participants, the findings suggest a possible effect of ad creativity on ad memory (but see Yang *et al.*, 2021).

To explore whether clicking on the banner was further related to banner recognition, we conducted a chi-square test with banner ad clicking and banner ad recognition for the banner_cool and banner_nature. The results indicated no significant relationship between banner clicking and recognition on the next day. However, there was a significant relationship for recognition in the next week (banner_cool: X^2 (1, N = 94) = 5.28, p = .022; banner_nature: X^2 (1, N = 94) = 4.17, p = .041).

We conducted a Pearson correlation between attention paid to the ad using the total time spent fixating on the ad for each task and ad recognition for the two time points. Banner_robot was not analyzed because recognition was at the chance level. The results showed no significant correlation between those variables for either of the ads, which aligned with the findings of a similar recent study (Schmidt & Maier, 2022) but contradicted other related studies (J. Lee & Ahn, 2012; Muñoz-Leiva et al., 2021)

Table I summarizes the findings of the study.

Table I. Summary of the findings.

Hypothesis	Outcome	Finding
H1: Attention paid to the banner ads is inversely proportional to the cognitive demand of the task being performed.	Supported	Visual attention paid to the banners while performing the Read task, a more cognitively demanding task, was lower than while performing the Click task, a less cognitively demanding task.
H2a: There is a positive relationship between attention paid to a banner ad and clicks on the ad.	Partially supported	The visual attention paid to the banners while performing the Read task was not related to further ad clicking. However, visual attention measured by total fixation time to the banners during the Click task was positively related to ad clicking.
H2b: The bottom position leads to less attention than the middle and top positions, hence leading to decreased ad clicking.	Partially supported	In the Read task, visual attention given to the banner ad located in the bottom position was lower than the middle location, but no difference was found when comparing it to the top location. In the Click task, visual attention given to the banners was similar across the positions.
H3a: To find similar results as those of previous studies for real (~20–65% of hits) and mock (~20% of false positives) banner ad recognition after one day of exposure.	Rejected	The percentage of false positives for the mock banners was much lower than the ~20% reported in the literature. The percentage of hits for the real banners was much higher than benchmark levels for two out of the three banners, while it had benchmark levels for the other banner ad.

H3b: A decay in ad recognition of both real and mock banner ad recognition after one week of exposure compared to after one day of exposure.	Partially supported	For the mock banners, the percentage of false positives increased one week after exposure, reflecting a decay in ad recognition (in this case, recognition that it was not present on the webpage). For the real ads, there was no statistical difference in ad recognition between one day and one week of ad exposure for two out of the three ads, while there was lower ad recognition for the other ad.

Conclusion

Companies continue investing in banner advertising despite consumers' avoidance of this form of advertising. Therefore, this study used a recreated webpage of an existing site, two usual tasks of reading the news and deciding what to see more, and eye tracking to investigate visual attention given to ads embedded in webpage content dependent on the task being performed. We also investigated how attention, banner clicking, and banner recognition relate to each othe.

Our main finding was that consumers ignore banner ads embedded in webpage during a focused task, but attention to banners increases in the absence of a goal-oriented process. In addition, banner clicks do not depend on the banner location, but middle locations tend to lead to more clicks. Even though visual attention toward banners during a goal-oriented task does not seem to influence banner ad clicking, this is not the case when users are engaged in a free-browsing mode. Most importantly, it is not necessary to pay full attention to a banner ad to be able to recognize it afterward.

Theoretical Implications

Our study contributes to the knowledge of how consumers attend to online advertising depending on whether they are involved in a goal-oriented activity or not. It differs from most of the existent studies investigating online banner advertising by assessing the performance of banner ads embedded in main website content: in our case, between paragraphs of a piece of news. In accordance with previous marketing research on online banner ads (e.g., Resnick and Albert, 2014) and research in the psychology and neuroscience fields (e.g., Dayan *et al.*, 2000; Gazzaley and Nobre, 2012), we have shown that when consumers are engaged in a focused task, they drive attentional resources to the task performance at the expense of directing visual attention to task-irrelevant stimuli, such as banner ads. However, when consumers are freely navigating a website, elements of the webpage (e.g., banner ads) seem to enter the “consideration set” of attention when they would be disregarded in other situations.

The deliberate avoidance of paying attention to banner ads can be indirectly measured using click-through rates (Drèze & Hussherr, 2003). Furthermore, it is accepted that in many situations, the location of eye fixation is a valid proxy to infer how much visual attention is given to a fixated element (Wedel & Pieters, 2006). Thus, eye-tracking metrics are appropriate to measure whether consumers attend to banner ads (Casado-Aranda & Sanchez-Fernandez, 2022), regardless of the task being performed. Indeed, there is a call for employing eye-tracking in ad avoidance research (Çelik et al., 2022). In this sense, our findings also contribute to a better understanding of how visual attention and banner ad position relate to marketing outcomes, such as ad clicks and recognition after exposure. While position does not seem to influence the probability of clicking on an ad, we have found that ads located in the middle perform well compared to ads located toward the top and bottom of the content. This supports previous research testing traditional far most top and lateral positions, as well as other positions (Burke et al., 2005; Goodrich, 2010; Kuisma et al., 2010; Muñoz-Leiva et al., 2021; Outing, 2004). While previous literature suggests that visual attention and clicking are positively correlated (Egner et al., 2018; Goodrich, 2010, 2011), our study suggests that this holds only when consumers are not involved in a goal-oriented task.

Considering memory effects, most past studies evaluated banner recognition or recall soon after ad exposure (e.g., Burke *et al.*, 2005; Drèze and Hussherr, 2003; Lee *et al.*, 2015; Schmidt and Maier, 2022). We add knowledge to this body of research by demonstrating that although attention to banner ads is shared with other webpage elements, consumers still can recognize the banners to which they were exposed one day and even one week after exposure. This indicates that information survived short-term memory and was stored in the long-term memory for at least one week. Conversely, in the case of mock banner ads (i.e., not present on a webpage), consumers are fairly accurate when identifying what ads they do not recognize in short-term periods (i.e., one day after the experiment), but they start to get confused in long-term periods (i.e., one week after the experiment). This demonstrates that memory is susceptible to failures, especially over time: a phenomenon largely recognized by neuroscience (Silva & Josselyn, 2002). Our results indicate that memory mistakes are more likely to occur for information not encountered prior than for information to which participants were exposed.

Managerial Implications

On the managerial side, metrics such as click-through rates suggest that online banner ads are an ineffective promotional marketing tool. However, the prevalence of banner ads on websites seems to contradict this. Supporting marketing practices, our results imply that online banner ads are indeed effective promotional means.

Our study has shown that although consumers seek to avoid looking at banner ads while engaged in goal-oriented tasks, their gaze still crosses banners embedded in the webpage content. Thus, managers can benefit from the mere exposure effect, at minimum (but see Duff and Faber, 2011). Advertisers are also advised to create banner ads aiming to increase the total time fixating on the banner because this can boost ad clicks when consumers are freely browsing a website. However, we found no correlation between attention paid to the banner ad and its subsequent recognition. Managers can positively interpret this result because even with low attention paid to the ads, a high percentage of our participants was able to recognize two out of the three banner ads one day and one week after exposure. This indicates that some information was processed and stored in the consumers' memory, which aligned with previous findings (e.g., Burke *et al.*, 2005; Drèze and Hussherr, 2003). Moreover, in our study, banner ad recognition was higher than benchmark levels. We speculate that this is due to the position of the banners on the webpage. Most of the past studies have assessed memory effects on banners located in traditional positions: horizontally at the top and lateral banners. In contrast, we placed the banners within the news content of the webpage, as many websites currently use this format. A recent meta-analysis found that consumers are becoming more accustomed with intrusive elements in online settings, decreasing the impact of irritation on consumers' attitude (Lütjens et al., 2022). Thus, we suggest brands embed their ads in the content of a page instead of in traditional locations due to its positive effect in ad recognition. However, further research is needed to fully understand the differences between these two strategies: whether to have the ads mixed with the webpage content or not.

Limitations and Future Directions

This study has limitations. First, the experiment was conducted in a laboratory setting with pre-determined instructions, which can hamper real behavior. Second, we did not evaluate the relevance of each ad for each participant and the effect of creative elements, including contrast levels, which could have influenced the results (Chiu et al., 2017; Drèze & Hussherr, 2003; Resnick & Albert, 2016). Third, we tested our hypothesis only using a desktop version of the stimulus. Recent research has shown that viewing patterns and ad memory can differ from desktop to mobile devices (Schmidt & Maier, 2022). Fourth, we did not counterbalance the order of the tasks. Although a similar study did not find any effect of task order in any eye-tracking metric (Resnick & Albert, 2014), the order of the tasks could have affected our results. Fifth, the term “free browsing” referring to the Click task may not be entirely correct, as the task required participants to click on something. Therefore, the task included a low goal-oriented process (Seyedghorban et al., 2016).

Future research can address the limitations of this study, particularly how our findings replicate in mobile settings. Furthermore, new types of banner ad formats embedded in content (e.g., banners that appear and disappear with content scrolling) deserve further exploration to better guide designers and managers on their choices. For this, the use of neuroscience tools besides eye-tracking (e.g., electroencephalography) may add value to self-reported and behavioral metrics.

CHAPTER 5

COMPLEMENTARY STUDIES

In this chapter, we present four complementary studies. These studies approach other forms of marketing communication and employ neurophysiological metrics not used in the above-reported studies. Therefore, this chapter servers to support the value of assessing neurophysiological states to investigate marketing communication elements in digital and extended reality contexts.

In the previous chapters, we assessed marketing communication elements more generally: the interplay between user and firm-generated content, the connection between brand-related cues and brand logo, and the strategy of placing online banner advertising embedded in the webpage content. The studies presented next deeper our understanding of the effects of more specific features of marketing communication elements: congruence of an ad with the page content, levels of narrativity in ads, and augmented-reality applied to ads. Furthermore, the last study is an initial step in the investigation of marketing outcomes in the metaverse.

Study 1 - Congruence of third-party adverting with the social media content

In this study, we investigated the impact of congruent/incongruent third-party ads in Trip Advisor on intentions to visit the restaurant by conducting an online study and a lab study using eye-tracking to investigate visual attention to the ads.

Study topic

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 et al., 2017), scant attention has been devoted to analyzing online ads embedded in social media sites through unconscious measurements, such as neurophysiological tools.

A research question that remains underinvestigated 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 et al. (2013) found that incongruence increases the visual attention paid to ads, whereas congruence improves ad recall. Kononova et al. (2020) showed that brands advertised in context-irrelevant ads were more recognized than brands advertised in context-relevant ads.

Therefore, we aim 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”). For this, we conducted an online questionnaire to assess the impact of congruence/incongruence on ad recall and measured the visual attention paid to embedded ads through eye-tracking.

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

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 (D. Y. Kim & Kim, 2021). This is important for advertisers as it is key for the decision on where to place ads. Moreover, the strength of ad congruence varies based on the properties that match the ads to the context in which they are embedded (Dahlén et al., 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 magazines positively affects ad recall (Moorman et al., 2002). De Pelsmacker et al. (2002) examined the 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 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 et al. (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:

RQ1: Does ad-context congruence on social media increase ad recall?

Although behavioral data provide 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 the brain (Bagdziunaite et al., 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 et al., 2019).

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 et al., 2007). Simola et al. (2013) suggested that incongruence increases the visual attention paid to ads, whereas congruence improves ad recall.

Accordingly, we pose RQ2:

RQ2: Does ad-context congruence on social media increase the visual attention paid to the ad?

Online study

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 x 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 .50 (using a 95% C.I.), and the four incongruent stimuli all had means below .50 (95% C.I.).

Here 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 x 2 design with ad congruence (congruent x incongruent) and rating valence (positive: 4.5 stars x 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 x four conditions). The presentation order was randomized across participants.

Data collection, sample, and procedure

The data were collected in January 2020. The 295 participants, whom 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 (Figure 1). 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 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).

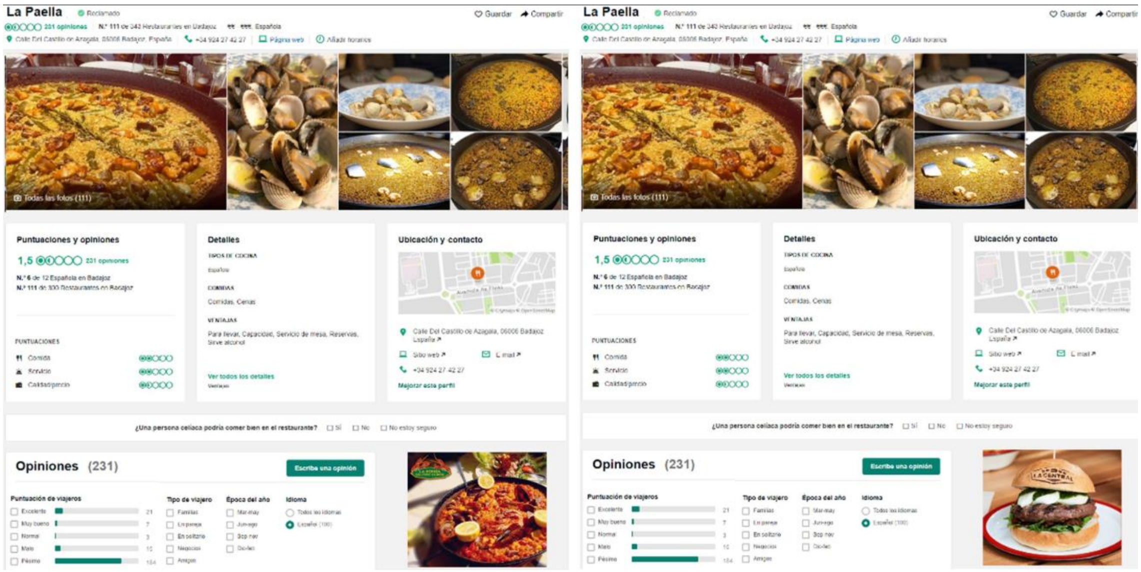

Fig. 1. Example of one of the four stimuli. Left picture: stimulus with a congruent ad. Right picture: stimulus with an incongruent ad.

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 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. Figure 2 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 (Figure 3).

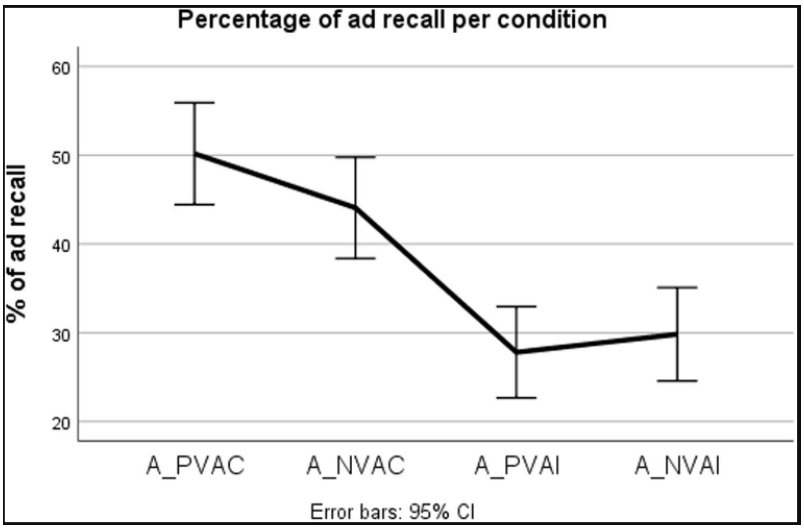

Fig. 2. Percentage of ads correctly recalled per condition. Error bars represent 95% confidence interval

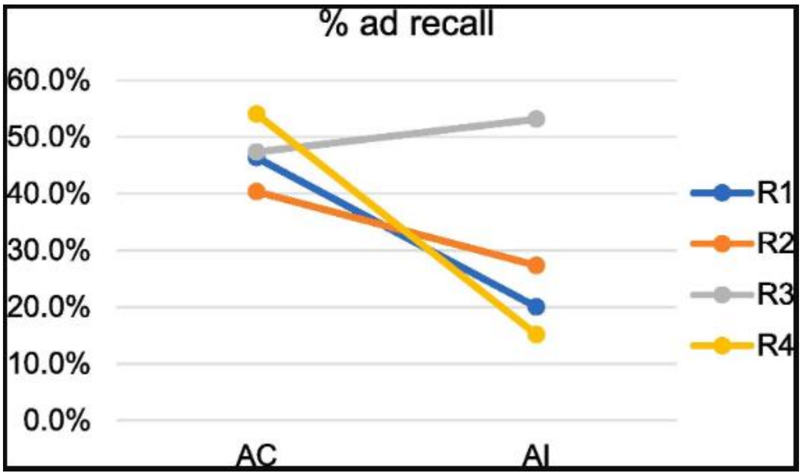

Fig. 3. Percentage of ads correctly recalled per restaurant type. Data were combined based on valence (AC = PVAC + NVAC, AI = PVAI + NVI). The error bars are omitted to facilitate visualization.

RQ1 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 the 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 et al., 2014; Simola et al., 2013).

Eye-tracking study

The laboratory study was designed to obtain unbiased insights into the effects of ad congruence on visual attention (RQ2). To this end, we collected neurophysiological data through eye-tracking.

Experimental design

We used the same task and design as for the online study. In addition to the metrics already described previously, here 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.

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 x 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 the online study, here the participants viewed each TripAdvisor stimulus for 30 seconds.

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 the lab study did not replicate the results of the online study. 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 Figure 4). 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.

The laboratory results showed 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 the number of visits metrics, and no difference in the attention paid to the ads, measured through the time spent in fixations and the 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 30s, and were in a higher-pressure environment than the online participants. The data showed that the online participants spent less than 30s on each stimulus.

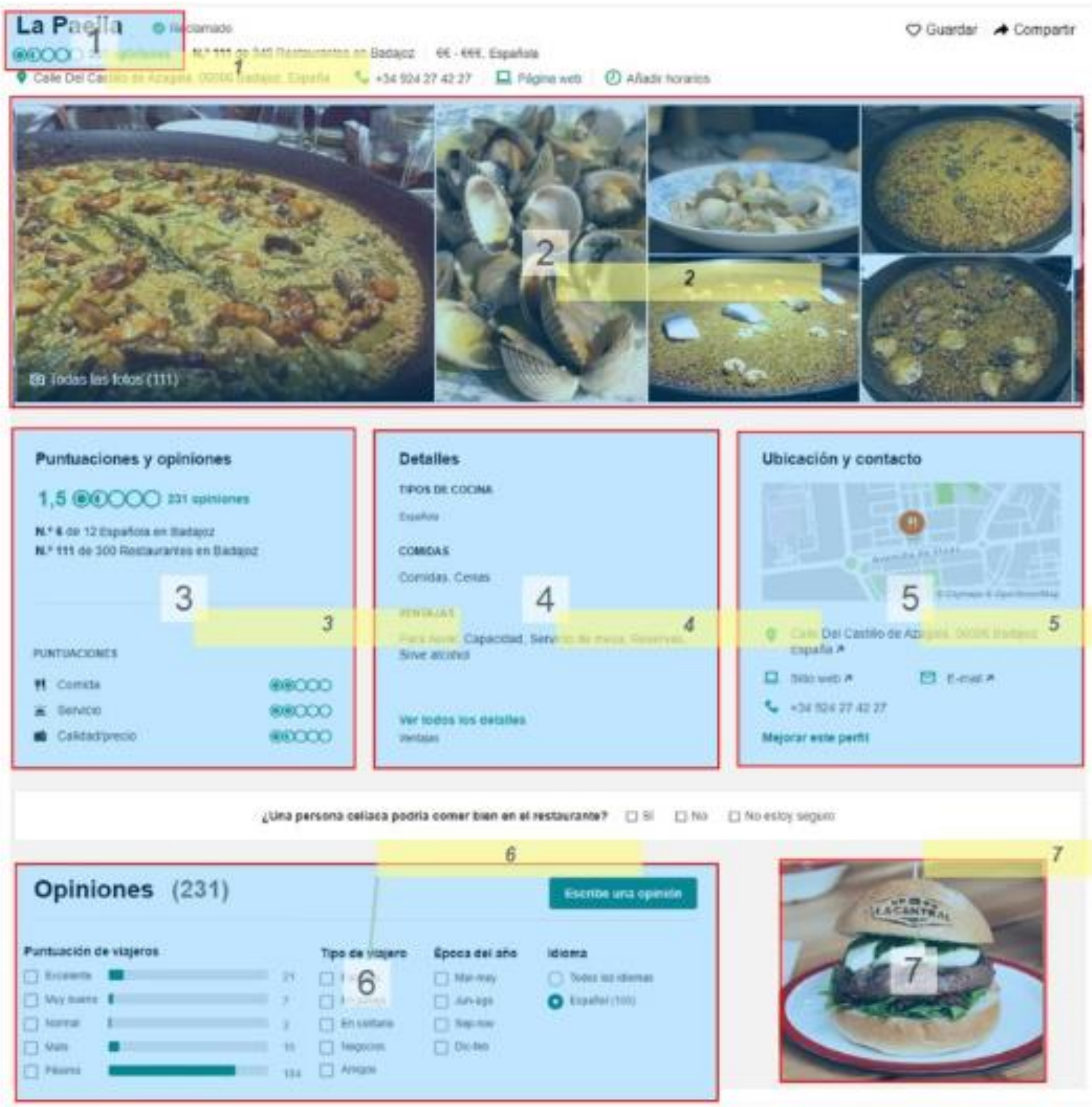

Fig. 4. Example of the distribution of the AOIs in one of the stimuli. The numbers indicate the label of each AOI.

Study conclusions

We 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 are geared toward processing the message centrally. Priming the relevant associative structures, in this case, is not important.

This study provides insight into which online advertising content (incongruent/ congruent) to use on social media such as TripAdvisor. Ad congruence, editorial content, and viewing time should be taken into consideration. When consumers peripherally process, subtle types of congruence can make a difference in ad recall. 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.

Study 2 - Conscious and non-conscious responses to branded narrative advertising with different narrativity levels

In this study, we investigated the impact of narrativity level in video ads on ad-related variables by conducting a lab study using self-reported, GSR, and EEG metrics.

Study topic

Narrative advertising leads to transformational experiences that ultimately increase message comprehension (Bruner, 1991). In fact, advertising hardly lacks narrative elements (Dessart, 2018; Wilkens et al., 2005). The concept of narrative has many context-dependent definitions. In advertising, two elements feature a narrativity style: event chronology and causality (Brechman & Purvis, 2015; Escalas, 2004). However, it is important to differentiate narrative from narrativity (Ryan, 2005). According to Ryan (p. 6), "being a narrative" depends on the audience's acknowledgment of the sender's intention to evoke a narrative script, whereas "possessing narrativity" refers to the ability to evoke such a script regardless of an author's intention or existence. In this sense, narrative ads can differ in their degree of narrativity. It is, however, not obvious how different narrativity levels impact ad and brand responses. Although many studies have been conducted on narrative advertising (Chang, 2009; Dessart, 2018; Escalas, 2004; Grigsby & Mellema, 2020; E. (Anna) Kim et al., 2017), they mostly focused on investigating storytelling vs. argument-based ads. However, narrativity is shown to be better represented by a continuum instead of story presence or absence (van Laer, Edson Escalas, et al., 2019). Thus, our study considers the increasing use of narrative ads (i.e., ads in a storytelling format) to investigate whether different degrees of narrativity lead to different consumer responses toward the ads and brands.

Both cognitive and affective processes are involved in narrative processing (Brechman & Purvis, 2015; van Laer, Feiereisen, et al., 2019). However, most of the previous studies use metrics that provide conscious responses, which tend to capture subjective information (Poels & Dewitte, 2006; Venkatraman et al., 2015). Because implicit cognitive and affective processes toward an ad are related to non-conscious measurements, the use of neurophysiological tools naturally complements traditional advertising research methods (Plassmann & Karmarkar, 2015; Venkatraman et al., 2015). With this approach, this study differentiates from previous marketing studies that have relied solely on self-reported metrics to assess consumers' ad and brand perceptions or the mechanisms of ad persuasion.

Motivated by the potential of narrative advertising and the value of combining self-reported and neurophysiological metrics for advertising research, we aim to assess conscious and non-conscious responses to narrative ads of varying narrativity degrees. To accomplish this, we conducted an experimental study using real video ads with high and low narrativity levels. Two sets of metrics were gathered: conscious responses through a questionnaire and non-conscious responses through neurophysiological tools, namely electroencephalography (EEG) and galvanic skin response (GSR). (Here we use the word non-conscious to represent spontaneous body and brain reactions to a stimulus.)

Narrative advertising

Video ads may possess different narrativity levels. Ryan posits that the degree of narrativity depends on how many of the following conditions are met:

> (1) narrative must be about a world populated by individuated existents;…(2) this world must be situated in time and undergo significant transformations; (3) the transformations must be caused by non-habitual physical events;…(4) some of the participants in the events must be intelligent agents who have a mental life and react emotionally to the states of the world; (5) some of the events must be purposeful actions by these agents;…(6) the sequence of events must form a unified causal chain and lead to closure; (7) the occurrence of at least some of the events must be asserted as fact for the story world; and (8) the story must communicate something meaningful to the audience (Ryan, 2007, p. 29).

Therefore, a video ad that fulfills all eight conditions has the highest degree of narrativity, whereas this degree lowers as fewer conditions are met.

Previous studies from Chang (2009), Escalas (2004), and Kim *et al.* (2017) have shown the overall superiority of narrative advertising to non-narrative advertising with respect to ad and brand perceptions, with exceptions conditioned by certain factors (Chang, 2009; Dessart, 2018; Grigsby & Mellema, 2020). Escalas (2004) demonstrated that upon successful mental stimulation, narrative advertising prompts recipients' mental engagement with ad content. Moreover, emotional content tends to play a key role in narrative advertisements, while analytical content and argument-based persuasion are avoided. Narratives also generally improve people's ability to memorize information (Bower & Clark, 1969). However, a deeper understanding of how narrative-specific factors, such as narrativity level, influence consumers' ad and brand perceptions, requires further examination.

Transportation is often a proposed mechanism to explain how narratives influence cognitive and affective processes, and consequently, reactions to narratives (Escalas, 2004; Green & Brock, 2000). Transportation is a specific mental state (Karpinska-Krakowiak & Eisend, 2020), a focus of attention, that people are more likely to experience when attending to narratives compared to other information formats (Green & Brock, 2000). With a broader perspective, Kim *et al.* (2017) state that four independent process variables jointly explain the enhanced persuasion effects of narrative vs. non-narrative ads on attitudes toward ads and brand evaluation. These process variables are the degree of emotional involvement with the ad, the degree of pleasure and entertainment perceptions associated with the ad, the degree to which the information from an ad is perceived as truthful, and the degree to which the advertised product or brand is perceived to help achieve consumption goals.

Past research has investigated differences between narrative and non-narrative ads, but they have not focused directly on differences in perceptions toward narrative ads with different narrativity levels. In the online review context, a study found that reviews with better-developed events and characters are more engaging and persuasive than less storified reviews (van Laer, Edson Escalas, et al., 2019). We consider that it may be easier to recognize and judge “clear” narratives over ambiguous or incomplete ones, given that narrative cognitive functions lead humans to try to narrativize any event. This might reflect on ad and brand perceptions, which often come from affective and cognitive dimensions (Eisend & Tarrahi, 2016; Rosengren et al., 2020). Thus, we selected a set of variables that is frequently used in advertising research. These variables include ad liking and feelings of entertainment to capture conscious affective responses, attention paid to the ad, ad understanding, and brand interest to capture conscious cognitive responses, among other variables. We hypothesize that:

H1: Ads with high narrativity levels will generate more positive conscious perceptions of (i) ads and (ii) brands than ads with low narrativity levels.

Neurophysiological metrics capture instantaneous, non-conscious biological reactions toward a stimulus. Recent literature shows that these metrics add value when assessing ad effectiveness, especially regarding emotional responses (N. Lee et al., 2018; Venkatraman et al., 2015). For example, skin glands secrete sweat proportionally to how emotionally arousing a stimulus is; GSR thus provides a direct measure of arousal, although without indicating its valence (Caruelle et al., 2019).

In the neurocognitive domain, EEG signals can also be used to infer emotional processes (Alsharif et al., 2021), such as the valence of arousal and approach-avoidance behavior toward a stimulus. In particular, approach or avoidance behavior measured through frontal alpha asymmetry is increasingly used in consumer neuroscience research (Rawnaque et al., 2020). The metric is acknowledged as a measure of user preference and engagement with advertisement content (Ausin-Azofra et al., 2021). Although the theta band can indicate emotion-related responses (Vecchiato et al., 2011, 2014), is also a good marker for cognitive inferences, such as workload (Dini et al., 2022). Persuasion effects have been reported to increase in individuals facing high mental workload due to their limited cognitive capacities (Campbell & Kirmani, 2000).

Researchers have found that, at the neural level, narratives (particularly more structured ones) tend to induce similar affective and cognitive states across viewers (Dmochowski et al., 2012; Song et al., 2021). However, whether consumers perceive stories in similar ways is of great interest, as this might affect whether they ultimately engage with the advertisement as expected. Inter-subject correlation (ISC) is an appropriate neural metric for investigating shared neural responses, especially when using naturalistic stimuli, including media messages (see Schmälzle, 2022, for a discussion of the topic). This data-driven method assumes the occurrence of common brain reactions to a narrative, which improves the generalizability of the findings. By correlating neural data across individuals, this metric can identify localized neural activities that react to a narrative in a synchronous fashion (i.e., in a time-locked manner) (Nastase et al., 2019).

Previous studies have analyzed narrative ads using neurophysiological tools. A study using EEG demonstrated that attention, working memory, emotions, and imagination are present when consumers watch narrative ads, and that the degree of these variables is ad-dependent (Gordon et al., 2018). Wang *et al.* (2016) compared video ads with and without a narrative structure. The narrative ads led to higher EEG theta power in the left frontal and bilateral occipital brain regions. The theta power in the left frontal region suggested that the ads with a narrative structure were more pleasant and engaging than those without (R. W. Y. Wang et al., 2016). Cartocci *et al.* (2017) used a multimodal approach to assess effort (i.e., cognitive load), approach-withdrawal, and emotional indices for three antismoking video campaigns. Two of them were narrative-based, but one of these was labeled as "effective" and the other as "ineffective" based on official market data. The third campaign had a symbolic communication style and was labeled as "awarded" because it had won several prizes. EEG frontal theta power results indicated that the "effective" narrative campaign had the highest effort index, attributed to the complexity of the storytelling, followed by the "ineffective" narrative campaign. Moreover, EEG frontal alpha asymmetry results showed that the "awarded" campaign had the highest value for approach behavior. The "effective" narrative video also produced the highest emotional index values measured through GSR and heart rate signals, which were attributed to the empathy evoked by the ad character's personal story. These findings demonstrate that neurophysiological signals are modulated by affective and cognitive perceptions.

Even though most of these past studies investigated differences between narrative and non-narrative ad formats, the findings confirm the suitability of neurophysiological metrics to uncover non-conscious cognitive and emotional responses evoked by ads. In the consumer behavior domain, "advertising" (or marketing communications) is, in fact, the second most cited term in consumer neuroscience studies (Oliveira et al., 2022). There is, however, fragmented literature on neurophysiological responses to advertising (N. Lee et al., 2018) and insufficient literature on non-conscious responses to different narrativity levels to propose a hypothesis. Thus, we ask the following research question:

RQ1: What are the neurophysiological (non-conscious) responses to ads with high vs. low narrativity levels?

Study methodology

Design and Stimuli

We conducted a 2×2 within-subjects design with "level of narrativity" (low [LL] vs. high [HL] level) and "device" (PC vs. VR). (For the context of this thesis, we omit most of the results and discussion related to the device used for ad presentation.) The classification of the two levels was based on the criteria defined by Ryan (2007) in the previous section. It was performed by one academic expert in the field of narratology and independently confirmed by another expert. We further validated it through an online stimuli validation test to confirm that the general public also interpreted the video ads as having either high or low narrativity (Wilkens et al., 2005). Examples of the stimuli: https://i.imgur.com/ckZp1hH.mp4 (HL), https://i.imgur.com/xRL9TJ8.mp4 (LL). There were 12 video ads from diverse product categories, as recommended by Chang (2009), representing six well-known brands (Barilla, Coke, Disney, Kellogg's, Nike, and Oculus), including one LL and one HL for each brand. We used 12 videos to ensure statistical power for the EEG analysis.

The video ads were real commercials retrieved from YouTube. We edited them to remove sound, as it could be a confounding factor in the responses (Plourde-Kelly et al., 2021), adjusted the length, and added the final scene revealing the brand name if necessary. Each video ranged from 57 to 63 s long. Overall, HL videos were highly storytelling-based, while LL videos conveyed product and service features and used fewer story elements. Half of the participants watched the videos on PC first. The videos' presentation order was the same across devices but counterbalanced across participants.

Stimuli Validation Test

The stimuli validation test was conducted online using the Clickworker platform (https://www.clickworker.com) with 156 participants. Participants who failed the attention question or answered faster than the minimum required time were discarded, resulting in 124 valid answers. Each participant watched three video ads and responded to five items used by Kim *et al.* (2017), such as “the commercial tells a story” after each video ad. All items were rated from 0 = strongly disagree to 100 = strongly agree. For the analysis, we used the average of the five items to compute each ad’s perceived narrativity level.

Task and Materials

The task comprised an instructions screen, the video ads, a questionnaire answered after each ad, and an ending screen. The same videos were shown on PC and VR, with each block lasting approximately 25 min. For VR, the videos were broadcast in 2D on a large, curved screen with the default background of the Steam VR software. To measure ad memory, the participants were asked via email 15 days after the lab experiment to write a brief description of the ads they remembered. The HTC Vive Pro VR headset was used for the task performed in VR, and a 27-inch monitor was used for the task performed on PC. The EEG signals were recorded using a 32-channel (10-20 system) EEG device from Brain Products with a sampling rate of 500 Hz. The impedance between the EEG active electrodes and the scalp was kept below the minimum threshold given by the hardware company (< 25 kΩ) during the entire experiment. The GSR signals were recorded using two Brain Products, gel-based electrodes on the first phalange of the index and middle fingers.

Participants

There were 32 right-handed participants (13 female) of 16 nationalities. Other demographics are as follows. Age: M = 26.84 (SD = 4.33, range = 20–37); occupation: 69% students, 16% employed, and 15% both; highest educational level (completed or ongoing): 12% bachelor’s degree and 88% master’s degree; previous experience with VR: 16% none and 84% had used it one or more times. The participants were paid [omitted for review purposes] for their time and effort. The local ethics committee approved the study.

Data

We gathered two types of data as our dependent variables (DV): (i) conscious responses to a questionnaire, and (ii) non-conscious responses obtained by neurophysiological tools.

Questionnaire

The questionnaire aimed to capture participants' perceptions about each ad and brand while approaching issues related to narrative ad formats, such as emotive responses, hedonic value, and credibility. The questions, possible answers, and sources are presented in Table 1.

Table 1. Questionnaire used to measure conscious responses to the ads and brands.

#	Label	Question	Scoring	Source
1	-	Have you seen this ad before?	Yes; no	Own elaboration
2	Ad_Liking	How much did you like the ad?	0 = not at all; 100 = very much	Own elaboration
3	Ad_Sharing	How likely are you to show the ad to someone else?	0 = not at all likely; 100 = very likely	Loewenstein *et al*. (2011)
4	Ad_Attention	This commercial really held my attention.	0 = strongly disagree; 100 = strongly agree	Escalas *et al*. (2004)
5	Ad_Immersion	This ad drew me in.	0 = strongly disagree; 100 = strongly agree	Escalas *et al*. (2004)
6	Ad_Understanding	The ad claims were easy to understand.	0 = strongly disagree; 100 = strongly agree	Smith *et al*. (2008)
7	Ad_Entertainment	The ad wasn't just selling the product—it was entertaining me and I appreciate that.	0 = strongly disagree; 100 = strongly agree	Schlinger (1979)
8	Brand_Trust	The brand in the ad is likely to possess the stated ad claims.	0 = strongly disagree; 100 = strongly agree	Lee and Mason (1999)
9	Brand_Attitude	I react favorably to the brand.	0 = strongly disagree; 100 = strongly agree	Lee and Mason (1999)
10	Brand_Interest	I am more interested in the brand as a result of seeing the message.	0 = strongly disagree; 100 = strongly agree	Kim *et al.* (2009)

We created an informative label for each question to simplify referencing throughout the paper rather than indicate that the question fully captures a construct. The first three questions were always presented in the same order. The remaining seven questions (4–10) were randomized across ads and participants to avoid state-dependent effects. Question 1 served as a control for familiarity effects. Each variable was measured using a single item from scales in the literature except for one item that we created. We borrowed scales from the literature; however, we did not use them in their entirety because (i) it would increase the duration of the experiment beyond practical levels; (ii) it would lead to participant fatigue and disengagement, as they would need to answer a long questionnaire 24 times; (iii) we aimed to cover a broad range of ad- and brand-related variables; and (iv) Diamantopoulos *et al.* (2012) suggest that single items tend to produce comparable predictive validity to multi-item scales for samples sizes smaller than 50. Ad memory was evaluated two weeks later using a free recall question, that is, a question asking the, to briefly describe the ads they had seen.

Neurophysiological Metrics

We used neurophysiological metrics to provide comprehensive results primarily for affective-related responses. As Rossiter and Percy (2017) observed, emotional responses need to be measured specifically, going beyond liking-disliking or overall affect assessments. In line with this, we focused on the following affective-related metrics: arousal and its valence, and approach-avoidance behavior. Arousal was measured by the number of GSR peaks. EEG was used to (i) estimate the valence of the arousal using the frontal alpha and beta powers (Blaiech et al., 2013), (ii) measure approach-avoidance behavior calculated using frontal alpha asymmetry (Ausin-Azofra et al., 2021; Cartocci et al., 2017), (iii) evaluate cognitive load (i.e., cognitive-related metrics) using mid-frontal theta power (Cartocci et al., 2017), and (iv) assess shared neural responses through intersubject correlation (ISC). We used the following formulas for the EEG metrics:

$$\text{Valence} = \alpha\,(F4)/\beta\,(F4) - \alpha\,(F3)/(F3) \quad (1)$$

$$\text{Frontal alpha asymmetry} = \ln(F4) - \ln(F3) \quad (2)$$

For the ISC calculation, we followed the procedure for multiple stimuli provided by Cohen and Parra, 2016, and Ki et al., 2016. (A complete description of the pre-processing and processing steps of the EEG data is reported in Dini et al., 2023).

Analyses

We analyzed the questionnaire data using SPSS 26. Ad memory was evaluated through the free recall question (n = 24), with answers collected between 16 and 21 days after the first part of the study. Two participants took 27 and 47 days. The GSR data were pre-processed and analyzed using the PsPM software version 5.1.0 (Bach & Friston, 2013). For the GSR analysis, one participant was excluded (no data recorded), and 23 participants had partial data (data loss in some trials). The EEG data were pre-processed, processed, and analyzed using in-house code running in MATLAB R2020b, with some tools from the EEGLAB 2021.0 (https://eeglab.org) and FieldTrip 20210128 (http://fieldtriptoolbox.org) toolboxes. Two participants were excluded from the EEG analysis due to excessive artifacts and the loss of some epochs. Note that all metrics are exempt from inter-person variation because the same participant was exposed to all conditions.

Study results

Stimuli Validation Test

An independent-sample t-test confirmed that the scores of the aggregated HL (M_{HL} = 70.95, *SD* = 10.79) and LL (M_{LL} = 47.71, *SD* = 13.52) video ads differed ($t\ (61) = 7.554$, $p < .001$). As the means followed the same pattern ($M_{HL} > M_{LL}$) for each brand, our classification was valid.

Conscious Responses

We first checked for previous exposure to the ad, a potential confounder. For most of the ads, a maximum of two participants reported that they had or might have already seen the ads. Two ads were seen by nobody, six ads were seen or maybe seen by one participant each, three ads were seen or maybe seen by two participants each, and one ad was seen or maybe seen by six participants. Thus, we did not consider previous exposure as a control variable.

We then proceeded to test the hypothesis that HL ads produce better conscious perceptions of ads and brands than LL ads (H1) do. Due to our factorial design, we also assessed whether these conscious perceptions differ depending on the device used for watching the ads. For this, we conducted a within-subjects generalized linear mixed model for each DV (Table 1). The parameters of the model were (i) repeated measures: trial (24 trials in total per participant) and brand (four repetitions for each brand per participant); (ii) fixed factors: narrativity level (HL, LL), device (PC, VR), and their interaction; and (iii) random factors: person (including its intercept) and brand. Brand was included as a random factor because (a) the selected brands represent only a sample of the large brand population, and (b) while brand-to-brand variation is expected in every DV, we are not interested in this variation for this specific study; we focused on the effects of narrativity level and device type regardless of the brands presented. Table 2 presents the results of the fixed and random effects for each DV. Although we found some significant interaction effects between narrativity level and device type, the analyses of the simple effects demonstrated no significant differences. We, therefore, are not describing the results of simple effects.

Table 2. Results of the linear mixed model for the fixed and random effects for each DV. *p ≤ .05; **p ≤ .01; ***p ≤ .001.

		Fixed Factors			Random Factors	
		Medium	Narrativity level	Interaction	Person	Brand
DV		**F (1, 759)**	**F (1, 759)**	**F (1, 759)**	**Z**	**Z**
Ad_	Liking	2.115	12.298***	0.033	2.926**	6.074***
	Sharing	0.376	9.859**	0.041	3.441***	4.899***
	Attention	0.471	16.090***	7.756**	2.776**	4.851***
	Immersion	5.570*	9.777**	2.671	2.934**	6.004***
	Understanding	0.123	1.011	0.401	3.562***	3.064**
	Entertainment	0.017	47.234***	17.501***	3.188***	4.509***
Brand_	Trust	0.175	27.633***	1.357	3.469***	5.320***
	Attitude	4.810*	0.006	8.470**	3.274***	7.490***
	Interest	0.744	1.065	4.539*	3.449***	6.050***

Table 3. Descriptives of each DV for each condition. HL: high narrativity level; LL: low narrativity level; PC: computer screen; VR: virtual reality head-mounted display.

		Mean (standard deviation)			
DV		**HL-PC**	**HL-VR**	**LL-PC**	**LL-VR**
Ad_	Liking	57.66 (12.46)	57.23 (15.39)	50.44 (14.05)	50.49 (14.82)
	Sharing	27.11 (15.47)	27.58 (17.37)	18.50 (15.27)	19.60 (17.96)
	Attention	57.18 (15.04)	55.91 (14.79)	44.47 (13.95)	46.92 (14.06)
	Immersion	54.23 (14.24)	54.31 (11.18)	42.99 (14.79)	45.33 (13.94)
	Understanding	66.28 (18.25)	66.13 (17.53)	69.89 (15.98)	68.38 (14.83)
	Entertainment	57.94 (15.90)	56.40 (18.57)	37.86 (17.33)	40.17 (17.30)
Brand_	Trust	46.55 (19.48)	47.63 (16.52)	57.10 (15.68)	56.63 (15.58)
	Attitude	55.04 (17.04)	53.22 (16.13)	54.92 (15.70)	54.13 (15.69)
	Interest	35.76 (15.41)	35.84 (15.11)	35.98 (16.23)	37.94 (17.92)

Note in Table 2 that there were inter-subject and inter-brand variations in every DV captured by the significance of the random factors, as expected. Table 3 presents the means and standard deviations for each condition.

Regarding H1, we analyzed six metrics related to ad perception and three brand-related metrics following our conceptual background. The results presented in Table 2 and 3 showed that while the HL ads scored on the positive side, the LL ads received a neutral score. Although the Ad_Sharing scores were low—indicating that the participants were not likely to share the ads with others—the HL ads still performed better than the LL ads did. This might reflect the positive relationship between liking an ad and the intention to share it (Petrescu & Korgaonkar, 2011). To investigate this possibility, we conducted a Pearson correlation between Ad_Liking and Ad_Sharing using the average scores of PC and VR combined. Surprisingly, there was a much higher correlation between the variables of the LL ads (r = .64, p < .001) than those of the HL ads (r = .43, p = .013). Moreover, it is plausible that the path is unidirectional: Ad_Liking Ad_Sharing. Therefore, we can infer that for LL ads, liking the ad is already a more significant contributor than the intention to share it, whereas for HL ads, other factors have more significant weights.

For Ad_Attention, the participants gave higher scores to HL than to LL. We speculate that HL ads sustained more attention due to their increased storytelling properties. Related to this latter finding, and following the same patterns, participants gave higher scores to HL than to LL in Ad_Immersion.

Narrativity level did not influence Ad_Understanding; the participants rated all conditions similarly. Therefore, they could understand the claims that the ads wanted to convey regardless of their narrativity level or device. The null effect of narrativity level is supported by Ryan (2007). She argues that “judgments of narrativity are variable, and that they are not crucial to understanding” verbal or visual information (p. 31).

Regarding Ad_Entertainment, the higher scores for HL reflect that narrative advertising is generally perceived “as a form of entertainment as much as persuasive communication” (Ching *et al.*, 2013, p. 417). Including more product-related information might increase awareness of the ad’s commercial intention and hamper feelings of entertainment.

For the brand-related metrics, participants gave lower scores on Brand_Trust for HL than LL. The direction and size of this effect (see means in Table 4) were unexpected because during immersion in the story, possible counterarguments to the story claims become less accessible (Green & Brock, 2000). Therefore, as Ad_Immersion was higher for HL than LL, we would also expect HL ads to score higher in Brand_Trust. Argument strength is one factor that might have caused LL ads to score higher than HL. When participants were not cognitively depleted beforehand, Chang (2009) found that strong arguments led to better attitudes toward the ad and brand than weak arguments did. Moreover, in Lien and Chen's (2013) experiment, argument strength positively affected attitudes only for non-narrative ads. Another complementary explanation concerns the types of claims made in the ads. The HL ads focused on storytelling without making explicit claims about the product and brand. In contrast, the LL ads had some product-related information, which might have increased participant awareness of the product's features and benefits. Although we neither measured nor controlled for argument strength or claim type across the conditions, the superiority of LL ads on Brand_Trust was consistent for all six brands.

Narrativity level did not influence Brand_Attitude or Brand_Interest. As narrative transportation can generate a change in attitude and intentions (van Laer et al., 2014), our findings imply that both levels lead to similar transportation effects; otherwise, we would expect to find HL ads performing better than LL in both metrics. Another possible explanation is that the participants already had strong opinions about the brands, but we did not measure this variable.

To investigate whether the narrativity level influenced memory for the ads, we aggregated the data of ad recall for each condition. If the participant described the ad with any length, we considered it as recalled, otherwise was non-recalled. We expected the potentially higher affective component of HL ads to create stronger emotional reactions than LL ads and improve lasting memory formation. However, we did not find any significant difference in unaided ad recall across the conditions ($X^2(1, N = 288) =$ 0.681, $p = .480$; recalled HL: 52%, recalled LL: 47%).

Non-conscious Responses

RQ1 concerns the neurophysiological responses to HL and LL ads. To answer RQ1, we conducted a within-subjects generalized linear mixed model. Narrativity level and device type, as well as their interaction, were the fixed factors, and person was the random factor. The DVs were the neurophysiological metrics (except ISC), each aggregated across brands. For ISC, we conducted a repeated measures ANOVA, with ISC as the DV.

Regarding arousal, the DV was the non-linear estimation of the number of spontaneous fluctuations in skin conductance (GSR) during ad watching. The GSR data were analyzed through PsPM software. To calculate the valence of the arousal, we used an EEG metric. The DV was the output of formula (1), aiming to identify the valence of evoked arousal. Both narrativity levels generated neutral feelings (M_{HL} = -0.09, *SD* = 0.54; M_{LL} = -0.09, *SD* = 058). Therefore, the results showed that different levels of narrativity did not influence arousal levels. A study compared three storytelling ads and found that all ads produced different patterns of continuous skin conductance and different mean GSR values (Micu & Plummer, 2010). The absence of differences in GSR across the two narrativity levels might be due to variability across the 12 ads in eliciting arousal levels.

EEG also provides insights into approach-avoidance behavior toward the ads. The DV was the output of formula (2), that is, frontal alpha asymmetry. There was no significant effect for narrativity level, device type, or their interaction. The average frontal alpha asymmetry values of each condition indicate that HL ads induced neutral behavior (M_{HL} = -0.04), whereas LL ads and both device types generated some approach behavior (M_{LL} = 0.18, M_{VR} = 0.10, M_{PC} = 0.22); however, this difference was not statistically significant. Therefore, ad narrativity level seems not to impact approach-avoidance feelings. Although the positive value for VR appears to contradict the finding for valence, both metrics had small values, which could reflect neutral emotional responses.

We then assessed cognitive load using the total EEG theta power of the mid-frontal region as the DV. There was no significant effect on narrativity level; cognitive load was the same regardless of ad type. Chang (2009) argues that narrative processing demands much cognitive capacity. Our results suggest that the narrativity level does not influence the processing demands of narratives.

To assess shared neural response, we used summed ISC over the first two strongest components. Results of the 2 × 2 repeated measures ANOVA showed a main effect of narrativity level, where ISC was higher when participants watched the HL ads than when they watched the LL ads ($F(1,28) = 4.467$, $p = .044$). (For the complete ISC results and its discussion, refer to Dini et al., 2023) ISC calculated from EEG data has been shown to predict levels of attentional engagement with auditory and audio-visual narratives (Cohen et al., 2017; Ki et al., 2016). ISC was also found to be related to perspective-taking (Lahnakoski et al., 2014) and shared understanding (Nguyen et al., 2019). In our case, high levels of narrativity better immersed participants in the story world compared to low levels. This might have eased participants to take the perspective of the character(s) in HL ads. In addition, ads with low narrativity levels might not have been so successful in leading to similar perspective taking because the story was more fragmented than in HL video ads.

Our hypothesis was partially supported. In general, high-narrativity ads performed better in all self-reported ad-related metrics except Ad_Understanding, for which there was no difference across levels. The most noticeable and consistent narrativity impact across brands was on Ad_Entertainment. The participants liked that the ads with a clear storyline were entertaining in addition to merely selling the product or service. We found different results regarding the brand-related metrics. Although Brand_Attitude and Brand_Interest did not differ across narrativity levels, the low-narrativity ads produced better Brand_Trust for all six brands. These ads showed product features and options explicitly, which seems to have increased the ads' credibility.

Concerning RQ1, we found similar neurophysiological responses to both ad types, except for higher ISC in the HL compared to the LL. The self-reported results suggested that ads with high narrativity levels would induce greater positive arousal, approach behavior, and potentially cognitive load compared to ads with low narrativity levels. However, we found that both ad types led to neutral or slightly positive non-conscious reactions—no differences in arousal level, with neutral valenced arousal as well as neutral to mild approach behavior—with no differences in cognitive load. Although the participants perceived the ads differently in a conscious way, their neural and physiological signals did not reflect these perceptions. Other studies have found disagreement between conscious and non-conscious responses. EEG frontal asymmetry evaluated awarded ads, which received high appreciation from experts and consumers.

Out of the three ads tested, only one showed significant approach behavior, while the other two did not differ from baseline levels (Ohme et al., 2010). In another study, participants indicated higher self-reported arousal for short TV scenes and movie clips presented in color compared to black-and-white; however, objective arousal measured through GSR did not differ between the conditions (Detenber et al., 2000). A more recent study found opposite responses between self-reported and physiological (e.g., GSR) metrics when watching and listening to narratives (Richardson et al., 2020). We should note that we compared ads within the same modality (i.e., videos) and type (i.e., narratives) varying only in their narrativity level. Thus, from a neurophysiological viewpoint, the narrativity level does not substantially change non-conscious responses to video ads, although our results suggest that perspective-taking is more similar for high vs. low narrativity level.

Study conclusions

Narrative has been shown to be a powerful mechanism for ad persuasion, as it can increase consumers' ad and brand evaluations. But storytelling ads vary in their narrativity levels, and it is not evident how this affects ad and brand perceptions. In this study, we chose six brands from different product categories and selected two real video ads for each brand: one with a high narrativity level and the other with low narrativity. We collected conscious responses through questionnaires and non-conscious responses through EEG and GSR signals. We used real ads from six different brands and product categories to mitigate a possible category influence, as suggested by Chang (2009). We also combined self-reported and neurophysiological metrics to obtain more comprehensive results.

Overall, ads with high narrativity produced more positive conscious responses compared to low-narrativity ads on liking, feelings of entertainment, sharing intentions, attention and immersion feelings; but ads with low narrativity led to higher brand trust, as they were perceived as more likely to follow up on their claims. In addition, there was no difference in neurophysiological responses between the two ad types; both types led to neutral or slightly favorable non-conscious reactions. However, the findings for the neural metric ISC imply that ads with high narrativity levels facilitate similar perspective-taking.

Implications

This study contributes to advertising knowledge in the following ways. First, it generally supports previous research by showing that ads with high narrativity levels evoke more positive conscious responses (e.g., liking, entertainment, immersion) than low-narrativity ads do. Second, it elucidates the neurophysiological reactions involved in narrative ad processing. We found that immediate non-conscious responses may differ from delayed conscious responses. While the brain and body signals did not generally react differently to high and low levels of narrativity, participants reported a general preference for ads with high narrativity levels when explicitly asked about it, and seem to adopt similar perspective-taking while watching those ads. Thus, our study supports the appropriateness and value of combining self-reported and neurophysiological metrics in advertising research, as each captures different processing stages; neurophysiological metrics target non-conscious and immediate responses and self-reported metrics target conscious and delayed responses.

Past research has shown that narrative ads tend to outperform argument-based ads. This might reflect the natural preference of human brains to use narratives to deliver information (Sugiyama, 1996). However, narrative inclusion does not equate to ad success (Brechman & Purvis, 2015). Stories differ in their degree of narrativity. Low narrativity levels seem to emphasize the ad’s persuasion techniques, as well as reduce ad liking and feelings of entertainment. Although narrative ads may require the audience to watch the entire ad to understand it, which is not the case for a non-narrative format (Wilkens *et al.*, 2005), ads with high narrativity levels are more engaging than low-narrativity ads. That is, they capture more attention and evoke higher immersive feelings. However, whether this is beneficial for brands requires more research. For example, Dessart (2018) found that high levels of transportation can backfire on expected marketing outcomes. In fact, ads with low narrativity levels are more trusted to follow up on their claims than high-narrative ads are. Therefore, what is the best narrativity level for an ad? We advocate both conscious and non-conscious measurements to evaluate different ad plots depending on the advertising goals. As we found, biological non-conscious metrics gathered through neurophysiological tools showed equal performance of both narrativity levels regarding arousal, approach-avoidance behavior, and cognitive load. We, however, used only the average output of each metric to compare narrativity levels, which does not provide full information about which parts of an ad are over- or underperforming. In the study by Micu and Plummer (2010), storytelling ads had very different arousal patterns. An argument-based ad elicited only flat responses across the entire ad, but the average arousal was higher for the argument-based ad. It is therefore crucial for advertisers to know whether and where their ads induce arousal peaks, as they are a clear indication of an emotional trigger. It is equally important for advertisers to assess ad moments leading to approach-avoidance behavior and increased cognitive load to adapt the story to their marketing goals. Moreover, our results of the ISC metric indicate the need to further explore engagement, perspective-traking, and shared understanding of ads varying in their narrativity level.

Limitations and future directions

However, the study has several limitations. First, we instructed the participants to watch the video ads, which implies high levels of attention toward the ads. In conditions outside the realm of study, consumers may not be fully focused. Second, there were no concurrent stimuli during ad watching, such as other stimuli in the same or different media, social presence, or noises. Third, there was no context. The ads were presented in isolation—that is, not embedded in an editorial content or programming context, which could generate spillover effects. Fourth, the ads had only visual components. We removed sound to avoid another source of variability in our measures; however, this might have altered the participants' ad perceptions.

These limitations point to new research directions. Future studies could target real-world settings (e.g., social media platforms, VR games) to assess the impact of narrativity and device on marketing metrics. It is also pertinent to investigate the effects of context and concurrent stimuli on ad processing for different narrativity levels.

Study 3 - Effectiveness of augmented reality advertising

In this study, we investigated the impact of using augmented reality in advertising on ad perceptions and ad effectiveness by conducting a lab study using self-reported, behavioral, GSR, and HR metrics.

Study topic

Augmented reality (AR) is still incipient in marketing applications, but interest in it is growing (Rauschnabel et al., 2022; Wedel et al., 2020). Forecasts indicate that the market size for extended reality will reach 100 billion US dollars in 2027 (Alsop, 2023), with the number of AR and VR users surpassing 2.5 billion by that year (Statista, 2022a). It is expected that “Augmented Reality will be as prevalent in the marketing of the future as the Internet is today” (Dwivedi et al., 2021, p.18). As Lavoye et al. (2021) and Chen et al. (2021) noted in their review and research agenda, further research is needed on whether and how AR achieves positive outcomes, such as improved brand attitudes and purchase intentions. Sung et al. (2022) recently suggested, in relation to mobile app AR-based advertising, that AR should be analyzed in the context of social media sharing, purchase intentions, brand attitudes and new brand engagement.

Using the customer journey approach (Lemon & Verhoef, 2016), this study aims to sequentially analyze (i) AR ad effectiveness, and (ii) the impact of ads on purchases through e-commerce and v-commerce (i.e., VR platform). AR-focused research has shown that AR ads have a positive impact on key advertising variables (de Ruyter et al., 2020; E. (Christine) Sung, 2021; S. Yang et al., 2020) and the impact of AR apps on sales (Tan et al., 2022). However, no studies have addressed both effects using a sequential approach with real purchase tasks. Here, we undertake a comparative analysis of the effectiveness of two types of advertising formats, AR-based and animated, through attention paid to the ad, attitude toward ads, perceived informativeness, product/brand recognition, and its effects on purchase. Therefore, our research question (RQ) addresses the two first stages of the customer journey: Does an AR-based ad (vs an animation-based ad) improve (a) ad-related metrics, (b) brand recognition, and (c) brand purchase? To answer this question, and minimize results bias, we combined self-reported, behavioral, and neurophysiological metrics (Karmarkar & Plassmann, 2019; Venkatraman et al., 2015).

Ad Effectiveness Assessment Framework

Following Rossiter and Percy (2017) schema, this study analyzes exposure, ad processing, brand communication effects, and brand purchase. Ad processing comprises four steps: attention, learning of the brand's key benefit, emotional responses, and acceptance responses. Furthermore, the stimuli-organism-response framework (Mehrabian & Russell, 1974) suggests that technological stimuli (e.g., AR ads) lead to behavioral changes (Van Kerrebroeck et al., 2017). Therefore, we focus on cognitive, affective, and behavioral effects evoked by advertising (see Eisend and Tarrahi's meta-analysis, 2016). These effects can be partially captured by behavioral and self-reported variables and complemented with neurophysiological tools (Venkatraman et al., 2015). Neurophysiological data capture automatic, unconscious processes (Karmarkar & Plassmann, 2019). That is, signals generated automatically by the brain (e.g., power changes in wave bands) and the body (e.g., changes electrodermal activity and heart rate) during reasoning and decision-making processes help to explain behavior and to assess the effectiveness of marketing communications (Karmarkar & Plassmann, 2019).

Effects of Augmented Reality in Advertising

Media richness theory (Daft & Lengel, 1986) allows to delineate differences in ad formats. AR-based ads have high degree of media richness (H. Lee, 2019), particularly due to the integration of consumers’ physical space into the ad and the possibility of consumer–ad interaction. AR technologies allow consumers to co-create by taking an active role in brands’ communication processes (Belanche et al., 2017), potentially increasing the attention they pay to the message (Mauroner et al., 2016) and user-brand engagement (Scholz & Smith, 2016). Indeed, media richness theory proposes that AR apps enhance the shopping experience (Amorim et al., 2022; Huang & Hsu Liu, 2014) and that ads with high media richness have a greater influence on attention, interest and search (Tseng & Wei, 2020).

Cognitive and affective responses to AR advertising appear to be intertwined. In fact, there is still little understanding of the drivers that motivate consumers to respond favorably to AR ads and why such ads seem to be more effective (S. Yang et al., 2020; Yussof et al., 2019). Print-based ads with AR hypermedia have been shown to score higher in novelty, informativeness and effectiveness than traditional and QR hypermedia code print-based ads (Yaoyuneyong et al., 2016). Also in printed ads, Tsai et al. (2020) demonstrated that AR ads enhanced ad informativeness and brand liking more than did non-AR-based ads. A recent study supported these findings by demonstrating that AR ads displaying AR 3D elements generate higher entertainment and informativeness perceptions, as well as ad attitude, than no-AR ads (Uribe et al., 2022).

Previous research attempting to uncover underlying reasons for the superiority of AR-based ads has indicated that entertainment but not informativeness positively affected ad attitude (Uribe et al., 2022). Moreover, AR enhances attitude toward ads through a surge in both curiosity and higher attention paid to the ad, but the impact of curiosity reduces when users become more familiar with AR ads (S. Yang et al., 2020). In line with this latter finding, Hopp and Gangadharbatla (2016) demonstrated that positive attitudes toward AR advertising dimmish with increased exposure time to the AR ad, which was attributed to a decrease in novelty effects. Still, it has been shown that for mobile ads—static vs AR-based—self-reported affect intensity is higher in the AR context (Pozharliev et al., 2022). Indeed, novelty is shown to raise interest (Izard, 2013) and partially mediate positive emotions (Mitas & Bastiaansen, 2018).

Neurophysiological responses

To our knowledge, no study has investigated AR-based advertising with neurophysiological tools, with two exceptions. The first study employed eye-tracking to identify the drivers of higher attitude toward the ad for an AR versus no-AR ad found in a previous field experiment (S. Yang et al., 2020). Participants were exposed to either a video advertisement featuring AR elements or a traditional video advertisement. The authors established that the AR ad increased ad attitudes indirectly via a surge in curiosity toward the ad, which increased attention paid to the ad, measured by the total time fixating on a pre-defined area of interest. The second study used GSR to investigate whether implicit (i.e., GSR) and explicit (self-reported) arousal can explain willingness-to-pay for a product (Pozharliev et al., 2022). Participants either saw an ad of a furniture-type product as a static electronic catalog image displayed in a mobile phone or used the IKEA Place app to see the product in AR in their physical space. The results revealed that both implicit and explicit arousal were higher in the AR condition versus the non-AR condition; however, only implicit arousal mediated the relationship between ad type and willingness-to-pay.

AR-based advertising is still a recent and novel advertising format compared to traditional formats. This fact, the developing empirical literature on AR advertising, and the media richness theory suggest that AR ads are generally superior to other ad formats. Therefore, we propose that:

H1: AR ads retain more attention than animated ads.

H2: AR ads trigger more positive ad attitudes than animated ads.

H3: AR ads are perceived as more informative than animated ads.

Effects of Augmented Reality Advertising on brand-related metrics

Interactivity in AR-based ads as well as informativeness, but not entertainment, was found to positively influence attitudes toward the product (J. Sung & Cho, 2012). Moreover, a study using traditional printed advertising (without interactivity) and AR-based advertising with different levels of interactivity showed that the higher the level of ad interactivity, the higher the probability that consumers recall the advertised brand (Mauroner et al., 2016). A study using digital ads varying in their interactive features—user control, connectedness, playfulness—found that the playful interactive mode “made users feel interested and amused”, leading to higher ad effectiveness by increasing consumers’ willingness to purchase (Su et al., 2016). Although a recent study did not find direct effects of entertainment, informativeness, and ad and brand attitude on purchase intention, it did find an indirect effect of entertainment on product purchase through ad and brand attitude (Uribe et al., 2022).

Imagery is central in advertising information processing. AR ads might be seen as a development of animated ads where digital content is embedded into the users’ view of their space. Although both ad types include imagery, self-related imagery affects purchase intentions more than non-self-related imagery (MacInnis & Price, 1987). Several Facebook AR campaigns, mainly make-up, try-on related, have been shown to be more effective (e.g., increased click-through rate, online purchases, brand awareness) than typical campaigns (Facebook, 2021).

Considering that AR-based advertising promotes self-imagery and possesses interactive features, we expect that AR ads will attract more cognitive processing than animated ads, which may influence brand/product recognition (a form of implicit memory; Shapiro & Krishnan, 2001) at the point of sale and affect purchase decisions (Valletti & Veiga, 2021). Therefore, we expect that:

H4: AR ads lead to higher product recognition than animated ads.

H5: AR ads lead to more product purchases than animated ads.

Study methodology

The study had three stages. Stage 1 included an advertising experiment; hence, it addressed the pre-purchase stage of the customer journey. Stages 2 and 3, both setting incentive-compatible tasks, covered the purchase stage. Stage 2 included two commerce platforms, which were used for a shopping task, and Stage 3 was a willingness-to-buy task. Figure 1 depicts a schematic representation of the experiment.

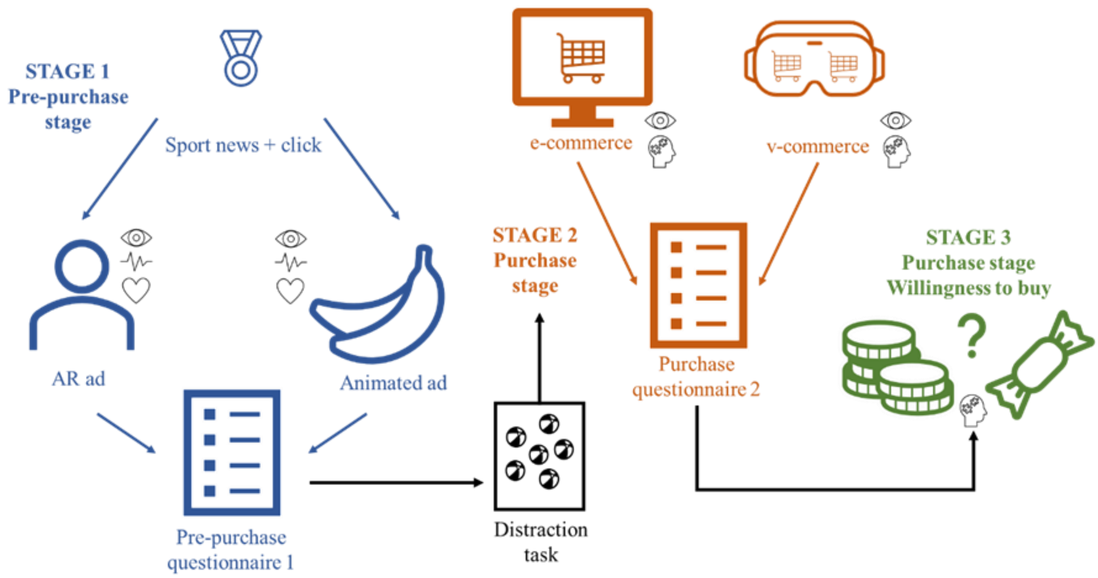

Figure 1. Schematic representation of the experiment. The small icons refer to the type of metric gathered during the task (eye = eye-tracking; line = GSR; heart = heart rate; head = behavioral).

The target product of the study was a sustainable protein bar, hereafter called the "target product". The product and the brand are real, but at the time of the experiment they had not been put on the market, hence they were unknown to the participants (they are now, in fact, on the market). We chose an unknown brand to avoid biases based on prior opinions of the brand. We recorded ET, GSR, HR, behavioral, and self-reported metrics. The study was approved by the local ethics committee.

Participants

The sample consisted of 100 participants (53 female) living in Spain, age range 22-53 years (*M* = 32.01, *SD* = 9.00), 49% workers, 16% students and 32% both working and studying. The participants were recruited via an external marketing company (n = 81), and by internal means using convenience sampling (n = 19). The external participants were paid 25€ for their time and effort. The experimental procedure lasted, on average, 45 minutes.

Design

A 2x2 between-subjects factorial design experiment with ad type (animated vs AR) and commerce type (e-commerce vs v-commerce) was conducted. (Note that for the context of this thesis, most of the results and discussions related to the commerce platform are omitted). The participants were randomly assigned to one of four groups (n = 25). The group order was counterbalanced.

Procedure and Task

The participants arrived at the university's laboratory, signed an informed consent form, and donned the GSR/HR device. In Stage 1 (the pre-purchase stage) the participants were instructed to read a pre-selected sports news item from a sports news website and then click on any hyperlink they wanted. On clicking, a new screen showed either the animated ad or the AR ad featuring the target product. After being exposed to one of the two ads, they answered a questionnaire (see metrics subsection). Before starting Stage 2 the participants carried out a six-minute (approximately) distraction task. The distraction task was either a free navigation in the Amazon website or a free navigation in a pre-determined VR environment. Stage 2 (purchase stage A): the participants were asked to buy one real snack bar brand—among 16 possible, including the target product—in a simulated e-commerce or v-commerce supermarket. The product images had been rendered by a professional developer. The participants were told that they were making an actual purchase, that is, they would receive the chosen product at the end of the experiment. Thereafter, they again answered some questions (see metrics subsection), undertook a visual product recognition task which required them to select the advertised product from among 16 possible products (presentation order was randomized across participants), and answered a support questionnaire (demographics and frequency of VR use). Following this stage, the researchers explained Stage 3 of the experiment. Stage 3 (purchase stage B – willingness to buy): the participants were given €2 and asked whether they wanted to purchase the target product with the money (the product was placed on a desk in front of them) or keep the money. Irrespective of their choices, they all received both the product and the money.

Stimuli

Stage 1: the sports news webpage was similar to a version of an existing website. The 30s animated ad, meant to be featured in the company's social media webpage, was created by the company which markets the target product. Animated ads have been shown to attract consumers' attention and deliver satisfactory marketing outcomes, such as a positive attitude toward the ad and brand, increased ad memory and purchase intention (Heiser et al., 2008; Neeley & Schumann, 2004). Many AR-based advertisements use cartoons with motion as the augmented element, for example filters applied to consumers' faces and illustrated objects displayed in the physical environment. In this sense, animated ads are a proximate format to cartoon-based AR ads, whereas live-motion video ads could be more comparable to realistic-based AR ads (i.e., ads that replicate real elements). The professionally created web-based AR ad was designed to deliver a message similar to that delivered by the animated ad. The AR-based ad mixed AR, traditional 2D animation and 3D interactive elements. The AR ad was self-paced but lasted on average about 60s. The ads can be seen here: https://i.imgur.com/BBgosGQ.mp4 (animated), https://i.imgur.com/5w55hXx.mp4 (AR).

Stage 2: 16 real snack bars, including the target product, well-known brands (e.g., Kit Kat, Twix), and niche brands (e.g., Clif, Nakd) were used. Their prices were not shown to avoid these influencing the participants' decisions. The products were displayed in four rows/shelf levels of four products each, and they maintained their actual, real-life proportions. This distribution was chosen to avoid centrality attentional bias in both vertical and horizontal directions. The product positions were pseudo-randomized (e-commerce) and randomized (v-commerce) across the participants to ensure that position did not influence gaze activity and purchase decisions. The purchase task was self-paced. The e-commerce resembled an actual online grocery website and featured a checkout procedure: the product selected goes to the "shopping cart" and the user opens the shopping cart area to proceed with the purchase by including the delivery information. The webpage displayed product pictures and descriptions. Additional information (i.e., nutritional facts) could be seen by clicking. The v-commerce was developed in Unity (unity.com) and displayed through the immersive HTC head-mounted display. The environment depicted a small supermarket with the usual elements (e.g., shelves, products, prices, banners, cashier). The snack bar shelf was positioned apart from the other shelves. Each product type had multiple units, as in a real supermarket. The participants could take hold of the snack bars and interact with them (e.g., rotate them). To purchase a product, the participants had to place it in a shopping cart positioned next to the shelf.

The study used three types of measures: (i) neurophysiological, (ii) behavioral, and (iii) self-reported. Table 1 describes the metrics.

Self-Reported. The pre-purchase questionnaire aimed to capture the four steps of ad processing, attention, learning, emotions and acceptance and, to a lesser extent, brand communication effects (Rossiter & Percy, 2017). We borrowed scales from the literature (Table 1), as follows. An "involvement with the task" scale (A. Y. Lee & Aaker, 2004) as a proxy for measuring attention paid to the ad; an "ad informativeness" scale (Sheinin et al., 2011) and an open-ended question ("In your opinion, what was the ad trying to say about the product and the brand?") as proxies for measuring the extent to which the participants learned about the brand's key benefits from the ad; a likeability question ("Give your opinion of the ad you just saw."); an "ad affective" scale (Pham & Avnet, 2004) and "ad intrusiveness" scale (H. Li et al., 2002) as proxies for measuring emotional responses to the ad; and an "ad believability" scale (Chang, 2011) as a proxy for measuring acceptance of the ad. In addition, we measured trust in the brand (Sheinin et al., 2011) as a loose proxy for brand attitude (part of the brand communication effects stage). We opted for measuring brand trust because attitude toward the brand is often positively related to attitude toward the ad (Miniard et al., 1990), and brand trust indicates competence perceptions (Aaker, 1997) rather than general brand perceptions. The purchase questions were designed to obtain more insights into brand communication effects and brand purchase. Thus, we asked an open-ended question to assess the participants' self-reported reasons for buying the chosen product ("Why did you choose the product you bought?"), and for assessing if, and how the target product was recognized ("Did you recognize the product/brand that was advertised after you read the sports news item and while you were making your purchase?"; "What made you recognize it?").

Behavioral. We recorded the product purchased and time spent in searching and shopping as behavioral metrics.

Neurophysiological. In this study we used eye-tracking (ET), galvanic skin response (GSR) and heart rate (HR) to obtain unbiased responses. ET technologies allow inferences to be made based on visual attention paid to stimuli (Orquin & Holmqvist, 2018); they have been shown to be among the best methods to achieve this aim (Karmarkar & Plassmann, 2019). The eye-tracking procedure measured time spent on fixations (i.e., total dwell time) and number of eyes visits as proxies of attention paid to the stimuli. Standardized total dwell time was used in the pre-purchase stage (advertising stimulus) to verify the time spent viewing the stimuli rather than to compare the conditions. A standardized number of eyes visits was used for the purchase stage to capture the level of relevance of the stimuli to the task (Orquin & Holmqvist, 2018). Research into affect mostly addresses the valence and arousal of the affective response provoked by ads. GSR measures arousal levels (Venkatraman et al., 2015), and HR is modulated by the valence of stimuli (Legrand et al., 2021). Thus, to assess physiological affective responses toward the ads we recorded the number of GSR peaks per minute as a measure of arousal, and heartbeats per minute (HR) as a measure of valence perception.

Table 1. Scales used in the study. The numerical scores are shown as a reference for interpreting the results, as in the experiment, the participants had only the descriptive labels on each extremity of a slider bar (with the cursor positioned initially at the center of the slider).

Stage	Type	Metric	Question	Scoring	Cronbach's α
Pre-purchase	Self-reported	Ad involvement (A. Y. Lee & Aaker, 2004)	Considering your interaction with the advertisement you just saw, you were:	0 = not at all involved 100 = very involved	.84
			…you were:	0 = not at all interested 100 = very interested	
			…you:	0 = paid little attention 100 = paid a lot of attention	
		Ad informativeness (Sheinin *et al.*, 2011)	The ad provided relevant information.	0 = Strongly disagree 100 = Strongly agree	.84
			The ad did a good job of building the product's image.		
			The ad did a good job of presenting the product's benefits.		
		Ad liking (own design)	Give your opinion about the ad you just saw. I:	0 = disliked it a lot 100 = liked it a lot	-
		Ad affective (Pham & Avnet, 2004)	Give your opinion about the ad you just saw. It was:	0 = not catchy 100 = catchy	.87
			It:	0 = didn't appeal to me 100 = appealed to me	
			It:	0 = didn't excite me 100 = excited me	
		Ad intrusiveness (H. Li et al., 2002)	When the ad was shown, I thought it was: Distracting	0 = Strongly disagree 100 = Strongly agree	.91
			…Disturbing		
			…Forced		
			…Interfering		
			…Intrusive		
			…Invasive		
			…Obtrusive		
			I think the ad is:	0 = Strongly disagree	.91

		Ad believability (Chang, 2011)	Believable	100 = Strongly agree	
			Trustworthy		
			Credible		
			Reasonable		
			Convincing		
			Unbiased		
		Ad claims (own design)	In your opinion, what was the ad trying to say about the product and the brand?	Open-ended	-
		Brand trust (Sheinin et al., 2011)	This brand is dependable.	0 = Strongly disagree 100 = Strongly agree	.84
			This brand is reliable.		
			This brand is trustworthy.		
	Neurophysiological	Attention	Total fixation time (eye-tracking)	%age of the total stimulus time	-
		Emotional responses	Had a GSR peak (GSR)	0 = no 1 = yes	-
			Number of GSR peaks	GSR peaks/min	-
			Heart rate (HR)	Heart beats/min	-
Purchase	Self-reported	Reason for purchase (own design)	Why did you choose the product you bought?	Open-ended	-
		Product recognition (own design)	Did you recognize the product/brand that was advertised after you read the sport news while you were making your purchase?	0 = No 1 = Yes	-
		Reason for recognition (own design)	What made you recognize it?	Open-ended	-
	Behavioral	Shopping behavior	Product purchase	Stage 2: 0 = other product, 1 = target product Stage 3: 0 = money, 1 = product	-
	Neurophysiological	Attention	Number of eyes visits (eye-tracking)	%age of the total new fixations on the products	-

Materials

A 23-inch 1920 x 1080-pixel computer monitor was used to present the stimuli and questionnaires. The HTC Vive Pro Eye (https://www.vive.com/uk/product/vive-pro-eye/overview/) VR headset was used to display the v-commerce environment. Gaze behavior was recorded using the Tobii X2-30 Compact screen-based eye-tracker (tobii.com), or with the ET being embedded on the HTC VR headset. GSR and HR were acquired concomitantly using the Empatica E4 wristband (empatica.com). This device has previously been used in studies combining behavioral and physiological metrics (Richardson et al., 2020). The data coming from all sensors were synchronized using iMotions software version 9.0 (iMotions.com).

Analysis

The data were analyzed using SPSS 26 and R (tidyverse, statsr, and BAS packages). The PROCESS macro 3.4.1 (Hayes, 2017) was used to analyze moderation effects. Details of the frequentist and Bayesian analyses are provided in the results and discussion section. The answers to the open question were pre-processed (e.g., removal of stop words, lemmatization) and analyzed (i.e., frequency count) using text analytics tool in Matlab 2022b. The neurophysiological data gathered from some participants were excluded due to sensor failure (i.e., no data were acquired, or only poor-quality data): ET = 7, GSR = 19, HR = 23. The neurophysiological metrics were obtained from iMotions software using the default parameters for the pre-processing steps. The eye-tracking metrics acquired from the VR device were provided by a professional developer.

Regarding a Bayesian analysis, the posterior (i.e., final) probabilities incorporate previous beliefs (i.e., priors) that can be either informative, that is, based on previous data or knowledge, or uninformative, that is, having no knowledge of a plausible distribution for the data. The choice of the prior and posterior family distributions depends on the type of data (e.g., binomial or continuous). We used a beta-binomial conjugacy family, $Be(\alpha,\beta)$, for the prior and posterior distributions. The parameters α and β define the shape of the distribution. In addition to the priors, a likelihood function defines the relationships between observed data and the unobservable parameters. The posterior distribution is then a function of prior beliefs and the likelihood function (see Rossi & Allenby, 2003, for a review on Bayesian statistics applied to marketing research).

Study results

The following results and their discussion are separate into three sections. The first section refers to the effects of AR in advertising—pre-purchase stage—and tests H1, H2, and H3. The second section refers to the effect of AR advertising on brand-related metrics—purchase stage—and tests H4 and H5. The third section complements the analysis of ad effectiveness following the Rossiter and Percy (2017) framework.

Effects of AR in advertising

Here we address the cognitive effects (i.e., attention to the ad and perceived informativeness) and affective effects (i.e., attitude towards the ad) of having AR elements in an advertisement versus not having it.

To test H1, which proposed that AR ads retain more attention than animated ads, we analysed the involvement with the ad scale (ad involvement). An independent samples t-test showed there was a statistically significant difference in attention (i.e., involvement) between the two ads ($t(98) = 2.587$, $p = .011$, $d = 0.52$). The AR ad led to higher attention ($M = 65.07$, $SD = 24.08$) than the animated ad ($M = 53.12$, $SD = 22.05$). The ET metric confirmed that the participants paid visual attention to the stimulus. The AR ad received 70.59% ($SD = 8.57$) of maximum visualization time, and the animated ad 64.41% ($SD = 6.65$). This was expected, as they were required to watch the ad.

To test H2, which proposed that AR ads trigger more positive ad attitudes than animated ads, we used a combination of self-reported ad perceptions (ad liking, ad affective, and ad intrusiveness) to define our comprehensive ad attitude metric. We conducted a multivariate general linear model because the dependent metrics were correlated among themselves, as it would be expected. The dependent variables were the average scores of each scale, and ad type was the independent variable. Ad type had no significant effect ($F(3, 96) = 0.384$; $p = .765$) on attitude towards the ad. The means and standard deviations for each variable were as follows. Ad liking: $M_{AR} =$ 64.54 (25.07), $M_{anim} = 61.66$ (21.82); Ad affective: $M_{AR} = 60.99$ (26.07), $M_{anim} = 56.23$ (19.23); Ad intrusiveness $M_{AR} = 54.74$ (20.56), $M_{anim} = 54.72$ (16.60).

Previous studies showed that the higher the attention paid to the AR ad, the higher the attitude towards the ad. To verify whether this relationship differs depending on the type of ad, we conducted a moderation analysis (model 1, PROCESS macro). The dependent variable was the ad attitude metric, calculated by averaging the three scales mentioned above. The independent variable was the ad involvement scale, and the moderator factor was the type of ad. The results showed a marginally significant moderation effect ($F(1, 96) = 3.626$, $p = .060$), where the effect of ad attention (i.e., involvement) on ad attitude was higher for the AR ad ($\beta = 0.65$, $t = 6.37$, $p < .001$) than the animated ad ($\beta = 0.45$, $t = 3.25$, $p = .002$).

We then evaluated attitude toward the ads using the physiological metrics. The GSR data showed there was no statistically significant difference in arousal levels—measured by the number of GSR peaks—between the ads, although the AR ad did generate more arousal. In the AR ad condition, 49% of the participants displayed at least one GSR peak, and in the animated ad condition 31% displayed at least one GSR peak (X^2 $(1, N = 81) = 2.67$, $p = .102$). Those who displayed peaks tended to display more peaks per minute in the AR ad condition ($M = 5.38$, $SD = 2.65$) than in the animated ad condition ($M = 4.37$, $SD = 1.96$); however, the difference was not significant ($U(32) = 154$, $p = .254$). Regarding the HR data, there were no differences between conditions ($M_{AR} = 79.79$, $SD = 12.73$; $M_{anim} = 80.51$, $SD = 13.00$; $t(75) = 0.926$, $p = .806$).

To Test H3, which proposes that AR ads are perceived as more informative than animated ads, we analysed the ad informativeness scale (ad informativeness). An independent samples t-test showed there was no statistically significant difference between them ($M_{AR} = 64.10$, $SD = 23.48$; $M_{anim} = 63.89$, $SD = 20.32$; $t(98) = 0.049$, $p = .961$).

Discussion

Ad type had a significant effect on attention paid to the ad, where the AR ad scored higher than the animated ad, supporting H1. This means the participants felt more involved with the interactive AR-based ad, in line with previous research on AR printed ads (Mauroner et al., 2016) and studies showing that ads with high media richness attracts more attention (Tseng & Wei, 2020). The possibility of playing with the ad (i.e., interacting with it), might be the main driver for this increased interest in the AR ad.

H2 proposed that the AR ad would generate more positive ad attitudes than the animated ad. Although previous studies have shown this was the case (Uribe et al., 2022; S. Yang et al., 2020), our findings from the self-reported and neurophysiological data did not show a difference in ad attitude between the two ad types, rejecting H2. Both ads generated self-reported positive feelings and similar physiological emotional responses. A study found that arousal measured by GSR was higher to an AR furniture image versus an static digital image (Pozharliev et al., 2022). Although we did not find statistical differences in GSR, our data showed the tendency of AR ads generating higher arousal. In our case, the AR-based ad featured AR elements on participants' faces; therefore, one plausible explanation for similar attitude toward the ad is that participants were familiar with AR features, mainly because of tools available in social media platforms (e.g., filters in Instagram). In fact, previous studies in AR advertising found that curiosity underlies attitude towards the ad (S. Yang et al., 2020), and that when novelty effects decrease, positive ad attitudes also decrease (Hopp & Gangadharbatla, 2016). Our demographic questionnaire revealed that 87% of the participants use Instagram (78% daily). Thus, this suggests that our sample is likely to be highly familiar with AR elements embedded on the view of the face. This familiarity effect potentially led to diminished sensitivity to our AR-based ad. Indeed, the heart rate data showed that the participants were in a relaxed state (no anxiety) while visualizing the ads. Although ad attitude was not higher for the AR ad compared to the animated ad, our results supported previous research (S. Yang et al., 2020) by showing that attention paid to ad is an important driver of attitude towards the ad, especially for AR-based ads.

Regarding informativeness, we found that both ads were perceived as slightly informative, rejecting H3. Previous studies have shown that AR ads are perceived as more useful (Mauroner et al., 2016) and informative than no-AR ads (Tsai et al., 2020; Uribe et al., 2022; Yaoyuneyong et al., 2016), which aligns with the propositions from media richness theory. However, those studies compared an ad with an AR element of the product against a static ad. In our study, the comparative advertising was an animated ad, which could deliver a higher amount of information compared to a static ad. The AR features of our AR-based ad were elements related to the brand claims, while the product was a non-AR 3D interactive element. Although the possibility of interacting with the product was also expected to contribute with informativeness perceptions, the model of the product featured its outside part (i.e., the packaging). The product packed was also shown in the animated ad. We speculated that the null differences in informativeness between the ads might be due to the stimulus type (i.e., videos) and the product itself, which does not require a thorough inspection compared to heavily design-based items, for example.

Effects of augmented reality advertising on brand-related metrics

This section addresses the cognitive effects (i.e., brand recognition) and behavioral effects (i.e., brand purchase) of the AR-based ad versus the animated ad.

Hypothesis 4 proposed that being exposed to an AR ad increases the chances of recognizing the advertised product (i.e., brand recognition) at the point of sale. We measured brand recognition through product recognition while shopping (ProdRec; self-reported) and the product recognition task (PicRec; see Methodology, procedure and task subsection). We tested H4 using Bayesian statistics (see Methodology, analyses subsection) to gain direct information on the probabilities of ProdRec and PicRec. We further investigated visual attention given to the product at the point of sale for both ad types.

In the Bayesian analysis, we assessed the posterior beta distributions and credible intervals within each condition (AR-based ad and animated ad) to calculate the probability that ProdRec and PicRec will occur in the assigned condition. The prior beta parameters for the ad conditions reflects a tendency of higher levels of product recognition for the AR ad condition vs the animated ad condition. From the posterior beta distribution, 95% credible intervals and point-mass probability were calculated. The point-mass probability is the center of the posterior distribution, and it is derived from the α and β parameters through the formula $\alpha/(\alpha+\beta)$. Table 2 presents the results of the Bayesian analysis.

To evaluate whether the type of ad influenced on visual attention to the target product, which is a pre-requirement for brand recognition, we used the ET metric number of eyes visits. We standardized the metric by calculating the percentage of the number of eyes visits made on the target product in relation to the total number of eyes visits on all products for each participant. The target product received a greater number of eyes visits than expected (the expected outcome would be 6.25%, that is, 100%/16 products). This effect was demonstrated for both ads (M_{AR} = 12.98, *SD* = 11.29, *t(46)* = -371,725, *p* < .001 from the test-value 6.5; M_{anim} 10.02, *SD* = 10.99, *t(45)* = -379,499, *p* < .001 from the test-value 6.5). An independent-samples t-test showed no difference between ad types (*t(91)* = 1.282, *p* = .203). To assess the effect of visual attention on product recognition at the point of sale depending on the type of ad, we conducted a binary logistic regression with ProdRec as the dependent variable. The independent variables were ad type, number of visits, and its interaction, as well as the commerce platform to control for its effect. The interaction between ad type and number of visits was marginally significant (*Wald* = 3.487, *p* = .062). To understand how being exposed to each add affected the impact of visual attention on product recognition, we conducted a binary logistic regression for each ad type, still controlling for commerce platform. The results showed that this impact was greater for those exposed to the animated ad (*B* = 16.492, *p* = .016) than those exposed to the AR ad (*B* = 7.811, *p* = .061).

Hypothesis 5 proposed that being exposed to an AR ad increases the chances of purchasing the advertised product (i.e., brand purchase) at the point of sale. We tested H5 by using the same Bayesian approach described above to gain direct information on the probabilities of purchase (Stage 2), as well as by analyzing the willingness-to-buy task (see Stage 3 in “procedure and task” subsection).

Although we proposed a hypothesis for product purchase based on ad type viewed, due to the lack of previous studies on actual purchase effects, the priors selected for the purchase Bayesian analysis reflect equal purchase probabilities for both ad types. Nevertheless, the sample should be large enough to reflect true posterior beta distributions. Table 2 presents the results of the Bayesian analysis.

We disentangled the effect of alternative products on purchase by analyzing the influence of ad type on purchase on the willingness-to-buy task. For this, we considered only the participants who did not purchase the target product during the Stage 2 purchase task. The results showed that 56.8% of the participants who viewed the AR ad bought the product, and 62.8% of those who viewed the animated ad bought the product. The difference between the groups is not significant (X^2 *(1, N = 80)* = 0.30, *p* = .583).

Table 2. Results of the Bayesian analysis, per condition. CI = credible intervals.

Metric	**Condition**	**Prior α**	**Prior β**	**Posterior α**	**Posterior β**	**Point mass (%)**	**Lower-bound (95% CI)**	**Upper-bound (95% CI)**
ProdRec	Animated	4	3	33	24	57.99	44.98	70.29
	AR	6	3	42	17	71.43	59.10	81.91
PicRec	Animated	6	3	45	14	76.57	64.73	86.13
	AR	9	3	56	6	90.75	81.90	96.30
Purchase	Animated	3	3	10	46	17.47	9.08	28.80
	AR	3	3	16	40	28.31	17.63	40.96

Discussion

The Bayesian analysis showed that the probability the product will be recognized at the point of sale is 58% when advertised using an animated ad, and 71% when using an interactive AR-based ad. In a neutral environment, that is, when only the pictures of the products are presented and no purchase is required, product recognition increases to 77% for the animated ad and 91% for the AR ad. These results align with H4 and with past research showing the superior effect of interactive ads, such as AR-based ads on brand recall, compared to non-interactive ads (Mauroner et al., 2016).

We argue that the participants were in the search and evaluation step of the brand purchase stage (Rossiter & Percy, 2017) as soon as they entered the shopping environment. On this assumption, we sought to gain further insights into browsing behavior for the target product compared to its alternatives, as this is a necessary condition for brand recognition. Our findings demonstrated that the target product received a greater number of eye visits than expected, which suggests that advertising has an effect on search and evaluation during shopping. In fact, advertising is expected to create brand awareness at the right moment and place (Batra & Keller, 2016). The proportion of visual attention was the same for both ad types, implying that the two formats promoted brand awareness. However, the impact of visual attention on product recognition was very different depending on the ad participants were exposed to. When participants were exposed to the animated ad, visual attention given to the product during shopping strongly predicted whether the advertised product would be recognized. This was not the case for the participants being exposed to the AR ad. While visual attention still impacted on product recognition, this influence was low, indicating that participants did not need to look at the advertised product several times to be able to recognize it. This suggests the AR ad was more effective in imprinting an image of the product on participants' mind that could be easily accessed.

The stimuli-organism-response framework (Mehrabian & Russell, 1974) proposes that a stimulus (e.g., AR ads) leads to behavioral changes (i.e., brand purchase), through its effect on an organism (e.g., consumer). Past studies have found that an ad with a playful interactive mode positively affects willingness to purchase (Su et al., 2016), and entertainment created by AR ads indirectly affect product purchase (Uribe et al., 2022). Our results showed that the probability of product purchase with the AR ad (28%) was higher than with the animated ad (17%), providing some support for H5. This suggests the superiority of AR ads over animated ads on product-revealed preference. However, we did not find that the AR ad increased purchases in the willingness-to-buy task. It might be that when participants performed this task (at the end of the experimental session), the persuasive effects of the AR ad were no longer present. Another possible explanation relates to the fact that participants had only a single exposure to the ad. A single exposure might have created a weak and short memory for the ad. Thus, it is possible that being previously exposed to the product both in the shopping task and in the picture recognition task simply reinforced the memory for the product itself, creating an availability bias and suppressing ad details. Hence, when participants were in the willingness-to-buy task, they might have not retrieved any ad information besides the mental image of the product, which could explain a null effect of ad type.

Ad effectiveness – further insights

To investigate ad effectiveness comprehensively, we followed the guidelines proposed by Rossiter and Percy (2017). Thus, in this section, we present the results of the remaining metrics that are not directly related to the hypotheses proposed, but which provide support information to the findings presented in the previous two subsections.

We assessed whether the ad message had been correctly understood by the participants (i.e., learning effects), as this potentially impacts purchase intentions. The frequently used words, including their derivations, to the question “In your opinion, what was the ad trying to say about the product and the brand?” were as follows. AR ad: product, try, banana, new, food, health, interest, sustainable, vegan, good; animated ad: product, food, try, health, waste, good, important, fruit, environment, vegan. Thus, both ads delivered the message about being a new product and the brand’s environmental propositions, confirming the participants had understood the message regardless of which ad they saw. The understanding of the ad claims in both conditions aligns with previous studies on interactivity effects. A meta-analysis on web interactivity revealed that interactivity may not affect knowledge acquisition and cognitive elaboration (F. Yang & Shen, 2018).

The analysis of ad believability (i.e., acceptance of the ad) showed no differences between the two ad types ($t(98) = 0.388$, $p = .699$). The participants slightly believed in the ad claims of the AR ad ($M = 58.29$, $SD = 20.77$) and the animated ad ($M = 59.76$, $SD = 16.79$).

As part of the communication effects and brand purchase stages, we analyzed brand trust and the open questions related to product recognition and product purchase. Brand trust did not differ between the two ad types ($t(98) = 0.043$, $p = .966$). The participants did not trust nor distrusted the brand when exposed to the AR ads ($M = 56.01$, $SD = 21.97$) and to the animated ad ($M = 56.18$, $SD = 16.78$). Although the animated ad devoted more time to the ad’s claims (in written and imagery format), the AR ad delivered the same message, while making fewer claims, interactively and playfully; both ad types evoked equal brand trust perceptions.

To identify which cue, or cues, led to product/brand recognition at the point of sale, we analyzed the answers to the open question asking what had made the participants recognize the product while they shopped. The most used words were as follows. AR ad: color, banana, packaging, product, image, bar, yellow, design; animated ad: color, banana, packaging, product, yellow, logo, name. Thus, the packaging and its features (i.e., colors and the banana picture) were the drivers of product recognition, regardless of which ad was viewed.

To understand the underlying reasons for brand purchase, we analysed the open question “Why did you choose the product you bought?”. For this, we considered those participants that purchased the target product (n_{AR} = 13, n_{anim} = 7). The most used words were as follows. AR ad: product, try, banana, like; animated ad: product, curious, taste, like. Thus, the participants gave similar answers for both ad types, with the curiosity aroused by the advertising being the main reason for purchasing the product, followed by sustainability and taste reasons.

Study conclusions

This study integrated two stages of the customer journey—pre-purchase and purchase—to compare the effects of an AR-based ad with an animated ad on ad perceptions and reactions (pre-purchase stage), brand recognition and brand purchase (purchase stage). An incentive-compatible task was used to investigate purchase behavior using two commerce platforms, an e-commerce and a v-commerce.

The self-reported, behavioral and neurophysiological data demonstrated that ad processing is similar for the two types of advertising, but that the AR ad promoted higher attention paid to the ad. The AR ad also created greater brand awareness (measured through product recognition) and increased the probability of product purchase.

Theoretical Implications

By using the Rossiter and Percy guidelines for assessing advertising effectiveness and the customer journey approach, we provide insights into the performance of AR-based ads. At the pre-purchase stage, the AR ad promoted greater attention deployment compared to animated ads. The possible driver of this increased attention is the intrinsic interactive nature of AR-based ads, where the consumers’ view of the world, including themselves, is part of the ad. In addition, we found that attention paid to the ad is an important factor in creating a positive attitude toward the ad, where this relationship is stronger for AR ads compared to animated ads.

Unlike other studies (e.g., Yang et al., 2020), we did not find improved attitudes toward the AR ad, rather we found that the two ad types performed similarly. It should be taken into account, however, that many previous studies employed print advertising as stimuli (e.g., Tsai et al., 2020). Moreover, we used a combination of ad perceptions (liking, affective, and intrusiveness), which go beyond only general responses toward an ad, to define our comprehensive ad attitude metric. Plausible reasons for our findings may be related to the good creative content in the animated ads (Feng & Xie, 2019), or even the fact that AR is becoming more present in consumers' lives (e.g., filters in Instagram), potentially creating desensitization to the technology.

We showed that perceived informativeness and message comprehension for the AR-based ad was satisfactory even with fewer direct ad claims compared to the animated ad. This finding adds extra empirical evidence to research investigating information processing in AR compared to traditional environments, which has so far reported rather inconclusive results (see H. Lee, 2019). Furthermore, it is important to further explore whether informativeness in AR ads is driven by any type of augmented element or only by the augmentation of the product. Our findings and the findings of previous research (Mauroner et al., 2016; Uribe et al., 2022) seem to indicate that the latter option is the case. This exploration could refine the media richness theory applied to AR advertising.

At the purchase stage, we demonstrated that AR-based ads are more effective than conventional ad formats (i.e., animated ads) for brand recognition. In addition, using an incentive-compatible task, we found that products advertised using AR ads have a higher purchase probability. The stimulus-response-organism framework indicates that the AR-based ad (i.e., stimulus) affected the consumer (i.e., organism) in a way that led to brand purchase (i.e., response). We found that for consumers exposed to the AR ad, visual attention given to the product during shopping was not a strong predictor that the product would be purchase. This opens an area for exploring how AR advertising influences brand purchase besides influencing the amount of visual attention to the advertised product at the point of sale.

Last, neurophysiological metrics are useful complements to self-reported and behavioral data. Total dwell time (ET) indicated attention was paid to the ads, supporting the assumption that forced exposure meets the exposure requirement for ad-effectiveness assessment. In addition, the number of eyes visits (ET) provides accurate information on visual attention allocated across the products, even for VR environments. The other two measures (GSR and HR) can be used to obtain objective affective reactions toward some stimuli. In our case, these metrics indicated there were no differences between the two ad types. This suggests that similar emotional responses were evoked, or that small variations in emotional intensity are not well captured by these metrics (number of GSR peaks and heartbeats).

Managerial Implications

The widespread use of mobile devices by consumers and technological advances are making AR more accessible (e.g., the possibility of creating AR campaigns on Instagram) and companies should harness this accessibility. Based on our findings, some managerial implications are derived as follows.

We encourage brands to use AR in marketing campaigns. The integration of consumers' physical environments into the advertising, together with the interactive nature of AR features, increases consumer-ad involvement (i.e., attention paid to the ad). Moreover, AR-based advertising can deliver the brand message in an interactive and playful way, while reducing direct claims, which might lower the cognitive load needed to assimilate the message and, at the same time, increase exposure time to the ad.

AR-based ads allow customization per the content (e.g., using consumers' faces or surroundings), which leads to higher levels of personalization. Thus, it is reasonable to infer that accessing consumers' physical space, including their faces, can be perceived as intrusive. However, our data did not show that there were differences in intrusiveness perceptions between the ads. Hence, consumers seem to tolerate this kind of invasiveness.

AR ads also seem to strengthen the consumer's recall of the product/brand advertised, which facilitates product recognition at the point of sale, potentially increasing purchase intention. Our results demonstrated that AR-based ads exert influence on immediate shopping behavior in both commerce platforms tested in this study—e-commerce and also the emerging v-commerce. The magnitude of this effect is higher for product recognition, but it also affects product purchase. Indeed, product/brand awareness has been identified as one of the primary, key goals of AR marketing (Rauschnabel et al., 2022).

Therefore, advertising a product using an AR-based ad is beneficial for the brand. AR-based ads create at least as positive ad perceptions as when compared to a conventional format and generate greater consumer-ad involvement and positive shopping outcomes. Moreover, we argue that the positive effects may be even stronger if the product is supported by a physical-digital combination (see Hilken et al., 2018), for example though AR and VR applications at the point of sale. This omnichannel perspective of combining v-commerce and physical interactions needs further research, particularly for products available in virtual try-on (e.g., glasses, make-up, apparel).

Limitations and Future Directions

This study has limitations that can be addressed by future research. First, the ads were shown to the subjects only once. Rossiter and Percy (2017) emphasized that ad repetition is essential for assessing the buyer response stages. Future research might employ longitudinal studies to evaluate whether differences arise when using single vs repeated ad exposures. Second, the purchase task was undertaken almost soon after the ad exposure. Despite its relevance to prompting immediate sales, it would be of interest to look at the decay ad effect over time. Our results for product recognition and purchase may be different if this stage was carried out later. Future studies might assess the impact of different ad exposure-shopping time spans, as well as test how in-store elements might affect ad persuasion. Third, our purchase task was conducted using two commerce platforms that have different levels of consumer familiarity. Although the v-commerce layout resembled a physical supermarket, and the participants benefitted in advance by being offered a familiarization task using the VR tool, future research might explore the influence of both environment and technology novelty on shopping behavior. Fourth, we selected physiological metrics that are easy to interpret and could be captured by the devices used. However, they might not have been sensitive enough to capture small variations in emotional responses that would have allowed inferences to be drawn about other emotional and cognitive processes. Other metrics, such as skin response amplitude and the frequency components of the heart rate variability spectrum (see Kakaria et al., 2022), could be used.

Study 4 - Brand choice in the metaverse and its relationship with personal and social factors

In this study, we investigate whether consumers are willing to pay for having branded virtual products in the metaverse. For this, we conducted an online study and analyzed self-reported, behavioral, and a reaction-time test.

Study topic

Marketers, consumers, and scholars are devoting growing interest to the metaverse, virtual worlds that computers generate, where users can interact with each other (Ball, 2022). Some brands are already present in the metaverse (e.g., Nike, Zara, Coke), and according to a recent PwC survey (2022), many others plan to follow them. From the consumer's side, surveys indicate that 39% of U.S. consumers are willing to buy and sell digital products in the metaverse (PwC, 2022) while almost 75% of Gen Z current users are willing to purchase digital fashion (Roblox & Parsons, 2022). Thus, whether consumers purchase virtual things using a decision-making process similar to purchasing real things has just started to become an essential question for brands. Recent papers on the metaverse highlight the need for further research on brand choices (Dwivedi, Hughes, Wang, et al., 2022; Giang Barrera & Shah, 2023).

This paper addresses brand choice in the metaverse by posing several questions. First, what are the psychological drivers of consumer purchases? Second, what is the value of price versus free-of-charge in brand choices? Third, how is social presence affecting brand choices? Fourth, how do consumer patterns differ between real life and the metaverse? The novelty of the metaverse construction suggests adopting an exploratory perspective that enriches future theoretical frameworks. As a result, this research contributes to the literature by delineating the influence of the following dimensions of brand choices in the metaverse: psychological drivers of purchase decisions, price effect, social presence, and differential behavior unlike that of the real environment.

We considered past literature on virtual scenarios and well-established psychological principles, combined with an explorative approach, to contribute answers to these issues. We conducted an online experiment with young consumers (i.e., Gen Z and Gen Y) from a developed and a developing country, using real brands as stimuli. We sought to answer the following research questions: (i) Are consumers willing to pay for having branded products in the metaverse when they have a free-of-charge default option? If so, are consumers willing to pay higher prices for having high-status branded products in the metaverse? (ii) What possible motivations lie behind branded-products consumption in the metaverse? (iii) Do (i) and (ii) change if consumers are in the metaverse together with friends or with random people? (iv) Do consumers switch from their real-life brand choices to different ones in the metaverse? (v) Do purchase choices in the metaverse relate to real-life choices, with the same motivation?

Influence of social and personal factors on consumption

In the real world, consumers make their brand choices for several reasons. Extensive literature has addressed those choices (Ballantyne et al., 2006), and emerging research has addressed decision-making in virtual reality (Bigné et al., 2016). Dwivedi, Hughes, Wang, et al. (2022) point out that in the metaverse, foundational psychological mechanisms of decision-making will likely remain unchanged. However, unexplored individual and social factors affect choices in those virtual worlds.

In the metaverse, most abstract and concrete product attributes are quite irrelevant, as the product is only virtually present. Hence, keeping design and computation-related features constant would result in no apparent differentiation among brands or even between branded and nonbranded products in the metaverse. Instead, candidates for justifying purchasing branded virtual products could be mainly of a psychological nature, including self-identity, and have social motives, including social status. Borrowing from consumer-behavior literature, we aim to explore whether personal identity (i.e., self, group, and status identity) and status-seeking are also present in the metaverse.

Possessions are a means of self-expression (Belk, 1988). Consumers relate to brands to both seek and construct identity (Arnould & Thompson, 2005). Identity refers to self-identification with any category label that consumers incorporate in their sense of who they are (Reed et al., 2012). Self-identity influences behaviors (Confente et al., 2020) and purchase intentions directly and indirectly (Puntoni, 2001). In fact, the importance of branded products over unbranded products is partially due to the use of brands as self-identity signals (Strizhakova et al., 2011). People acquire or abandon objects to manage both self and group identities (Wheeler & Bechler, 2021). In this sense, products and brands are also means of expressing one's self to others (Fitzmaurice & Comegys, 2006; Puntoni, 2001), and brands reflecting in-group identities enhance self-brand connections (Escalas & Bettman, 2005). Moreover, consumers wanting to dissociate from an out-group seek to purchase products with salient brand signs related to an in-group (Raimondo et al., 2022), and strategies for coping with identity threats also influence consumption behavior (Nikolova, 2022). Another related motivator of social consumption is status. Indeed, brand symbolism has two dimensions: personality expression and prestige (Bhat & Reddy, 1998). The former relates to self-identity, the latter to status. Consumption status refers to the acquisition of products "that confer and symbolize status both for the individual and surrounding significant others" (Eastman et al., 1999, p.42). Hence, the underlying reasons for purchasing high-status brands are status enhancement and social-status signaling (Strizhakova et al., 2008). In summary, intertwining self-identity, group identity, and status can appear as dimensions of personal identity (Strizhakova et al., 2008).

Extensive research has shown that personal identity modulates consumption behaviors in real-life (Strizhakova et al., 2008). However, whether and how it influences consumption decisions in virtual worlds has suddenly become an important question. Literature from the field of psychology suggests similar behaviors in real-life and virtual environments. Simulated 3D first-person-view virtual environments show people reducing the frequency with which they provide help to others when under time pressure or bystanders are present (Kozlov & Johansen, 2010). However, in the metaverse, avatars commonly represent users. An "avatar is a medium that projects one's identity within virtual spaces" (Dwivedi, Hughes, Baabdullah, et al., 2022, p.9), one that allows identity re-embodiment (Giang Barrera & Shah, 2023). Avatars tend to be an idealized version of the self (Bessière et al., 2007; Dwivedi, Hughes, Wang, et al., 2022), and they possess both physical and psychological characteristics. Indeed, an avatar's personality appears to shape a user's virtual behavior (Praetorius & Görlich, 2020). Therefore, preferences, needs, and desires in virtual worlds might differ from those in the real world, influencing virtual buying choices. Consequently, brands must understand consumers' behaviors and preferences in the metaverse (Dwivedi, Hughes, Wang, et al., 2022).

A recent survey with 1,000 young American metaverse users (Roblox & Parsons, 2022) revealed that 42% of them find self-expression through clothing and accessories more important in virtual worlds than in the real world; 70% dress their avatars similarly to their real-life style; 66% are eager to wear virtual branded products. The participants also reported that how they dress their avatars helps them to connect with their peers both in the virtual (32%) and real (25%) worlds. Moreover, 24% change their avatar's style to match the style of the group of which they are part at the moment. Paradoxically, only 29% say that their avatars represent their real self, while 37% say the avatar represents someone they want to be. Additionally, for 24% of these Gen Z users, dressing their avatars is a means to achieve recognition in the digital community, representing a form of social status.

The excitement about the potential of the metaverse becoming prevalent in consumers' lives comes with several open questions for businesses, including what drives branded consumption in these virtual worlds and whether the real world influences virtual purchase choices. In real environments, brands, social influence, and personal identity factors influences consumption (Raimondo et al., 2022; Strizhakova et al., 2008, 2011). As the metaverse can serve as an extension of the physical world, we argue there are similarities between virtual and real consumption behavior (see Branca et al., 2022). Therefore, we provide general guidance for our findings. First, it is plausible that consumers will spend money to have a branded product in the metaverse. Second, we expect underlying reasons for a choice to reflect the social environment (i.e., being together with friends or random people). Third, it is possible that brand choice in the metaverse reflects brand choice in real life. Finally, we anticipate psychological motives (i.e., self-, social-, and status-identity, and status-seeking) driving those choice decisions.

Study methodology

We conducted a between-subjects design online experiment in two countries with different levels of economic development, manipulating a social factor involving friends (i.e., the "known" condition) or random people (the "unknown" condition). The experiment comprised three parts: two choice tasks, a survey, and a reaction-time test.

Our target product was mobile phone brands. Despite phones being value-expressive products (Millan & Reynolds, 2014), unlike clothing, shoes, or accessories, market data on the phone category is available for many countries, and a few brands dominate the market. This makes possible the comparison with real-life purchases. Moreover, they are not gender- and age-specific, and we did not indicate models nor use images of the product, to avoid the influence of aesthetic preferences.

We collected data from Spain and Colombia, two countries that share the same language but have different levels of economic development, representing a developed and a developing country, respectively. They have similar population sizes and a mobile phone market where five brands represent 90% of sales (GlobalStats, 2022; Sava, 2022).

Participants

The participants were part of the panel of the market research company Netquest. We had a total of 240 valid participants (49.6% female, 49.2% male, 1.2% not identified), of ages ranging from 19 to 41 (M = 28.63, SD = 6.36), comprising millennials and part of Generation Z. Together with Generation Alpha, they represent most metaverse users (Dwivedi, Hughes, Wang, et al., 2022). Eighty-one percent of the participants had never been in a metaverse, and 7% were not sure whether they had. The data was collected online in December 2022. The experiment was conducted in Spanish, both in Spain (n = 119) and in Colombia (n = 121), and the participants were paid a small amount of money. The two countries did not differ by age, gender, previous metaverse experience, and the four psychological metrics described below.

Tasks and Survey

We instructed participants to imagine they were in a metaverse where all avatars represented real people and were a perfect virtual copy of themselves and others. The participants (i.e., their avatars) would go to a virtual party with their friends ("known" condition; n = 120, 49% Spain, 51% Colombia) or with random people ("unknown" condition; n = 120, 50% each country), and each drink at the party would cost five coins. Figure 1 depicts the experimental situation.

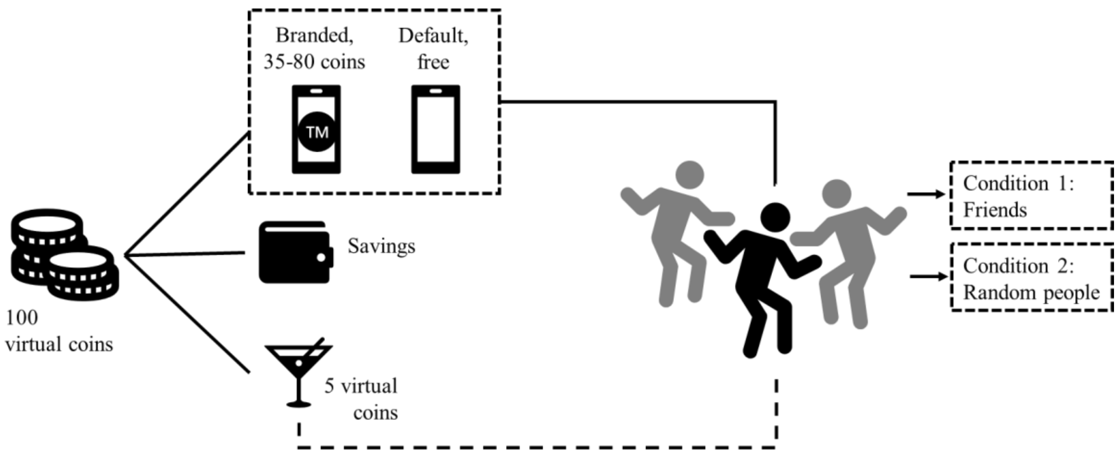

Figure 1. Schematic representation of the metaverse hypothetical scenario.

Participants had a budget of one hundred virtual coins, which they could use and/or save for another occasion. We told participants they had already chosen the outfit for their avatars and now they should choose a mobile phone from among six options (Figure 2). Five of the options represented the current most-purchased real brands (90%) in the countries under study (GlobalStats, 2022; Sava, 2022). One of the options represented a default version, depicted by the logo of the Meta company, to have all options representing global companies. We used the term "brand" to refer to existing phone brands in real life. We randomized the position of the five branded options across participants, and the default option was always the last. Except for the free default option, all other options had a monetary cost that a pretest determined (see subsection 3.2., "Pretest"). After the participants selected an option, they answered an open question about the choice. Next, we asked them to imagine they were back in the real world and needed to purchase a new phone for themselves. We presented participants with the same five branded options and an extra option (i.e., the sixth most purchased brand in the country of study) to keep the same layout as previously used (i.e., six boxes with a brand logo in each), and an option for "none of these brands." Option positions were randomized across participants. After choosing, they answered other questions (see subsection 3.1.2., "Questionnaire"), including demographic data and a question about familiarity with the brands present in the survey, rated on a 5-point Likert scale. The survey translated into English appears in the appendix (demographic questions were removed). After completing the survey, the participants were redirected to another application to perform a reaction-time test (see subsection "3.1.3. Reaction-Time Test").

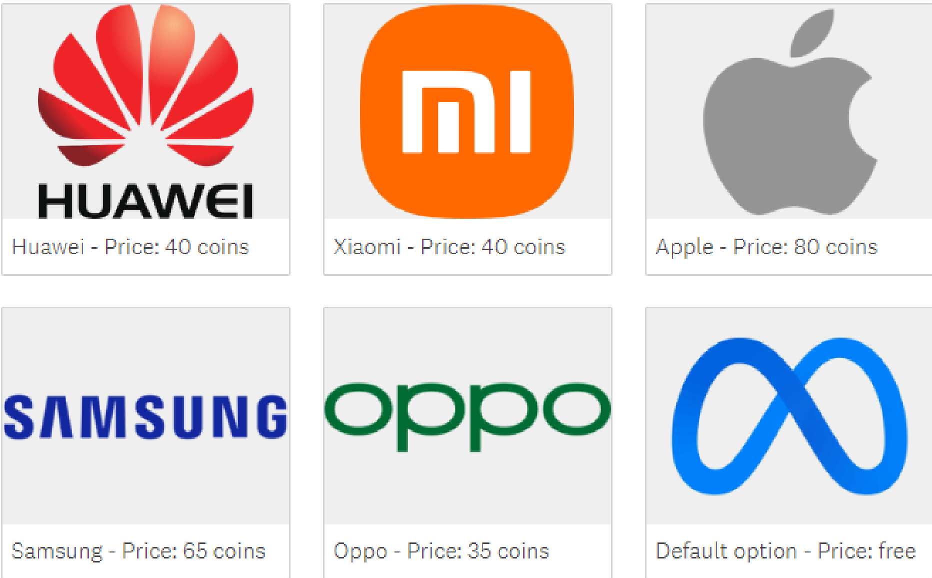

Figure 2. The layout of the virtual phone choice task for Spain, translated into English. For Colombia, Motorola replaced Oppo, and the prices were modified according to the pretest conducted in that country.

Questionnaire

The questionnaire consisted of open questions and scales. The open questions asked: Why did you choose this phone brand for your avatar? Why would you choose that phone brand for yourself? And, as a support metric, we asked What is the brand of your current phone? The scales, borrowed from the literature, were the five-item "status consumption" (i.e., status-seeking) scale (Eastman et al., 1999), and three factors, with five items each, of the "meaning of branded products" scale (Strizhakova et al., 2008): (i) self-identity factor, (ii) group-identity factor, and (iii) status-identity factor. The items were translated from English to Spanish by one person and back-translated to English by another, for comparison purposes. Further, to obtain more information regarding the choices, we asked participants to select the brand that best represented them and to classify the five brands in order of perceived status.

Reaction-Time Test

The test aimed to assess perceptions of status and self-identity with each brand used in the metaverse phone-choice task. We presented participants with the logo of each brand and a dichotomous choice—yes or no—to answer the questions: "Does this brand represent me?" (identity) and "Does this brand give me status?" (status) (Figure 3). The assumption is that either a positive or negative strong association between an attribute and a brand will cause a faster response than if this association were weak (Maison et al., 2001). Each pair of brand logos and sentences above (see Figure 3) was repeated three times; the pairs appeared randomly, a choice was required within four seconds, and the participant had to click on a fixation cross in the center of the screen after each choice, to reset the mouse position. There was a short training section with unrelated questions (e.g., “Do you have siblings”) at the beginning of the experiment.

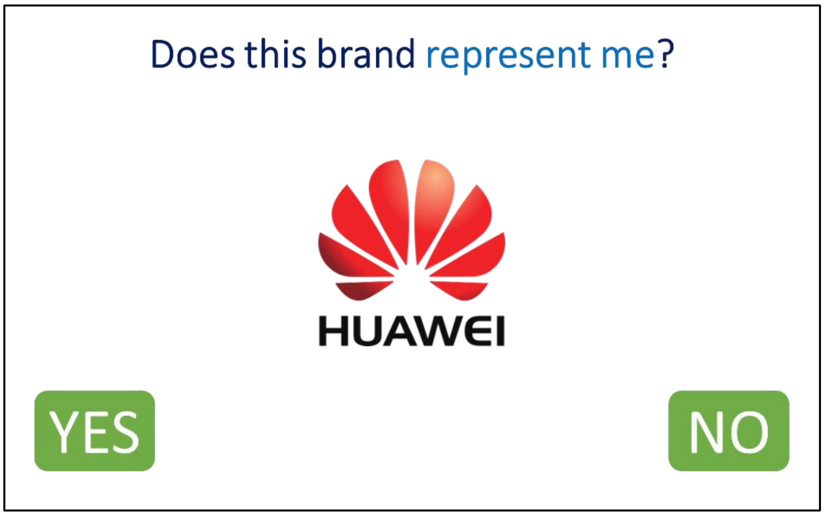

Figure 3. Layout of the reaction-time task. The figure shows an example for one brand and one attribute, translated into English.

Pretest

To determine the prices of each brand, we conducted an online pretest using the panel from Netquest. We had 49 valid participants (24 female, M_{age} = 33.14, *SD* = 4.79) for the sample in Spain, and 50 valid participants (25 female, M_{age} = 32.94, *SD* = 4.40) for the sample in Colombia. Participants were asked to report how much they were willing to pay for each brand, from 0 to €1,500 in Spain and from 0 to $7,000,000 in Colombia. In addition, they classified the brands in order of perceived status. With this information, we computed the price relationships among the brands, leading to the final prices in the main experiment. The most expensive brand was set to represent 80 virtual coins.

Analysis

Participants who failed any of the four comprehension questions were automatically excluded and did not complete the experiment. For Spain, 125 participants completed the choice tasks and survey. We excluded six participants due to the lack of compliance that we inferred from their survey answers. For Colombia, we excluded no participants. We performed the analyses with SPSS V28 software. The results section describes the statistical tests. We assessed the reliability of the scales, and all reached a Cronbach's alpha > .90. We averaged the items within a scale factor to obtain the mean value for each factor for each participant. The answers to the open questions were translated into English and preprocessed manually (e.g., homogenizing singular and plural, verb tenses, and synonyms) and in WordCloud (https://www.wordclouds.com; e.g., removal of stop words, removal of the words "brand" and "phone"). The WordCloud app enabled the construction of the word clouds, and the word size indicates its frequency of use.

Completing the reaction-time test were 27 participants in Spain and 57 participants in Colombia. We excluded two participants from Spain who had been excluded from the choice tasks and survey. To obtain the reaction time for each paired brand-sentence, we averaged the answers across repetitions. We excluded contradictory answers (possibly due to mistakes) within the same pair, using the following criteria: (i) if a participant said yes (no) twice and no (yes) once, we excluded the no (yes) answer; (ii) if a participant said yes and no once each, we excluded both answers. We then calculated the final metric for consumer-brand representation and consumer-brand status (personal status) as follows: The brand that received the fastest "yes" response across brands was assigned "1," the others "0."

Study results

Pretest

The average willingness-to-pay pattern for Spain was Apple > Samsung > Xiaomi = Huawei > Oppo. The ranking of perceived status followed the same pattern as that of the willingness to pay. The average willingness-to-pay pattern for Colombia was Apple > Samsung > Xiaomi = Huawei > Motorola. The ranking of perceived status was Apple = Samsung > Xiaomi = Huawei = Motorola.

Sample Characteristics

The mean age of both condition groups (i.e., known and unknown) did not differ. There were also no statistical differences regarding gender, familiarity with the brands, or any of the four psychological metrics.

Otherwise stated, the results appearing below refer to the data of the countries combined, as preliminary comparative analysis showed no statistically significant difference between the countries for the metrics reported.

Choice in the Metaverse

To evaluate our expectation that consumers forgo money to have a branded product in the metaverse, we computed how many participants chose a branded phone for their avatars. We found that 67% of the participants preferred to pay for having a branded phone over having the free default option. Of those, 70% chose the same brand as the phone they currently had in real life. Afterward, we computed the average amount of virtual money spent in the phone-choice task. The results showed that participants spent an average of 37.25 (SD = 29.93) virtual coins in the metaverse. The average amount spent among those who purchased a branded product was 55.53 virtual coins (SD = 17.80). Note that the cheapest brand cost 35 coins and the most expensive brand cost 80 coins.

We analyzed the open question, “Why did you choose this phone brand for your avatar?” for those who bought a branded product for their avatars and those who selected the default option. We replaced the word “have” with “use” in the translation, to prevent biasing the results, as the sentences implied the same: “It is the brand/phone I use/have.” The most cited words in order of frequency for the brand group were: use, good, like, quality, price, now, real-life, and quality-price; for the default group, they were: free, coins, spend, money, and things.

We expected that consumers would forgo money to have a branded product in the metaverse and found that most consumers were willing to make that purchase. The data showed that 67% of the consumers surveyed would pay for a branded product even when a default free option is available. Among those who purchased branded products, the average budget spent represented more than half of the total budget available.

Considering that only two of the five options cost more than half of the total budget, the results indicated reduced price sensitivity among consumers. Indeed, about one in three consumers would choose an expensive, high-status branded product in the metaverse (i.e., Apple and Samsung).

Few studies have generally investigated virtual purchases in social worlds and gaming (see Bleize & Antheunis, 2019). In summary, their findings showed that social influence, enjoyment of the virtual world, and avatar customization are some factors that modulate purchase intentions (Bleize & Antheunis, 2019). Our study differed from those, by investigating whether consumers are willing to pay for branded products. We found that the main self-reported reasons for choosing a branded product were having the same brand in real life, positive brand or product attitudes (e.g., liking the brand/product, its being a good brand/product), and brand or product attributes (e.g., quality, price). The main driver of opting for a default free option was the absence of monetary cost and saving the money for other uses. Some consumers also mentioned the lack of usefulness of a virtual product.

Social Influence on Brand Choice in the Metaverse

Here we assessed whether the choice changed depending on the social conditions (i.e., known and unknown). A chi-squared test showed that the choice between a default or a branded option did not differ across conditions ($X^2(2, N=240)= .47$, $p = .492$). Regarding the money spent to buy a phone in the metaverse, an independent sample t-test revealed that expenditure did not differ across conditions ($t(238) = 1.17$, $p = .245$).

We then analyzed the open question “Why did you choose this phone brand for your avatar?” for those who bought a branded product for their avatars, separated across conditions. The most cited words, in order of frequency, for the known condition were: good, use, like, quality, price, and quality-price; for the unknown condition, they were: use, like, good, real-life, quality, and price. Thus, the reasons for brand consumption did not differ across conditions.

Contrary to our assumption, the data suggest that decisions in the metaverse are not affected by the type of social context, namely, being with friends or being with random people. The choice made in the metaverse and the motivations behind it did not differ whether consumers would join a virtual event with closely related peers or with unknown people.

Previous literature shows scattered and inconclusive findings on whether social influence impacts virtual purchases. An early qualitative study with virtual-world users revealed that they considered the opinions of friends when making virtual purchase decisions (Guo & Barnes, 2009). However, a further quantitative study by the same authors did not find any effect of social influence on purchase intention (Guo & Barnes, 2011). The explanation the authors gave was that social influence will impact purchase behavioral intentions only if the act of buying an item can lead to a reward or avoid punishment via others, which happen in social virtual gaming. Whereas social presence was found to influence (Jin et al., 2017) virtual purchases or not (Mäntymäki & Salo, 2013), perceived network size was a strong predictor of purchase intention (Mäntymäki & Salo, 2013). The network was defined as other users, perceived as friends, peers, or as a group relevant to the user. A later study demonstrated that beliefs about peers' attitudes in virtual worlds positively related to willingness to purchase virtual products (Hamari, 2015). However, none of these studies directly investigated the metaverse; rather, they investigated virtual worlds considered its antecedents (Dwivedi, Hughes, Wang, et al., 2022). In light of the evidence that peers influence behavior, our findings might be particular to objects like phones, not very visually salient or having not much design differentiation across brands. As an example, a consumer stated: "[A phone] is not too visible to the rest of the avatars." Still, consumers who join the metaverse together with friends probably adapt their avatar style to conform with the group, choosing clothing, accessories (e.g., jewelry, watches, glasses), and hairstyles that identify them with a certain group.

Comparison of Real-Life and Metaverse Choices

We found that 70% of the participants who purchased a branded product for their avatars chose the same brand as their current mobile phone. Perhaps those consumers who bought different brands in the metaverse were already planning to switch brands in real life. Thus, we first assessed whether the brand chosen for the avatar was the same as the brand chosen for a real-life purchase. The results showed that 75% of the consumers who purchased a branded product for their avatars would purchase the same brand for themselves in the future.

Regarding the choice in the metaverse, 78% of the participants who chose a branded product bought the brand that best represented them; for a future real purchase, 72% of all participants would buy a brand that best represented them. To confirm the relationship between brand-person representation and brand choice, we used the output metric from the reaction-time test question “Does this brand represent me?” and correlated it with brand choice in the metaverse and the real world. All correlations were positive and significant ($p < .05$). We then split the data according to the type of choice in the metaverse (i.e., branded vs default option), to compute the future real purchase for both groups. Of the participants who chose a branded product for their avatars, 77% would buy a future real phone that best represents themselves, while this dropped to 63% for those who chose a default option for their avatars.

Finally, to verify whether similar reasons drove virtual and real-life choices, we analyzed the answers to the open question, “Why would you choose that phone brand for yourself?” The most frequent words in responses were: use, good, like, quality, best, quality-price, and works. The words for the choice related to the metaverse are reported previously.

Considering the metaverse an extension of the physical world, we expected that brand choice in the virtual world would reflect brand choice in the real world. A recent study found that consumer behavior in virtual reality only differs from everyday life in minor ways (Branca et al., 2022). Our findings showed that this is also the case for brand choice of virtual products. Brands chosen in the metaverse heavily reflect real-life choices and possessions. We asked consumers to indicate the brand they would purchase for their next real phone and compared it with the choice made for their avatars. Among those who chose a branded product for their avatars, 75% selected the same brand as the one they would purchase for themselves in the future. Moreover, 70% chose the same brand in the metaverse as their current phone. These combined results reflect great brand loyalty—that is, consumers tended to elect the same brand for use in the virtual and real worlds. Also, consumers may have experienced an “inertia effect” at this moment

(Bawa, 1990). In this case, they were biased toward sticking with current brands to avoid the cognitive effort of evaluating other options across the physical and digital worlds.

We asked participants which brand best represented themselves. Among those who purchased a branded product in the metaverse, 78% chose the brand that best represents themselves. This result was the same for a future real-life purchase. It agrees with previous research on virtual communities, showing that online self-presentation—that is, the image that users want to project to others—strongly impacts digital-item purchase intention (H.-W. Kim et al., 2012). However, among those who chose the default free option in the metaverse, only 63% would purchase a real phone of the brand that best represents themselves. These findings are revealing and suggest that consumers who do not have a strong brand representation-choice relationship in real life are also less sensitive to brands in the metaverse. The support metric derived from the reaction-time test confirmed a link between consumer representation and brand choice.

The stated reasons for selecting a certain brand for a next real-life purchase were similar to those for purchasing a certain brand in the metaverse: already having a phone of that brand, positive attitudes (e.g., like, good, best), and quality and price attributes. Thus, consumers seem to weigh the same features they value in real life in virtual life, even if those features cannot be assessed in a virtual object.

The Impact of Psychological Factors

Self-identity, group-identity, status-identity, and status-seeking can weigh differently across cultures. Thus, we split the data by country for the following analysis.

To evaluate whether self-identity, group-identity, status-identity, and status-seeking related to choosing branded or default products in the metaverse, we correlated the average score of each scale with the choice made in the metaverse (0 = branded product, 1 = default option). For Spain, only status-seeking had a significant effect (self-identity: $r(117) = -.02$, $p < .845$; group-identity: $r(117) = -.13$, $p = .146$; status-identity: $r(117) = -.14$, $p = .117$; status-seeking: $r(117) = -.20$, $p = .017$). For Colombia, all metrics but status-identity significantly correlated with choosing a branded or the default option for the avatar (self-identity: $r(119) = -.30$, $p < .001$; group-identity: $r(119) = -.29$, $p = .001$; status-identity: *r(119)* = -.14, *p* = .129; status-seeking: *r(119)* = -.30, *p* < .001). We also tested demographic characteristics (i.e., age, gender), and neither statistically significantly correlated with the type of choice for Spain. For Colombia, as consumers' age increases, the probability of choosing the default option increased (*r(119)* = .20, *p* = .028).

Through a binary logistic linear regression with a backward procedure, we then tested the influence of these factors—self-identity, group-identity, status-identity, and status-seeking—on choosing the brand that best represented the person, for a virtual phone and a real phone. Collinearity analysis indicated VIF values less than 5; therefore, we proceeded with the tests. For Spain, the regressions for the avatar's phone (0 = different from the brand that best represents the person, 1 = the same as the brand that best represents the person) indicated the model containing only the intercept and group-identity was best (*F(1, 117)* = 8.74, *p* = .004). Thus, group-identity alone was a significant predictor (*t* = 2.96, *p* = .004, β = .264) and explained 7% of the variance in the type of choice. The regressions for the person's future choice did not show any model or psychological factor as a significant predictor. For Colombia, the model containing only the intercept and group-identity was the best (*F(1, 119)* = 11.31, *p* = .001). Thus, group-identity alone was a significant predictor (*t* = 3.36, *p* = .001, β = .295) and explained almost 9% of the variance in the type of choice in the metaverse. Contrary to the results for Spain, the regressions for the person's future choice had all models significant (*p* < .05). The model containing only the intercept and self-identity was the best (*F(1, 119)* = 10.13, *p* = .002). Thus, self-identity alone was a significant predictor (*t* = 3.18, *p* = .002, β = .280) and explained almost 8% of the variance in the type of choice in the real world.

To better understand the influence of status on choices, we correlated the stated perceived status for each brand with a choice for that brand (0 = brand not chosen, 1 = brand chosen) for both the avatar and the person. The average perceived status for all brands followed the same pattern as in the pretest for both countries (see subsection 2.3, "Pretest"). For each country, there was no significant correlation for any of the brands in any of the choices, except for one significant correlation. (This correlation possibly represented a type I error due to the lack of correlation in the other 19 pairs; thus, it is not discussed further.) However, perceived status does not necessarily reflect how much status a brand brings to a particular consumer. Thus, we used the metric captured from the reaction-time test, which assessed brand personal status, and we conducted the same correlation analysis. For this analysis, we aggregated the data of the two countries because of the low number of answers in the reaction-time test and considered the brands that were common to both countries (i.e., Xiaomi, Samsung, Apple, and Huawei). The results showed a positive, significant correlation between brand personal status and brand choice for the virtual and real worlds for all brands. The correlations were as follows: Xiaomi_metaverse: $r(80) = .31$, $p = .005$; Xiaomi_real: $r(80) = .23$, $p = .041$; Samsung_metaverse: $r(80) = .27$, $p = .014$; Samsung_real: $r(80) = .28$, $p = .011$; Apple_metaverse: $r(80) = .27$, $p = .016$; Apple_real: $r(80) = .42$, $p < .001$; Huawei_metaverse: $r(80) = .64$, $p < .001$; Huawei_real: $r(80) = .22$, $p = .045$.

Previously, we demonstrated that identification with the brand also drove choices in the metaverse. Thus, we expected that consumers who attributed high importance especially to self-identity, but also to group-identity and status-identity, would prefer to buy branded products instead of a default, common option. However, for Spain, only status-seeking related to the type of choice. The higher the degree of status-seeking behavior, the greater the chances were that the consumer would choose a branded product. For Colombia, self-identity, group-identity, and status-seeking related to choices. The higher the degree of importance that consumers gave to these factors, the greater was the probability that they would choose a branded product over a default option in the metaverse. Therefore, the findings imply that developing countries emphasize identity-related factors in purchase decisions between branded and default products more than developed countries, whereas status-seeking exerts influence in both country types. Indeed, previous research found that self-identity impacts purchases of global brands in developing countries but not in developed countries (Strizhakova et al., 2011).

Those psychological factors could have been powerful influences on choosing a product from the brand that best represents the person. In Spain, our analysis identified that the stronger the group-identity behavior was, the greater the probability was that consumers would purchase a brand that best represented them in the metaverse. In Colombia, group-identity scores were also predictors of choosing a brand that best represents the consumer for the virtual phone, while self-identity scores were predictors of choosing a brand that best represents the consumer for a real phone. For both countries, the feeling that the brand represents the person is the main influence on choosing a certain brand. Group-identity seems to be the driver of "representation" in virtual worlds, in both developed and developing countries. Indeed, brands act as "creators of social identity with social group linking value" (Bagozzi et al., 2021, p.585). Therefore, consumers chose brands that represented themselves to signal with whom they want to associate, in line with the findings of Kim et al. (2012).

While identification with the brand (i.e., consumers feeling the brand represents them) related to brand choice, perceived status of the brand (i.e., how much status consumers think the brand has) did not. Perceived status influenced neither choices in the real world nor in the virtual world. However, personal status (i.e., if the brand brings status to that particular consumer) related to brand choice in both the virtual and real worlds. The path might be bi-directional: if consumers feel the brand gives them status, the greater the probability is that they will purchase the brand regardless of its being a real or a virtual product; or, if consumers chose the brand, it could evoke a feeling of personal status.

Study conclusions

This study assessed whether consumers are willing to pay for a virtual product in the metaverse, whether virtual choices reflect real-life choices, and the motivation behind virtual purchase decisions. In addition, we analyzed whether the virtual social context—being with avatars representing friends or random people—affects these decisions. For this, we created a hypothetical situation to manipulate the social factor and asked consumers to choose a phone for their avatars. The phone could be from among known brands, each with a monetary cost, or a free default option of the metaverse. The respective findings from a developed and a developing country demonstrated that most consumers would pay for having a branded virtual product. Moreover, the chosen brand for the virtual product is most likely to be the same as for a future real-life purchase and/or the same as the current phone. Most consumers selected a brand for both worlds that they consider the one that best represents them. Although the perceived general status of the brand did not correlate with brand choice, personal status—the feeling that the brand brings status to the consumer—did. Furthermore, group-identity appears to be the underlying factor of brand-consumer representation for choices made in the metaverse. We have used phones as the tested product, but our findings should apply to other product categories that also signal status and identity to others (e.g., clothing, shoes, accessories).

Theoretical Implications

Common reasons for choosing one brand over another (e.g., physical attributes or intangible features, such as product performance) may not apply to products in the metaverse. Thus, we could expect psychological motives to heavily impact purchase decisions in the metaverse. Past literature on real-life environments has demonstrated that self- and group-identity, as well as status-related factors, modulate product and brand choices (Eastman et al., 1999; Puntoni, 2001; Raimondo et al., 2022; Strizhakova et al., 2008; Wheeler & Bechler, 2021). However, virtual consumption could imply unique consumer behaviors that remain to be understood (Shen et al., 2021). Our study provided an initial step toward extending previous research to the metaverse context. Specifically, we have shown that while many consumers accepted having a default option for a virtual product, most preferred incurring monetary costs to have branded products. Out of the psychological constructs we analyzed (i.e., self-, group-, and status-identity, and status-seeking), status-seeking related to preference for a virtual branded product over a default option in both developed and developing countries. Self- and group-identity also played a role in preference for a branded product, but only in the developing country. Among those who purchased a virtual branded product, the feeling that a brand brings personal status to the user correlated with brand choice. Self-reported reasons for the purchases revealed that not spending money is the main argument for choosing a default free option, whereas possessing a product from the same brand in real life is the main argument for purchasing a branded product. Furthermore, group-identity behavior could explain part of the underlying reasons for purchasing a virtual product from the brand that best represents the consumer in both countries.

Particularly related to group-identity, our study contributed to the literature on this topic by also assessing the impact of the virtual social context—avatars representing friends or random people—on preferences for a virtual product. The findings demonstrated that social context is not powerful enough to change purchase decisions on virtual mobile phones. The survey conducted with metaverse users reported in the introduction implies that peers impact virtual clothing choices for at least a quarter of users (Roblox & Parsons, 2022). Some caveats to our study are the use of a hypothetical situation, participants who have never been in metaverses, and the product type. All might have downsized the possible impact of the social context. Also, on the theoretical side, we provided indications that their country's developmental level might not affect consumers' choices in virtual worlds. Our findings in all metrics we analyzed were the same between the developed and the developing country. However, the factors underlying metaverse choices were partially different across countries.

Practical Implications

Virtual products may be functionally useless in the metaverse. Nevertheless, consumers expect to have those products at their disposal, including branded products (Roblox & Parsons, 2022). Hence, some major brands are already present in the metaverse, while many others plan to join (PwC, 2022). Our study provides practical implications for brands. We found that many consumers demonstrated risk-averse behavior or increased brand loyalty, preferring to purchase a brand that they had already experienced in real-life. From these consumers, some answers suggested a lack of complete understanding of what a virtual product is. Some consumers seemed to think that a virtual phone in the metaverse would work exactly as in real life. Other consumers did not see any usefulness in a virtual product and, therefore, were not willing to pay for a branded product. For this latter group, companies could emphasize experiential aspects to attract and engage them. For example, they could provide forms of personalizing or customizing the virtual product. Brands could also use more symbolic appeals to attract consumers with weak consumer-brand relationships (Bauer, 2022).

Another revealing finding for practitioners is that three in four consumers willing to have a branded product in the metaverse would choose the same brand they have in real life. This implies that consumers are not brand switchers, and real-life brands have a potential market in the virtual context. Most consumers chose the brand already experienced in real life first. Moreover, they tended to purchase the brand that best represents themselves, which they feel can provide personal status. Thus, to avoid losing market share to possible future competitors beyond those already established, companies should employ strategies to deliver and strengthen the message that the brand represents the consumer in both the real and virtual worlds. However, our study did not investigate whether choices would change if well-known virtual-only brands appeared as competitors (see Muzellec et al., 2012). Underlying factors for "representation" in real life were not clear. We found self-identity an important factor in Colombia, but none of the psychological factors investigated were relevant in Spain. However, group-identity appears to be the hidden reason for choosing a brand that best represents the consumer in a virtual world. These findings demonstrate that although choice outcomes are very similar in the virtual and real worlds, their mechanisms may differ. Thus, brands operating in the metaverse should promote strong community-identity feelings (Shukla & Drennan, 2018) and a sense of pertaining to a virtual group, as our results suggest that group-identity is more important in virtual than in real life.

Limitations and Future Directions

We asked participants to imagine the social situation and having an avatar. They may have fully incorporated neither the situation nor the avatar perspective. Also, we only provided the brands of the phones. Although brand image impacts phone purchase decisions (Rakib et al., 2022), the phone design or other factors may also matter in the metaverse.

The anticipation of the metaverse and its unlimited possibilities of creation being prevalent in people's future life in the future indicates much yet to explore. Future research could extend our study by investigating whether choices differ if an avatar does not resemble the user (Giang Barrera & Shah, 2023), if the virtual product does not reflect an existing product in real life (e.g., new products or new designs), if other virtual users cannot easily see or infer the brand of the product, if options have the same price, the default option also has a monetary cost, or even if the brand exists only in the virtual world. Furthermore, future studies could investigate preferences for experiential and material virtual purchases, following research investigating these issues in real life (Han et al., 2023). What is certain is that the metaverse offers "a potential boon to marketing research" (Hilken et al., 2022, p.1668).

CHAPTER 6

CONCLUSIONS

In this chapter, we first summarize the main findings of each study alongside the core insights obtained by the analysis of neurophysiological data. The purpose is to provide an overview of the contribution of each study to the main goal of the thesis. Next, we provide a general conclusion of the work done for this thesis, including its limitations and future research lines.

Summary of the individual findings and conclusions

In Chapter 2, we used eye-tracking to investigate which elements of the social media platform Trip Advisor for restaurants influence consumers' decisions of visiting the restaurant announced and their liking expectations regarding the restaurant, as well as the element that captures initial attention. In addition, we explored whether viewing patterns to the webpage change depending on the valence of the ratings of the restaurant announced. We found that consumers rely on both user- and firm-generated content to define their visit intention and liking expectation, and that the impact of the firm-generated content is opposite to the user-generated content. Moreover, consumers use extra user-generated content in their thought process when viewing restaurants reviewed negatively compared to restaurants reviewed positively, although viewing patterns were the same regardless of review valence. The eye-tracking data also revealed that the pictures of the restaurant attract initial attention whereas third-party advertising is the last area seen. The study demonstrated the crucial role of the pictures posted by restaurant managers and the opinions of other consumers on consumers' decisions. In Chapter 5, subsection "Congruence of third-party adverting with the social media content", we used eye-tracking to obtain deeper insights into potential factors, such as congruence effects, that can affect attention paid to third-party advertising present on a Trip Advisor page. We subtly manipulated congruence: the ads could be either from the same type of cuisine of the restaurant being announced in Trip Advisor (congruent condition) or from a different type of cuisine (incongruent condition). The results demonstrated that visual attention to the third-party ad on a Trip Advisor webpage is the same regardless of congruence or incongruence of cuisine types.

These two studies demonstrated the power of relating objective metrics (i.e., eye-tracking data) with subjective metrics (i.e., self-reported intentions). With the information provided by eye-tracking, we could unveil that visual attention to firm-generated content differently affects intentions and perceptions compared to user-generated content. Moreover, even though viewing patterns are the same regardless of the valence of the ratings (user-generated content), the direction of the influence of both the firm- and user-generated content is dependent on that overall valence. The complementary study suggested that visual attention to a third-party ad embedded in social media content is the same regardless of the congruence of the ad with the webpage content. Although more studies are needed investigating different levels of congruence, our study implies that, for the level and type of congruence investigated, managers do not need to be concerned that attention to the ad will drop if the ad is placed in a congruent or incongruent context.

In Chapter 3, we used electroencephalography to investigate whether brands are deeply encoded in the mind of consumers as everyday life elements (e.g., words, objects) are. The results of the analysis of EEG signals were aligned with studies in the linguistic field using verbal or non-verbal formats of language or representations. We found a significantly greater N400 ERP effect and theta band power for brand logos that did not represent the brand of previously shown brand cues (e.g., products or services) compared to brand logos that in fact represented the brand of the cues presented. Taken together, these results indicate that consumers must have stored in their long-term memory representations of a brand, such as its logo and products/services, and that this knowledge becomes accessible (i.e., it is retrieved from the long-term memory and accessible in the working-memory) when a brand element is present. Therefore, our findings suggest that brands and their representative elements (e.g., products, services, logo) are indeed deeply encoded in consumers' minds.

This study confirmed that brain reactions to incongruences also occur in the brand-level domain. The study reinforces the undesired effects when there is a mismatch between a brand (represented by its logo) and brand-related cues. For example, a retailer that uses a freezer sponsored by The Coca-Cola Company but stores inside drinks from competitors may be inducing incongruence effects. Furthermore, the study suggests the possibility of using electroencephalogram metrics related to incongruence effects to address important business issues. For example, how strongly the brand competitors are represented in consumers' minds, how strongly consumers associate a brand with its product category, whether the placement of a brand product/logo in an advertisement is perceived as congruent by the consumers, whether the price of a product is perceived as "correct" by the consumer.

In Chapter 4, we used eye-tracking to investigate how much attention is given to banner advertising embedded in news content depending on what the user is doing: reading the news (a goal-oriented task) or browsing the website. Furthermore, we examined how visual attention to the banner correlates with clicking on the banner (a behavioral metric) and self-reported ad recognition (a self-reported metric), and whether the position of the banner in the content has some influence on ad clicking. The results of the eye-tracking data demonstrated that attention given to the banners is much lower when users are engaged in a focused task (i.e., reading the news) than when they are freely navigating the website. Moreover, although the banners did not receive big amounts of visual attention, they were largely recognized one day and one week later after ad exposure. Visual attention is related to ad clicking, but only when users are browsing the webpage; the position of the ad does not influence ad clicking, but there is a tendency for the middle location to perform better than the top and bottom locations.

This study demonstrated that what a consumer is doing highly affects the amount of visual attention paid to marketing communication. The quantification of attention could be objectively measured because of the use of the eye-tracking technique. The quantitative attentional metrics also made it possible to demonstrate how attention is linked to behavioral performance indicators, such as clicking on the advertisements, and to different positions of an ad. Moreover, the study's results imply that the amount of visual attention does not seem to be always correlated with memory.

In Chapter 5, subsection "Conscious and non-conscious responses to branded narrative advertising with different narrativity levels", we used two neurophysiological tools, namely, electroencephalography and galvanic skin response, combined with self-reported responses to evaluate whether different levels of narrativity (high vs. low) in video advertising affect ad and brand perceptions. The results revealed an overall superiority of high levels of narrativity in the self-report ad-related metrics, but not in the brand-related metrics compared to low levels of narrativity. Particularly, advertisements with low levels of narrativity outperformed ads with high levels of narrativity in conveying the belief that the brand fulfills the claims stated by the ad. The neurophysiological metrics did not show any difference in arousal levels, cognitive load, and approach/avoidance behavior between the two levels of narrativity. However, an advanced electroencephalography metric namely inter-subject correlation—which represents shared neuronal responses across individuals—revealed that ads with high levels of narrativity lead to increased neuronal reliability (increased shared responses) than low levels of narrativity. This indicates that the ads with high narrativity levels were perceived and/or interpreted in a more similar way across persons than the ads with low levels of narrativity.

This study showed that conscious responses are not always aligned with unconscious responses. This brings important implications for businesses because relying solely on consumers' self-reported perceptions may not provide the full picture of a performance of advertising, for example. Furthermore, we have shown that metrics such as electroencephalography inter-subject correlation could be used to understand whether a marketing communication produces similar activation in consumers' brains, possibly reflecting a shared interpretation of the communication piece. Because of the possibility to assess common reactions to a stimulus, inter-subject correlation can be potentially used as a marker for forecasting the success of marketing communication elements, as has been shown elsewhere.

In Chapter 5, subsection "Effectiveness of augmented reality advertising", we used a set of neurophysiological metrics, explicitly eye-tracking, galvanic skin response, and heart rate combined with behavioral and self-reported data to investigate advertising effectiveness. We aimed to assess whether an ad with augmented reality and a 3D element would perform better than an animated ad on ad and brand perceptions, as well as on purchase metrics. The results showed that both ad types lead to similar unconscious emotional reactions toward the ad and similar ad and brand conscious perceptions, except for the perception of involvement with the ad (i.e., attention), which is greater for the augmented reality ad. In addition, eye-tracking data in the purchase stage revealed that the advertised product received the greatest attention than all other competitor products present in the shopping platforms. We also found that the augmented reality ad increases product recognition and the probability of product purchase compared to the animated ad.

This study suggested that AR advertising leads to higher attention paid to the ad as well as a higher impact on brand-related metrics. However, the hype of using advertising with augmented reality to increase emotional responses in consumers may not be justified anymore. Although the physiological metrics revealed that augmented reality still tends to induce emotional reactions (i.e., arousal levels) in part of the consumers, the findings of our study imply that consumers are getting desensitized from the novelty of the tool. Furthermore, eye-tracking data showed that an advertised product receives around double of attention at the point of sale compared to non-advertised products.

In Chapter 5, subsection “Brand choice in the metaverse and its relationship with personal and social factors”, we used a reaction time test to complement self-reported data to explore the underlying reasons for choices in the metaverse. The main findings demonstrated that consumers forgo money to have a branded product in the metaverse, and that brand choice mostly reflects real-life experiences and choices. Different psychological drivers were behind a virtual product choice or a real choice and also changed for a developed or a developing country. The reaction time test showed that it is possible to capture implicit brand-personal status (i.e. if the brand brings status to that particular consumer), and this brand-personal status is related to brand choice both in the virtual and real worlds.

This study showed that while the self-reported perceived status of a brand does not relate to brand choice in virtual and real worlds, implicit brand-personal status captured through a reaction time test does. Thus, it shows the usefulness of gathering metrics related to a construct through both explicit (e.g., self-reported) and implicit (e.g., reaction time tests) methods. Moreover, it demonstrates that variations of traditional reaction time tests (e.g., an implicit association test) also bring insights to marketing studies.

General conclusions

The set of studies presented in this thesis indicated the potential of using neurophysiological tools in marketing communication research to uncover data that cannot be objectively obtained otherwise. These data can prove crucial for brands planning and delivering more effective marketing communication elements, especially in areas where marketing knowledge is still developing (e.g., in digital and, particularly, extended reality contexts). The studies reported in this thesis revealed a piece of knowledge obtained using neurophysiological tools that adds to marketing theory and practice. In fact, we have approached several future research topics in digital advertising proposed by Lee & Cho (2020).

The studies investigated different topics within the marketing communication area and used different neurophysiological techniques. Eye-tracking metrics were shown to be suitable to uncover how much visual attention given to a marketing communication element correlates with intentions and behaviors. EEG metrics were shown to be powerful to uncover how features of marketing communication elements alter brain states. GSR and HR were shown to be adequate to infer emotional states while facing marketing communication elements. Finally, reaction time tests were shown to be compelling, straightforward, and easy ways to assess associations between marketing communication elements and abstract attributes.

None of the findings reported in this thesis could have been obtained if only using explicit (e.g., self-reported) metrics. However, as could be noticed in most of the studies presented in this thesis, explicit metrics do bring valuable information. The issue is that when there is a need to understand consumer behavior beyond the superficial, conscious, and observational levels, these metrics are not sufficient. Therefore, the application of neurophysiological tools proves essential to have a deeper assessment of consumers' perceptions and reactions to a marketing communication element.

General Limitations

The studies presented here have several limitations. These limitations are discussed in detail for each study in the corresponding chapters. However, common limitations are as follows. First, as with most of the existent academic studies, our studies were conducted in a laboratory setting and/or using hypothetical situations. While a controlled environment increases internal validity, it usually has low ecological validity. Therefore, our findings may not be taken as an exact representation of how consumers would behave in a real-life situation. Second, the samples used may not include all types of consumers. We sought to either use participants coming from the general population when the majority were from the same nationality or to have participants from different nationalities when they had similar profiles. Nevertheless, our findings may not apply to different cultures or groups of consumers besides the ones used in the studies. Third, we used neurophysiological tools that were available to us and analyses that were in our level of expertise. Several different metrics can be obtained from the tools we have used. These metrics may be more sensitive to captured cognitive and affective responses than the ones we used. Therefore, our findings may not be considered definitive.

Future Research Lines

It is evident that the digital world is becoming increasingly intertwined with the physical world. This enables brands to approach consumers in ways that until few years ago were not conceivable. The studies presented in this thesis put a step forward in understanding marketing communications-consumers relationships in this digital context using also signals coming from the body and brain. However, several open questions remain unanswered. Potential research lines to further explore the topic are:

* To explore different forms of marketing communication in recent digital formats. Should an avatar endorse the brand in an immersive VR environment? Should the physical background be replaced by an interactive hologram when viewing a physical product using mixed reality? Should brands sponsor virtual experiences in the metaverse to promote their products?

* To explore neurophysiological metrics to measure marketing communications effectiveness. Are the signals coming from common wearable devices (i.e., smartwatches) able to detect consumers' states? Which visual attention metrics

obtained by VR glasses eye-tracker best predict attention? Can avatar expressions indicate consumers' emotions?

List of Appendices

APPENDIX 1

HOW VISUAL ATTENTION TO SOCIAL MEDIA CUES IMPACTS VISIT INTENTION AND LIKING EXPECTATION FOR RESTAURANTS

How visual attention to social media cues impacts visit intention and liking expectation for restaurants

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Abstract

Purpose – The purpose of this study is to examine how social media (TripAdvisor) content influences restaurant visit intentions and liking expectations, how online review valence affect the viewing behavior of the social media page and which social media elements capture the initial attention of the consumer.

Findings – The pictures posted by firms and opinions posted by users attracted consumers' attention. However, in the negative valence condition, participants needed to expand upon the content by reading additional (and more detailed) online reviews with specific cues, revisited the content more often and more closely fixated on specific online ratings. Moreover, the picture of the restaurant was the first area seen (reflecting a bottom-up process) and the third-party ad tended to be viewed last (reflecting selective attention).

Research limitations/implications – All social media elements are seen but only some affect decisions, with negatively (vs positively) valenced reviews requiring consideration of an extra element. Of relevance to managers, this study stresses the importance of the pictorial element and the influence of user-generated content on the attention and judgment of consumers.

Originality/value – This study suggests that, to form an opinion, viewers devote more cognitive effort and attention when evaluating restaurants with negatively (vs positively) valenced reviews. However, viewing patterns appear unaffected by review valence. It also demonstrates how consumers pay attention to different social media elements.

Keywords Attention, Consumer behavior, Eye-tracking, Online reviews, Social media content, Valence

Paper type Research paper

1. Introduction

Social media platforms contain online reviews from users as well as communicative content from the companies themselves (Li *et al.*, 2021). Academic research, including meta-analyses, has shown that online reviews influence consumer choices (Babić Rosario *et al.*, 2016, 2020; Pourfakhimi *et al.*, 2020), including sales (Chu *et al.*, 2020). Furthermore, a TripAdvisor survey of restaurateurs in five markets revealed that social media marketing channels generate greater return on investment than other media (TripAdvisor LLC, 2017). Notwithstanding, the effect of restaurant reviews in social media remains understudied (for a review, see Rodríguez-López *et al.*, 2019).

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Social media content features three distinct characteristics. First, it contains both user-generated content (UGC) and firm-generated content (FGC). Second, it displays different formats: mainly text and pictures. Third, its content can be positive or negative – typically termed as valence. Therefore, social media content differs in origin, format type and valence. Lang's (2000) limited capacity model suggests that people have limited mental resources with which to process all available information. Thus, in tension with the principle of least effort, processing social media content can be cognitively demanding. Furthermore, the assumption that consumers pay attention to all cues, in the same order and with the same intensity, contradicts such existing postulations as signaling theory, information processing theory (Kirmani, 1997) and selective attention. Extending such theoretical bases to social media, we expected consumers to view each social media cue in varying ways, ultimately affecting their choices.

Relevant literature reviews have examined a variety of research directions for studies on the role of social media in hospitality, tourism and travel (Chu *et al.*, 2020). Further, extensive research has used surveys and, to a lesser extent, crawled data (Chu *et al.*, 2020; Nusair, 2020) to investigate how consumers process online reviews (Risselada *et al.*, 2018), but virtually, no studies have used eye-tracking measurements to investigate "whether and how consumers use different elements of reviews in the decision-making process" (Maslowska *et al.*, 2020, p. 283). Recent studies have called for "research to employ eye-tracking methodology to advance understanding of consumers' processing of eWOM [electronic word-of-mouth]" (Babić Rosario *et al.*, 2020, p. 439). Eye-tracking research has proven that consumers' attention drives decisions (Orquin *et al.*, 2013). Indeed, very few previous studies have examined social media viewing patterns (Bigne *et al.*, 2020, 2021; Muñoz-Leiva *et al.*, 2019), and to the best of our knowledge, ours is the first to explore the relationship between social media visual attention and the intention to visit and expected liking of the service under different valence conditions. We, thus, seek to fill the research gap concerning how attention paid to heuristic cues in social media shapes consumer decision-making. To achieve this, we investigated how consumers view social media content (both UGC and FCG) in different formats (text and pictures) and with different valence, as well as how these heuristic cues influence consumers' intention to visit and their liking expectations in the context of restaurants.

Online reviews can be deconstructed into several distinct cues, thereby enabling our investigation into which are the most impactful on consumer decision-making. We sought to identify which elements of information consumers consider when viewing business social media pages. On social media platforms, many elements are classified as heuristic cues (Chung *et al.*, 2017; Hlee *et al.*, 2018). Heuristic processing is associated with decisions based on cues featuring limited information (e.g. heuristic cues). For example, overall restaurant ratings posted on TripAdvisor are evaluated by consumers heuristically (Yoon *et al.*, 2019), for instance, by their using the "consensus implies correctness" heuristic. These star ratings have become highly important; firms are witnessing firsthand the significant sales impact of well-managed star ratings (Yoon *et al.*, 2019).

The valence of social media content remains a challenging research topic. In general, positive content elicits purchases. However, research suggests that negative content can more strongly impact purchase decisions and can even benefit the brand (Luan *et al.*, 2022). We argue that these inconsistent findings could be explained by the filters that consumers apply when sorting and choosing between positive or negative content (Tata *et al.*, 2020), as filtering leads to different visual attention patterns. Therefore, how consumers view social media content containing multiple UGC/FGC information cues, particularly with varied valences, requires further research.

Therefore, this study has three aims:

(1) to understand how UGC valence affects consumers' social media content viewing;
(2) to examine the influence of the content viewed from a TripAdvisor page on visit intention and liking expectations; and
(3) to evaluate how consumers respond to the content, particularly in terms of which elements capture their initial attention.

To achieve these aims, we conducted an empirical study based on explicit self-reporting measures and implicit eye-tracking measures. This research contributes to the relevant literature through its analysis of viewing behavior. It demonstrates how consumers process specific content cues based on review valence. It also provides evidence on how consumer intentions and expectations relate to the information processing of restaurant content. Moreover, we offer managerial insights into comprehensively understanding the role that content plays in consumer behavior and the ways in which attention is allocated to different social media elements. Our results may help managers delineate their strategies for social media communication, particularly when the valence of a comment is negative.

The remainder of the work is structured as follows. Section 2 introduces the main theoretical background and poses our research questions (RQs). Section 3 outlines the methodology and measures. Section 4 provides the results and discusses them. Section 5 addresses the general conclusions of our findings, provides the theoretical and managerial implications and examines the study's limitations in addition to potential avenues for future research.

2. Theoretical background

2.1 Social media valence

Although the findings of previous studies are inconclusive, it is generally recognized that valence can affect consumers' perceptions of a review's usefulness (Liu and Park, 2015; Park and Nicolau, 2015). Whereas some studies have posited that negative electronic word-of-mouth (eWOM) has a greater influence on sales than positive eWOM (Chevalier and Mayzlin, 2006), others have demonstrated the reverse (Babić Rosario *et al.*, 2016), including eye-tracking studies analyzing online comments (Shi *et al.*, 2020). Surprisingly, little attention has been paid to what – and how – social media content is viewed. Research has shown that consumers may filter information cues and, thus, may view either the entirety of the content or only parts of it (Bigne *et al.*, 2020; Varga and Albuquerque, 2019). However, while many previous studies have analyzed the effects of social media content's elements (Hlee *et al.*, 2018), they have neglected to offer an integrative perspective in examining the effects of both its types (i.e. UGC and FGC).

The literature demonstrates that trust in UGC generates expectations about destinations, that is, positive UGC creates positive expectations and vice versa (Narangajavana *et al.*, 2017). However, for online booking of hotels, negative online reviews negatively influence the number of bookings, whereas positive reviews have no impact on it (Zhao *et al.*, 2015). For restaurants, ratings regarding the service, environment and especially the food have all been found to correlate positively with online popularity (Zhang *et al.*, 2010). Daugherty and Hoffman (2014) manipulated message valence (positive, neutral and negative) of two product categories, cars and restaurants, and found that eWOM valence had a main effect on fixation duration, with participants viewing negative stimuli for the longest periods of time, followed by positive, then neutral. The same experiment was conducted to include the structural elements (text and images) as independent variables and restaurants as the product (Hoffman and Daugherty, 2013), with attention measured as the total number of fixations on pre-defined areas of interest (AOI). The authors found that participants fixated most often on non-luxury restaurant pictures and on luxury restaurant text. Valence was found to have an interaction effect with element type for luxury restaurants.

As mentioned above, social media valence is key to consumer decision-making. Depending on UGC valence, consumers might attach different degrees of importance to UGC and FGC in decision-making and, consequently, follow different screening strategies. Thus, we assessed whether consumers view social media content differently based on the valence of the reviews they read. Because firms cannot interfere in TripAdvisor's metrics, we have instead focused upon the valence of user evaluations. Therefore, we pose the following RQ:

RQ1. Does viewing behavior vary depending on user-generated content valence?

2.2 Viewing social media cues

Daugherty and Hoffman (2014, p. 95) stated that "consumer attention is a critical variable that should not be neglected in research, theory and practice pertaining to eWOM communication within social media." In fact, a bibliometric study on the hospitality and tourism field (2002–2016 period) showed a steep growth on consumer behavior research (2011–2016 period), particularly related to eWOM topics (Nusair *et al.*, 2019). So far, research has established that consumers' viewing of social media UGC is a "complex phenomenon" that should be examined to understand the effects of eWOM and that message elements are impactful only if viewers notice them (Hoffman and Daugherty, 2013). A product's social media page usually contains UGC and other product-related FGC (e.g. pictures and technical information). These elements may well vary in importance to the consumer. Indeed, the literature contains inconclusive findings concerning how review elements affect consumer behavior (Baek *et al.*, 2012; Chung *et al.*, 2017; Yang *et al.*, 2017). Furthermore, the literature has tended to ignore how users' social media viewing affects visit intention and liking expectations.

Visual attention has been described as a proxy for preference (Wedel and Pieters, 2014); in other words, an effective indicator of the viewer's focus is to identify what is being looked at. Just and Carpenter (1975) revealed a direct link between visual attention and mental processing when the visual stimulus is important in a task's encoding and processing. Filtering content viewing is the result of selective attention, which itself is driven by the principle of least effort. To reduce cognitive effort, people use heuristic mechanisms in which they apply previously formed schemas, rules of thumb, in viewing stimuli instead of carefully analyzing each piece of information presented. Social media elements tend to differ in how they capture attention (bottom-up or top-down) (Maslowska *et al.*, 2020). For example, in social media settings, consumers' attention follows a top-down mechanism when only text is present, yet this changes to a bottom-up process when pictures are included (Bigne *et al.*, 2020).

Consumers may examine some or all of social media content's multiple UGC and FGC cues. In addition, the visual attention paid to each cue may differ, thereby influencing the cue's ability to impact consumers' judgments. As the overall rating condenses the assessment of the service provided, one could argue that, in accordance with the principle of least effort, consumers will tend to view this cue first. Furthermore, Bigne *et al.* (2020) have shown that the online rating is viewed the most. Therefore, we posit that, because of the nature of social media content, consumers may form impressions about services based on the overall ratings provided by other consumers and that these impressions ultimately drive visit intention and liking expectations for restaurants. When presented with less informative cues (i.e. heuristic cues) compared to message content cues, consumers might pay varying levels of attention to them and may consider all – or only some –to reach a decision. Therefore, we pose the following RQ:

RQ2. Which social media content cues (overall rating, pictures, detailed ratings and opinions) affect (a) intention to visit and (b) liking expectations?

Following the attention capture and transfer (AC_TEA) model (Pieters and Wedel, 2004) proposed in printed advertisements, we acknowledge that stimuli can engage bottom-up or top-down visual mechanisms. The former occurs involuntarily by diverting attention to a stimulus's salient features, whereas the latter involves cognitive strategies and is goal-oriented. For example, Pieters and Wedel (2004) found that pictures capture attention more effectively (e.g. they attract higher initial attention) than text.

Social media content consists of multiple cues, but is the first the most important? The "first impression" aspect has been previously addressed in advertising research (Lindgaard *et al.*, 2006; Pieters and Wedel, 2012). Pieters and Wedel (2012) suggested that readers can understand the essence of a printed advertisement within 100 milliseconds or less, typically during the first eye fixation. Using self-reported measures, Lindgaard *et al.* (2006) found that a website's visual appeal is gauged in the first 500 milliseconds. These rapid judgments are recognized as cognitive confirmation bias effects (Nisbett and Ross, 1980) that lead viewers to search for confirmatory evidence of what they first saw. In a Facebook-based study in which the participants viewed a series of posts (social, news and political), the eye-tracking data revealed that posts containing richer content, such as pictures and links, attracted more attention (Vraga *et al.*, 2016). To the best of our knowledge, no previous study has explicitly addressed the question of what users initially view in social media content, with some exceptions (Bigne *et al.*, 2021). Therefore, we address the following question:

RQ3. Do different content types (i.e. picture vs text) capture different levels of initial and subsequent attention?

3. Methodology

This study relies on the eye-tracking data and self-reported data that we obtained from our experimental design. We created TripAdvisor-type online review pages for four types of specialty restaurants: pasta, pizza, paella and steak. We chose these categories for being the most representative in the study context and for their popularity on TripAdvisor. More generally, we chose restaurants because of their economic importance and the influence of online restaurant reviews on consumer choices. The global full-service restaurant (i.e. table-service restaurants) market in 2020 was estimated at US$1.2tn and has been projected to reach US$1.7tn by 2027 (Lock, 2021). Thus, it is notable that, despite the steep increase in food delivery demands because of the COVID-19 pandemic, the full-service restaurant format continues to experience positive growth. We chose to use TripAdvisor as the model for our online review pages because it is among the largest restaurant review platforms and claims to be more influential than Google, Facebook and Yelp in consumers' choices of eateries (TripAdvisor LLC, 2017, 2018).

3.1 Experimental design

We applied a two-within-subjects (WS) design, with rating valence (positive = 4.5 stars vs negative = 1.5 stars) as the independent variable and:

- the probability of visiting the restaurant; and
- the expected liking of the restaurant as the explicit dependent variables.

We treated the eye-tracking metrics as independent or dependent variables, depending on the analysis. We mimicked the same upper-page layout as TripAdvisor's desktop display. Written comments were excluded because of their subjective interpretation. The experiment featured four restaurant types and two conditions, namely, positive and negative valence. We used two groups of participants to cover both conditions for all restaurants and all participants viewed four stimuli (two restaurants per condition; Table 1). We counterbalanced the presentation order across the participants.

3.2 Participants

Our sample comprised 128 Spanish residents representative of the area's population, of whom 100 were recruited by an external agency and 28 internally to account for possible data loss. We recorded the following demographic information: 51.6% female; M_{age} = 32.97, SD_{age} = 10.14, age range: 18–56; 68.5% employed, 26% students, 5.5% unemployed; 83% users of the TripAdvisor restaurant platform; and 98% restaurant patrons. The participants recruited by the external agency were financially compensated. The internal recruitment was conducted by two researchers, who approached staff and students enrolled at the university where the study took place. All participants were fully informed as to the nature of the study and their participation. We selected Spain because of its representative size and increasing potential in the restaurant market (TripAdvisor LLC, 2019). Following the analysis of the raw data, we excluded four participants and included only partial data from another five because of poor eye-tracking data quality (recordings below the 70% threshold).

3.3 Procedure and task

The participants signed informed consent forms. The eye-tracking system, the Tobii *X*2–30 Compact, was calibrated. The stimuli were viewed through a 23-inch 1920 × 1080-pixel monitor, and the data were recorded through iMotions software (iMotions 8.1, https://imotions.com). We collected the data in February 2020.

The first screen showed the experiment's instructions, then the TripAdvisor stimuli were displayed. To standardize viewing time, each restaurant page was shown for 30 s. Because of the participants' familiarity with TripAdvisor, we expected them to reproduce their actual viewing patterns. After being exposed to each restaurant for 30 s, participants were redirected to a survey showing the same stimulus to aid recall and were asked to rate the probability of visiting the restaurant on a slider bar (range 0–100%). Next, participants were asked how much they believed they would like the restaurant (i.e. whether they should visit it) by using a slider bar ranging from "I would dislike it a lot" to "I would like it a lot." The process was repeated for each restaurant, and the presentation order of the restaurants was counterbalanced among the participants. Finally, the sample answered demographic questions.

3.4 Measures and analyses

We used a questionnaire and eye-tracking as our measurements. The questionnaire captured participants' intention to visit and liking expectations for the restaurant. Eye-

Group	Restaurant 1	Restaurant 2	Restaurant 3	Restaurant 4
Group 1	PV	NV	PV	NV
Group 2	NV	PV	NV	PV

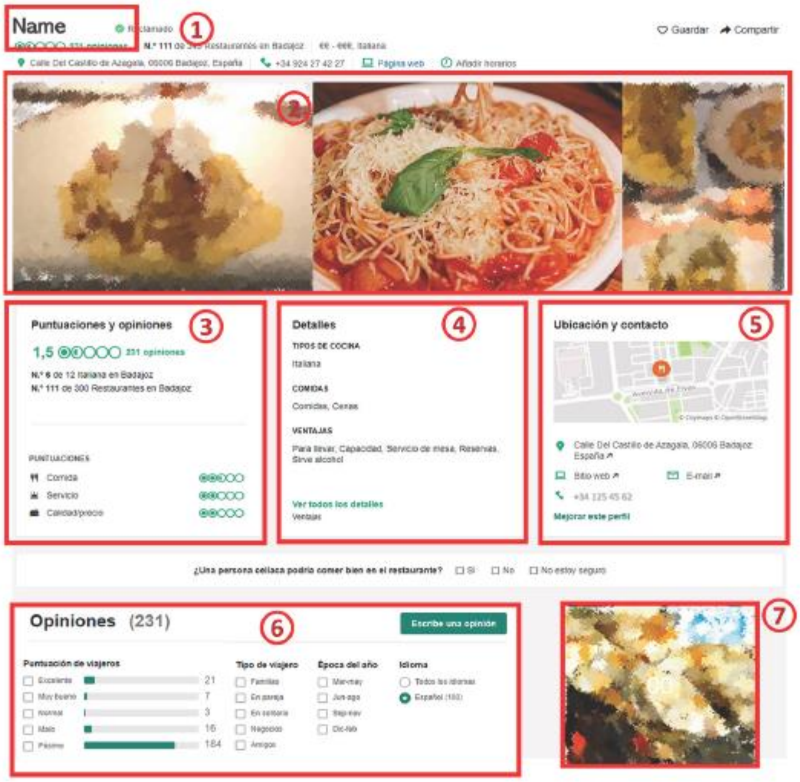
Notes: P: positive; N: negative; V: valence

Table 1. Groups and experimental conditions

tracking studies (Wedel and Pieters, 2006) tend to use the following metrics: time to first fixation (TTFF; ms), time spent in fixations (s), number of visits (revisits) and fixation count (i.e. the number of total fixations) by AOIs. TTFF is valuable in identifying which element first captures the participant's attention and facilitates mapping the initial viewing pattern of the entire stimulus. Time spent in fixations measures the attention focused on an element. High attention could indicate either the element's importance or its greater cognitive processing demand. Revisits identify how often participants look at elements, while fixation count reveals how many fixations each element receives.

To analyze the eye-tracking data, we divided each TripAdvisor page into seven AOIs reflecting both UGC and FGC (Figure 1) as follows:

(1) AOI_1: overall restaurant rating (top-left corner);



Notes: Name of the restaurant was removed and images were blurred for reproduction. The original name was a generic restaurant name, indicating the type of the food. The photo not blurred is an example of the original type of images used. Credits: photo by Cottonbro from Pexels (pasta), TripAdvisor/Google Maps (location map)

Figure 1.
TripAdvisor areas of interest content

(2) AOI_2: pictures posted by company (top);
(3) AOI_3: detailed ratings of services, such as food, quality and price (center-left);
(4) AOI_4: details of restaurant type (center-center);
(5) AOI_5: location and contact details (center-right);
(6) AOI_6: distribution of opinions, from excellent to terrible (bottom-left center); and
(7) AOI_7: third-party online advertisement (bottom-right).

Regarding the analyses performed, we describe here the main approach used for each RQ. Further and post hoc analyses can be seen in the Results and Discussion section.

To answer *RQ1*, we performed a repeated-measures (WS) ANOVA for each dependent variable. The four abovementioned eye-tracking variables for each AOI served as the dependent variables. We set valence as the independent variable. The four trials were condensed into two by aggregating the two positive and the two negative, valence trials.

To answer *RQ2*, we performed four generalized linear models: a WS regression (GLM-WS) with a robust estimation procedure for each dependent variable (i.e. the questionnaire metrics). The independent variables were valence and the time spent in fixations for AOIs 1, 2, 3 and 6. We excluded AOI_4 (details), AOI_5 (location and contact details, which was identical for all restaurants) and AOI_7 (third-party advertisement) because of their low relevance for the dependent variables. We included restaurant type to control for it. Following the GLM-WS formula with the fixed factors (Formula 1), Y = dependent variable, β_i = regression coefficients, A_i = time spent in fixations for each AOI (i = 1, 2, 3, 6), V = valence, R_i = dummy variable for restaurant type and ε = residual term.

$$\begin{aligned} \mathrm{Y} &= \beta 0 + \beta 1\mathrm{A}_1 + \beta_2\mathrm{A}_2 + \beta_3\mathrm{A}_3 + \beta_4\mathrm{A}_6 + \beta_5\mathrm{V} + \beta_6\mathrm{A}_1\mathrm{V} + \beta_7\mathrm{A}_2\mathrm{V} + \beta_8\mathrm{A}_3\mathrm{V} \\ &+ \beta_9\mathrm{A}_6\mathrm{V} + \beta_{10}\mathrm{R}_1 + \beta_{11}\mathrm{R}_2 + \beta_{12}\mathrm{R}_3 + \varepsilon \qquad \text{(Formula 1)} \end{aligned}$$

We combined all four trials and conducted descriptive analyses to answer *RQ3*.

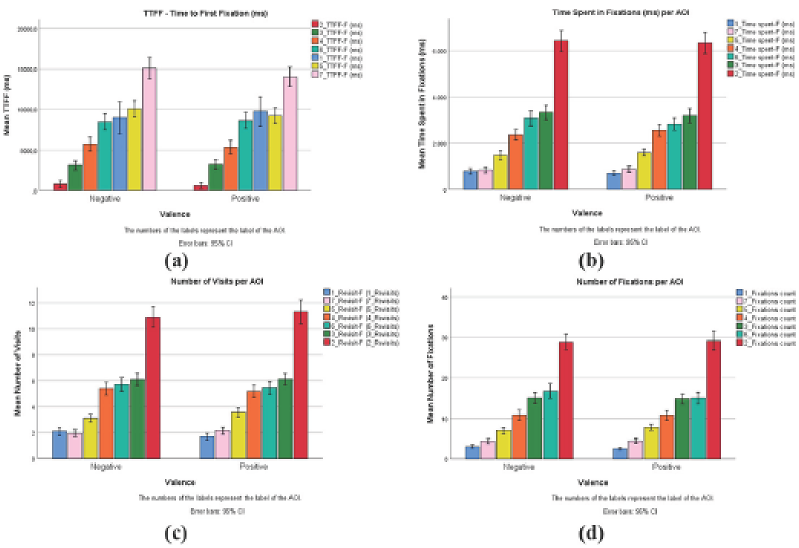
4. Results and discussion

4.1 Manipulation check

As stated previously, we expected valence to affect the dependent variables of *RQ2*. Accordingly, we first conducted a repeated-measures ANOVA to compare valence's effects on visit intention (VisInt) and expected liking (ExpLik) as the dependent variables in both the positive and negative conditions. The results revealed that valence had a statistically significant effect on VisInt ($F(1, 127)$ = 168.98, p = 0.000, η^2 = 0.57), where positive (negative) valence increases (decreases) VisInt (M_{pos} = 72.37, SD = 17.69; M_{neg} = 34.67, SD = 24.61) and ExpLik ($F(1, 127)$ = 155.22, p = 0.000, η^2 = 0.55), where positive (negative) valence increases (decreases) ExpLik (M_{pos} = 72.67, SD = 17.00; M_{neg} = 40.57, SD = 23.04). Therefore, the valence manipulation significantly affected behavior.

4.2 Does viewing behavior vary depending on user-generated content valence?

To address *RQ1*, we set the following eye-tracking metrics as the dependent variables: TTFF, time spent in fixations, revisits and fixation count across the valence conditions. Our first step involved plotting each metric by valence condition to visually observe the participants' viewing behaviors (Figure 2). The visual inspection of the plots showed no valence influence on stimuli viewing patterns.



Notes: A: time to first fixation ; B: time spent in fixations; C: revisits; and D: fixations count

Figure 2. Visualization pattern across valence conditions

The second step involved the statistical analysis using a WS-ANOVA (Subsection 3.4). The significant results are shown in Table 2. The TTFF results showed no difference across valence for any of the AOIs, meaning that the TTFF of each was the same for each valence condition. The analysis revealed that time spent in fixations on AOI_5 and AOI_6 differed across the valence conditions. The time spent in fixations was longer in AOI_5 in the positive condition and longer in AOI_6 for the negative condition. The revisits results showed that AOI_1 and AOI_5 differed across the valence conditions. AOI_1 was revisited more times in the negative condition and AOI_5 more often in the positive condition. The results for fixation count mimicked the revisit results.

In summary, participants followed the same viewing patterns across stimuli regardless of UGC valence. This is consistent with Bigne *et al.* (2021), who also found a common viewing pattern independent of valence while using positive and neutral TripAdvisor

Metric	AOI (source)	*F(1,123)*	*p*-value	Positive valence *M (SD)*	Negative valence *M (SD)*
Time spent in fixations (sec)	5 (FGC)	3.62	0.059	1.60 (0.82)	1.48 (1.03)
	6 (UGC)	3.72	0.056	2.83 (1.48)	3.07 (1.80)
Revisits	1 (UGC)	6.51	0.012	1.70 (1.50)	2.10 (1.75)
	5 (FGC)	5.82	0.017	3.57 (2.05)	3.12 (1.69)
Fixation count	1 (UGC)	7.54	0.007	2.54 (1.91)	3.08 (2.32)
	5 (FGC)	5.16	0.025	7.79 (4.22)	6.99 (4.30)

Note: *p*-values were not corrected for multiple testing

Table 2. Statistically significant ($p < 0.10$) tests of each area of interest on valence effects

ratings. However, we found some variations for certain AOIs. For the time spent on fixations, AOI_5 (location and contact) had more viewing time in the positive than in the negative valence condition, whereas the opposite was true for AOI_6 (reviews). In line with Shi *et al.* (2020), we found that participants fixated longer on the opinions element of written comments (AOI_6) in the negative valence condition than in the positive condition. Regarding AOI_5, we would propose that the higher attention paid to this element in the positive valence condition might be because of searching for practical information (i.e. address) derived from a positive but unconscious, attitude (i.e. intention to visit). The number of visits and fixations were higher for AOI_1 (overall rating) in the negative rather than in the positive valence condition, whereas the reverse was true for AOI_5.

Although some neurological studies have demonstrated that negative stimuli evoke more attention than positive or neutral stimuli (Smith *et al.*, 2003) and that negative reviews generally receive higher and longer-lasting fixation counts than positive ones (Daugherty and Hoffman, 2014; Moriuchi, 2021), we found no substantial differences between the two valence conditions. This could have been because of how we presented the stimuli to the participants: both conditions were shown for the same amount of time. This might have masked a possible difference in time spent fixating on the stimuli across conditions compared to if the task had been self-paced. However, we did find that parts of the UGC received more attention when negatively (rather than positively) valenced, corroborating the importance of well-managed star ratings (Yoon *et al.*, 2019).

4.3 The effect of visual attention of social media content on intention to visit and liking expectations

RQ2 aimed to address which FGC (AOI_2 [picture]) and UGC areas – overall rating (AOI_1), detailed rating (AOI_3) and opinions (AOI_6) – affect intention to visit (VisInt) and liking expectations (ExpLik). We used the time spent in fixations to measure visual attention. As mentioned earlier (Subsection 3.4), we performed a GLM-WS.

For VisInt and ExpLik, the interactions terms of valence with time spent in fixations were significant. To analyze the simple effects, we conducted two further GLM-WS, one for each valence condition (see Table 3 for the results). The data for the positive valence condition revealed that, for AOI_2, an increase of one second in fixation time decreased VisInt by 1.01%, but that this same addition increased VisInt by 1.69% for AOI_6. In the negative valence condition, a one-second increase in fixation time on AOI_2 led to an increase of 1.29% in VisInt and 2.00% and 1.98% decreases for AOI_3 and AOI_6, respectively. For ExpLik, the data for the positive valence condition revealed that, for AOI_6, a one-second increase in fixation time increased ExpLik by 1.38%. In the negative valence condition, for AOI_1 and AOI_2, a one-second increase in fixation time led to increases of 4.17% and 0.97% in ExpLik, respectively. For AOI_6, this same increase led to a 2.11% decrease in ExpLik.

The time spent in fixations indicated that the four AOIs differed in their effects on VisInt and ExpLik and that these differences depended on UGC valence. The pictures (AOI_2) and the opinions section (AOI_6) affected VisInt scores. However, the effect went in opposite directions depending on UGC valence. With positive UGC, the greater the fixation on pictures, the lower the VisInt, but the more the participants fixated on opinions, the higher their VisInt. Conversely, with negative UGC, longer fixations on AOI_2 led to higher VisInt, whereas longer fixations on AOI_6 led to lower VisInt. Moreover, for the negative valence stimuli, AOI_3 (detailed ratings) also negatively influenced VisInt (i.e. increased fixation time on AOI_3 decreased VisInt).

These direction effects were the same for ExpLik, although the participants relied on a slightly different set of cues. Only AOI_6 influenced ExpLik in the positive valence condition. For the negative condition, the participants considered pictures and opinions

Table 3. Statistically significant (p 0.10) tests of each area of interest on intention to visit and expected liking of the restaurant

Independent variable: time spent in fixations									
Metric	AOI (source)	Interaction valence × time spent in fixations		Simple effects					
				Negative valence			Positive valence		
		F(1, 476)	*p*-value	*F(1, 237)*	*p*-value	*Beta coefficient*	*F(1, 236)*	*p*-value	*Beta coefficient*
Intention to visit	3 (UGC)	4.77	0.029			–	3.96	0.048	−2.005
	6 (UGC)	7.73	0.006	4.09	0.044	1.685	4.43	0.036	−1.975
	2 (FGC)	6.53	0.011	3.10	0.080	−1.012	4.03	0.046	1.291
Expected liking	1 (UGC)	–	–	–	–	–	4.01	0.046*	4.171
	3 (UGC)	4.26	0.039	–	–	–	–	–	–
	6 (UGC)	9.35	0.002	3.40	0.066	1.381	6.25	0.013	−2.106
	2 (FGC)	5.10	0.024	–	–	–	3.40	0.066	0.968

Note: p-values were not corrected for multiple testing. *This result might reflect a Type I error

(AOI_2 and AOI_6) in their ExpLik ratings. Moreover, for the negative valence condition, the participants also took AOI_1 into account, although somewhat unexpectedly the effect's direction was opposite of that found for AOI_6. Given that both AOIs conveyed ratings information, it seems implausible that a longer fixation duration on the overall negative rating (AOI_1) would increase their VisInt. Accordingly, as this result may be based on a Type I error, it should be treated with caution.

Therefore, the answer to *RQ2* is that FGC pictures of a restaurant (AOI_2) and the UGC opinions regarding it (AOI_6) are the cues that affect VisInt and ExpLik (for the positive valence, only AOI_6 was significant). In the negative rating condition, participants also considered AOI_3 as an additional UGC cue in assessing their VisInt. These findings appear to suggest that UGC functions as an "indicator of information credibility" impacting consumers' behaviors and attitudes (Flanagin and Metzger, 2013). Moreover, negative UGC had a stronger impact on intention and expectation than positive UCG (see beta coefficient values). This supports previous findings that negative (vs positive) reviews tend to be more influential (Chevalier and Mayzlin, 2006), especially for experience goods (Park and Lee, 2009).

Surprisingly, we found that the direction of firm-posted pictures' influence was opposite that of its UGC counterpart. To the best of our knowledge, no study has previously evaluated the interplay between the attention paid to a firm-posted picture and the ratings provided by consumers on purchase or visit intentions. However, it should be noted that previous FGC studies have reported mixed results. Indeed, prior research has found FGC (including highly visual elements, such as Instagram posts) to positively influence visit (Ballester *et al.*, 2021) and purchase intentions (Poulis *et al.*, 2019) but to negatively impact the purchase intentions of new clients (Santiago *et al.*, 2022).

In our case, one might conclude that an FGC picture is perceived as less credible than a UGC photo because of the restaurant's motives for posting it. However, this would not explain the results for the negative valence, in which pictures increased self-reported VisInt. One possible explanation is that the picture did not sufficiently "match" the positive and the negative valence scores. For example, the positively evaluated restaurants had an overall rating of 4.5 stars; thus, the picture might have been perceived as not sufficiently "good" or "attractive" for such a high rating. Moreover, the reverse may be the case for the negative valence, in which the overall rating was 1.5 stars; in this case, the pictures might have been perceived as more attractive or of a higher quality than might be expected for such a low rating and they may even have triggered a biological desire to eat the food.

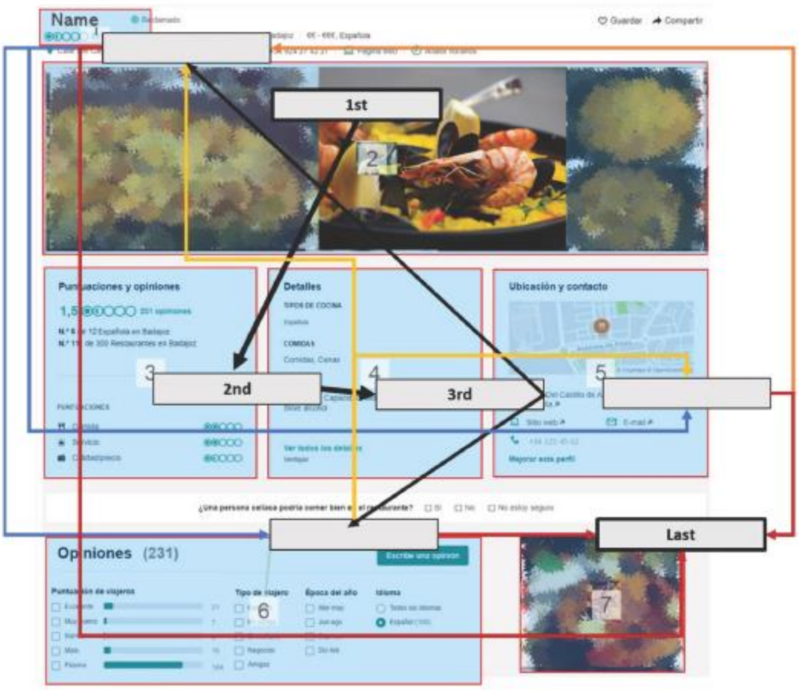
We found that participants did not use all the information available to make their judgments. Chaiken (1980) found that information processing is more exhaustive for high, rather than low, levels of involvement with the message's topic. Given that our participants were passively receiving restaurant information and were not organically motivated to find a place to eat, their use of few cues to reach a decision is consistent with the principle of least effort. Nonetheless, it is noteworthy that those simple cues still shaped intentions and expectations, possibly by activating the "consensus implies correctness" heuristic, as can be inferred from the analysis of the explicit data (Subsection 4.1). More interesting still is that, with a positive UGC valence, the participants relied on two cues to form opinions but needed an additional cue when the UGC valence was negative. This supports Varga and Albuquerque's (2019) finding that exposure to negative content motivates additional information-seeking, even if this implies the use of more cognitive resources.

4.4 The effect of initial attention to social media cues on subsequent attention

Because UGC valence did not affect the participants' viewing patterns, to address *RQ3*, we combined all four trials to gain insights into their viewing patterns during the social media stimuli. This involved three complementary analyses:

(1) the order of initial fixations on the AOIs to determine which first captured viewers' attention;
(2) the percentage of participants who looked at each AOI in every possible viewing order; and
(3) the time spent in fixations on each AOI based on the total fixation and stimulus presentation times (30 s).

Based on the averaged data, the ranking order is clear for the three first-viewed AOIs and the last position. As shown in Figure 3, the FGC pictures (AOI_2) were the first to be viewed, followed by detailed ratings (AOI_3) and restaurant type (AOI_4). The participants next viewed either overall rating (AOI_1) or opinions (AOI_6). The TTFF of overall star rating (AOI_1) did not differ significantly from AOI_5 (location or contact details) or AOI_6,



Notes: Each light blue box represents a different AOI. The gray numbers inside the small squares represent the AOIs' labels. The arrows represent the pattern of the first fixation across AOIs. Name of the restaurant was removed and images were blurred for reproduction. The original name was a generic restaurant name, indicating the type of the food. The photo not blurred is an example of the original type of images used. Credits: photo by Boris Hamer from Pexels (pasta), TripAdvisor/Google Maps (location map)

Figure 3. Order of time to first fixation of each area of interest for one of the four types of restaurants

whereas AOI_5 did differ from AOI_6 ($F(1, 123) = 5.32$, $p = 0.023$). Thus, from AOI_1 or AOI_6, they looked at either AOI_5, AOI_1 or AOI_6, depending on which AOI was previously viewed. The third-party advertisement (AOI_7) was the last to be viewed.

This pattern of viewing order was similar to that found by Bigne *et al.* (2021), who used a TripAdvisor-like layout excluding the picture at the top (our AOI_2). They found that the areas on the top-left and top-center (comparable to our AOI_3 and AOI_4) attracted the fastest initial attention. In contrast to our findings, their third-party advertisement (our AOI_7) captured attention faster than UGC elements (our AOI_6). However, important layout variations may explain these differences. We presented two pictorial elements: the top picture (AOI_2) and the small advertisement (AOI_7). However, in Bigne *et al.* (2021), the advertisement was the only pictorial content and was of a larger size. These differences might have generated increased and quicker attention.

A viewer's initial attention can be a signal of either:

- motivation to look, that is, a goal-oriented, top-down mechanism; or
- an involuntary response to a random stimulus, that is, a bottom-up mechanism.

Therefore, to more comprehensively understand the variation of the TTFFs across AOIs, we computed the percentage of participants that looked at each AOI in every possible viewing order (Table 4).

Table 4 shows that AOI_2, a pictorial element, captured the initial attention of most participants (81.4%), a result consistent with Pieters and Wedel (2004). The opposite was the case with the third-party advertisement (AOI_7), which tended to be the last area viewed. The superior performance of the picture (AOI_2) in grabbing initial attention may reflect a bottom-up mechanism, especially because of this AOI's comparative salience. Although the third-party advertisement also had salient features (colors and images), it was much smaller than AOI_2 and was positioned in a low-attention area. Moreover, we observed an interplay between salience effects (bottom-up mechanism) and top-down mechanisms. The fact that the third-party advertisement was the last-viewed AOI was potentially indicative of a strong top-down influence on initial attention, such as a deliberate lack of interest in the advertisement (Kowler, 2011, for an explanation on the notion of a saliency map and how it relates to top-down processes). Because of the participants' familiarity with the TripAdvisor layout, they would have been aware that the bottom-right area is dedicated to advertising. Hence, they might have used a selective attention process, at least regarding initial attention.

Furthermore, our results showed a transfer effect from pictorial to text content in a social media setting, which is in line with Pieters and Wedel's (2004) model of attention capture

Table 4. Percentage of participants for each ranking position of time to first fixation of the areas of interest

Order TTFF	AOI 1 (UGC) (%)	AOI 2 (FGC) (%)	AOI 3 (UGC) (%)	AOI 4 (FGC) (%)	AOI 5 (FGC) (%)	AOI 6 (UGC) (%)	AOI 7 (FGC) (%)
First	4.03	**81.45**	8.87	5.65	0.00	0.00	0.00
Second	27.42	16.94	**37.10**	16.13	0.81	1.61	0.00
Third	16.13	1.61	34.68	25.81	7.26	13.71	0.81
Fourth	8.87	0.00	12.90	**28.23**	15.32	25.00	9.68
Fifth	5.65	0.00	5.65	14.52	**34.68**	**30.65**	8.87
Sixth	9.68	0.00	0.00	6.45	32.26	22.58	29.03
Seventh	28.23	0.00	0.81	3.23	9.68	6.45	**51.61**

Note: The first row contains the table of each AOI and the first column represents the ranking order fixation and transfer (AC_TEA model). In addition, we observed that behavior varied depending on the AOI. Whereas AOI_2 and AOI_7 had a clear, common response across the participants, the behavior in relation to AOI_1 was diverse. AOI_1 captured the immediate attention of a representative percentage of the participants, as evidenced by the large percentage in the second and third positions, whereas another representative portion of the participants were unattracted to it (see the percentages in the sixth and seventh positions). Many participants also looked at AOI_3 in the second or third positions. The remaining AOIs (4, 5 and 6) occupied the intermediary positions. A study using an Amazon.com-like stimulus found that consumers initially examined product information (product title, image and descriptions) before turning to ratings (Moriuchi, 2021). We observed this general behavior in our participants in that they glanced at product-related pictures before the ratings. However, we saw that participants focused on ratings (AOI_3) before product-related information (AOI_4), perhaps because in the context of food, pictures are sufficiently informative and for experiential products (e.g. restaurants), the quality assessment is initially more important than further product-related information.

To analyze the time spent fixating on each AOI, we calculated the percentage of time spent looking at all AOIs (M = 18.21s, SD = 3.11) by measuring the total time spent viewing the stimulus (30 s). The results are depicted in Figure 4, which also contains a heat map for one of the stimuli. Although only one such map is provided, the remaining stimuli showed similar distributions. The percentages shown in Figure 4 depict the average value of all 16 stimuli used in the different scenarios.

5. Conclusions

This study analyzed viewing behavior and the influence of cues in firms' and users' social media posts on consumers' intentions to visit a restaurant and their expected liking of the experience. Participants viewed four restaurants in a mock-up TripAdvisor social media page, two of which were rated positively and two negatively. We measured visual attention through eye-tracking and, subsequently, used a questionnaire to ask the participants about their intention to visit and their expectations of liking the four restaurants.

The analyses showed that social media elements had different impacts on consumers' intentions and expectations toward restaurants depending on the UGC valence (*RQ2*). A closer inspection of viewing behavior revealed that the patterns for social media content were identical, regardless of UGC valence, although with certain particularities (*RQ1*). Moreover, we noted that, in general, although relevant and salient pictures captured consumers' initial attention, text sustained their attention for longer intervals of time (when controlled for area size; *RQ3*).

Two main ideas can be generalized for the hospitality industry that will impact users and commercial practices alike. Social media is changing the communication field and appears to be increasingly influential in decision-making in the hospitality industry (Litvin *et al.*, 2018). Users' influence through UGC is ubiquitous. However, social media also allows for the influence of FGC, thereby preserving the need for focused research to improve it (Santiago *et al.*, 2022). Accordingly, both UGC and FGC coexist and compete for consumers' attention. However, how consumers examine the social media content of users and firms alike is the essence of their influence. Our study provides insights into how visual attention influences two outcome variables: visit intention and liking expectations in both positive and negative valence settings.

Previous studies have established a positive relationship between review quantity and restaurant performance rating (Kim *et al.*, 2015). However, the massive amount of content delivered by social media is forcing potential consumers to focus their instant gaze on

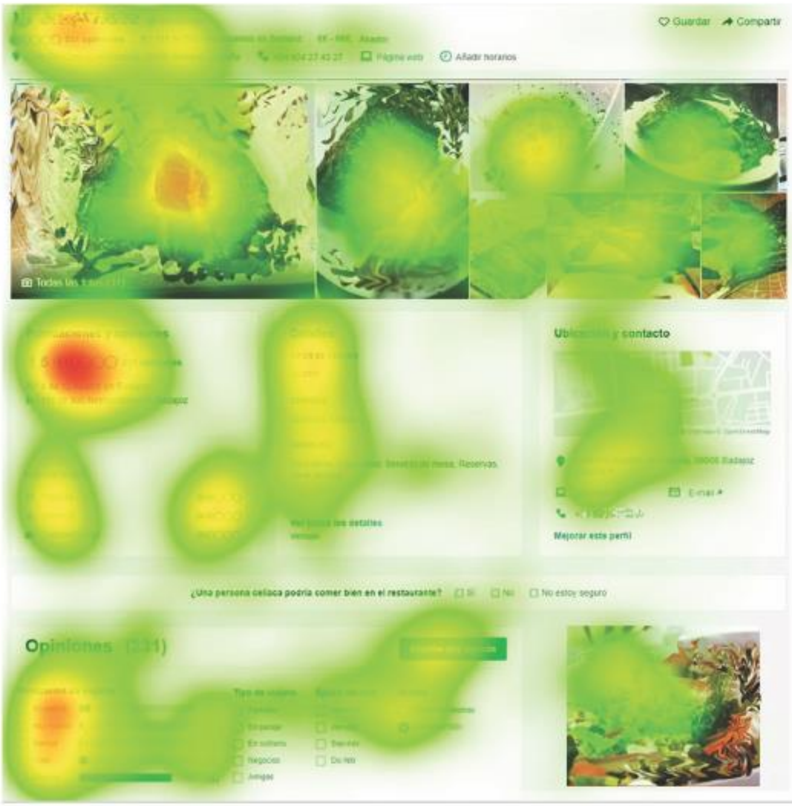


Figure 4.
Heat map of one of the stimuli (Restaurant 4 NV) and time spent in fixation metric

Note: The name and photos were distorted for reproduction
Source: TripAdvisor/Google Maps (location map)

salient and attractive pictures. Therefore, the visual content is significant in two directions. First, as proposed by Litvin *et al.* (2018), social media and the deep selection of pictures should be included in overall marketing and communications strategies. Second, because UGC and FGC compete in the same setting, the weighted influences of both demand targeted research. As such, the actual value of social media is driven by how potential consumers view social media content and how firms strategize in selecting appropriate content.

5.1 Theoretical implications

In a recent review of studies related to social media in tourism and hospitality journals, Lin *et al.* (2020) have identified UGC as one of the five main lines of research used. Moreover, the field of tourism and hospitality has demonstrated a steep interest in social media since 2006, and TripAdvisor was identified as a trend in the field, mainly in the hotel industry (Nusair, 2020). Our study, therefore, contributes to this area by investigating both UGC and FGC in a social media context (i.e. TripAdvisor) for restaurants.

The main theoretical implications of our study concern the influence of social media elements on consumers' viewing behavior and judgments (i.e. their visiting intentions and liking expectations). This is especially pertinent to the tourism, hospitality and travel sector, as it was suggested that economic and social factors would determine consumers' use of social media platforms related to this sector (Chu *et al.*, 2020). Our results revealed that, although our participants viewed all relevant elements, they did not use all to reach a decision. This might be because participants' motivation to assess the reliability of the information and their confidence in the decision-making outcome were not strong enough to overcome the tendency to save cognitive resources (the principle of least effort). Consequently, participants relied on few heuristic cues during their decision-making processes. However, by measuring attention via eye-tracking, we found neurological evidence that consumers use greater levels of cognitive effort to form opinions when faced with negatively valenced reviews compared to positive ones. This suggests that negatively valenced reviews increase uncertainty about product/service quality, which requires the consideration of additional cues to remedy. This could explain, for example, why consumers search more extensively for competing items when faced with negative reviews (Varga and Albuquerque, 2019).

As to the social media cues that first attract visual attention (*RQ3*), we found that the participants were initially attracted to the picture, possibly because of its saliency (e.g. colors, content and size) and its location, indicating a bottom-up visualization process. Furthermore, we noted an indication that this initial attention was transferred to the text. However, normalizing for the size of the area of elements, it seems likely that the participants used a top-down process to evaluate the UGC elements, as the time and number of those fixations were especially significant. The social media page also contained a third-party advertisement (AOI_7). Because AOI_7 was the last element to be seen, our participants tended to engage in a top-down process and to use selective attention related to the third-party advertisement. This is a relevant finding to better understand the intersection area of tourism and hospitality with social media and advertising and warrants further research (Chu *et al.*, 2020). Finally, we also contributed to the theory by providing findings which expand the current models of social media influence based on measurements of actual attention given to the cues. Such an approach has not been addressed to the hospitality domain (Chu *et al.*, 2020).

5.2 Practical implications

To managers, we would stress the importance of the pictorial element, which tends to attract initial attention, possibly via a bottom-up mechanism. This is especially important as the features of visual content tend to influence several consumer–company behavioral responses (Ballester *et al.*, 2021). Moreover, the restaurant would be in complete control of the pictorial element. We emphasize this element's importance because of the intriguing finding that the picture influenced judgments in opposite directions depending on the UGC's valence. Whereas UGC increases (decreases) intention to visit and expected liking with positive (negative) valence, pictures evoked the opposite behavior. We interpreted this to mean that the participants perceived the picture as incongruent with the star rating valence. Therefore, our advice is to always pretest the attractiveness levels of pictures to be posted on social media pages.

UGC also appears to significantly impact consumers' decisions. Our results showed that participants based their judgments on the opinions of others expressed via star ratings, possibly by activating the "consensus implies correctness" heuristic. Importantly, with positive valence reviews, the participants considered only how many others voted on each rating score (i.e. the breakdown of star ratings, AOI_6) to reach a decision. However, when review valence was negative, participants displayed a need for further restaurant-related data – such as food, service and value-for-money information – to form their judgments. Knowing that these factors (mainly food) correlate positively with restaurant popularity (Zhang *et al.*, 2010), it is imperative for restaurants to deliver high-quality service in these areas.

Another implication of our study regards the different AOIs. When correcting for area size, we found that UGC elements attracted a significant proportion of the participants' attention. This supports behavioral findings on the importance of considering UGC in marketing strategies (Babić Rosario *et al.*, 2016, 2020; Pourfakhimi *et al.*, 2020). Furthermore, it is crucial that companies using social media for their advertising be fully aware of the selective manner in which their (potential) customers respond to content. We found that the third-party advertisement is the last area viewed, suggesting a deliberate effort by site visitors to ignore advertising. Therefore, companies should diversify their marketing investments across different media and social media platforms and seek innovative advertising formats (e.g. augmented reality) to most effectively capture consumers' attention.

Although we set restaurants as our context, we argue that the implications of this study can be generalized to other sectors of the hospitality industry, such as hotels and other touristic services (trip packages and attractions). Indeed, the layout of social media platforms for these sectors also includes UGC and FGC, text and images. Furthermore, the metrics we used would suitably apply to these sectors as well.

5.3 Limitations and future research

This study has limitations that must be considered when examining its findings. However, they present opportunities for future research. First, participants viewed the stimuli for a fixed period of time, which would not be the case in real settings because of individual differences in total time spent looking at stimuli. We fixed the time to control for this variable and to obtain consistent eye-tracking data across conditions and participants. However, in so doing, we may have masked some potential differences in viewing behavior between the positive and negative valence conditions and may have influenced information processing. A follow-up study could remove this time constraint to assess the reliability of our findings. Second, the participants faced a hypothetical situation, thereby possibly removing any true motivation to perform the task. This could have led them to follow the principle of least effort and form heuristics-based judgments. Future studies might use incentive-compatible tasks to test the reproducibility of our findings. Third, our stimuli did not include written reviews, which, because of their subjective nature, may have been differently interpreted among the participants. Written reviews could potentially moderate the effect of the other page elements on visit intention and liking expectations. A future study might consider testing their potential influence. Fourth, we considered only one platform, TripAdvisor; our findings may not apply to other social media platforms. Moreover, future research could explore attentional patterns of the content elements with different elements and layout configurations. For example, in a TripAdvisor restaurant-based study, Bigne *et al.* (2020) manipulated review comments with or without pictures and showed that the attention participants paid to the review text (identified via gaze patterns) differed depending on the inclusion of a picture. In this vein, other types of social media platforms that are heavily based on pictures (e.g. Instagram) could be used for further research. Fifth, our statistical analyses were not corrected for multiple testing, which are known to increase Type I errors.

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APPENDIX 2

EEG THETA AND N400 RESPONSES TO CONGRUENT VERSUS INCONGRUENT BRAND LOGOS

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EEG theta and N400 responses to congruent versus incongruent brand logos

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Neuroimaging and behavioral studies have shown that brands convey meaning to consumers. To investigate the immediate reactions of the brain to brand logos, followed either by congruent or incongruent pictorial brand-related cues, can deepen understanding of the semantic processing of brands, and perhaps how consolidated the logo is in consumers' minds. Participants were exposed to different brand-related image sets, that were either congruent (a match between brand-related images and brand logo) or incongruent (a mismatch between brand-related images and brand logo) while having their brain signals recorded. Event-related potential and EEG time–frequency domain features were extracted from the signals of the target image (brand logo). The results showed significantly larger N400 peak and relative theta power increase for incongruent compared to congruent logos, which could be attributed to an error-monitoring process. Thus, we argue that brands are encoded deeply in consumers' minds, and cognitive processing of mismatched (vs matched) brand logos is more difficult, leading to greater error monitoring. The results were mostly consistent with previous studies investigating semantic incongruences in the linguistic field. Therefore, the error-monitoring process could be extended beyond linguistic forms, for example to images and brands.

The world's 100 most valuable brands reached a record value of 7.1 trillion U.S. dollars in 2021[1]. It is widely accepted that brands often represent the most important asset of a company and can influence purchasing decisions[2,3]. Neuroimaging and behavioral studies have shown that brands convey meaning to consumers[4,5]. However, how the brain connects brand elements (e.g., products) with brand representations (i.e., brand logo) is poorly understood. Thus, the immediate reaction of the brain to brand logos that are followed by congruent or incongruent pictorial brand cues can deepen our understanding of the semantic processing of brands.

Incongruence can be understood as a form of violation of pre-encoded rules or previous knowledge at the syntactic, semantic, or pragmatic levels, including contextual and background knowledge[6,7]. Because incongruences are most often unexpected, a violation of expectations may happen when they occur. Previous studies, mainly in the linguistic field, have found different brain responses to congruent and incongruent stimuli (see Baggio and Hagoort[8] for a review of this topic). A specific electrophysiological marker related to congruence is the N400 event-related potential (ERP), a negative deflection in the electroencephalogram (EEG) signals that peaks around 400 ms after stimulus presentation. This marker was first found by Kutas and Hillyard, in 1980, who defined it as "an electrophysiological sign of the 'reprocessing' of semantically anomalous information"[9] (p.1). After this initial work, several studies investigated the N400 effect on conflicting tasks (e.g., Stroop and flanker tasks)[10–15], affective influences[16,17], gesture representations[18,19], sentences/words[20–26], text and image[27,28], and pictures[29] (see Kutas and Federmeier for an extensive review of N400 studies[30]).

Brand logos are symbolic visual elements, consisting of image and/or text cues that aim to represent a brand in order to differentiate it from its competitors. They are so important that early definitions of "brand" could be summarized as "brand as a logo"[31]. In fact, competitive brands imitate features of leading brands, including brand logo, to benefit from brand equity of these leading brands[32]. Thus, it is crucial for companies that consumers associate a brand logo with the brand products and features. The N400 effect could indicate whether this link exists. Previous literature investigating semantic violations in sentence processing shows larger N400 amplitude, usually centro-parietally distributed, for words that are incongruent with a context, are infrequent, or have low cloze probability compared with congruent, frequent, or high cloze probability words[9,20–26]. However, studies using pictorial content as stimuli may be more relevant to this study as the brain could react differently to sentences as against images. Those studies provide evidence of the sensitivity of the N400 ERP to the semantic relationships

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between pictures[18,29]. Participants presented with pairs of either matched or mismatched pictures (e.g., knife-fork or cup-leaf respectively) had larger N400 amplitude (centering around 450 ms) broadly distributed over the scalp after a second mismatched picture, compared to a second matched picture[29]. Another study presented participants with words that were related or unrelated to succeeding pictures, regarding categorical or specific levels[33]. The N400 effect was found in the centro-parietal electrodes for all the manipulations, reflecting semantic mismatches in general. Gestural representations were investigated by presenting a short cartoon segment, followed by a short video with an actor reproducing the cartoon non-verbally (with spontaneous gestures)[18]. The video was either paired with the corresponding cartoon or with another cartoon segment. The results showed a wide, spatially distributed N400 effect, though more pronounced over the frontal and frontal-central midline sites, where a larger amplitude was found for incongruent than congruent gestures.

Overall, a violation of expectations seems to trigger the N400 response. It can be argued, however, that expectations exist because of previous knowledge of the world and of structures. It is therefore plausible to assume that memory is actively involved in stimulus processing. The findings of several studies suggest that the N400 effect reflects both the activation of working memory (e.g., immediate stimulus-context relationships) and also accessibility to long-term memory (e.g., context-independent relationships)[34]. Hence, stored knowledge related to a stimulus has to exist in the person's mind in order to judge whether some piece of information is expected or not[18,34]. Indeed, the magnitude of the N400 effect is sensitive to the ease of retrieval of this previous knowledge, which can be interpreted as proportional to the cognitive load needed to process the stimuli[19]. Though such a time-domain EEG feature (i.e., N400) already indicates that memory plays a role in semantic processing—with implications for cognitive load—information from the EEG frequency-domain can confirm and extend the role of memory.

Neural oscillations pertain to the EEG frequency-domain analysis. The theta band—an oscillation in the frequency of 4–7 Hz—has been shown to differ in power depending on stimulus congruity level, where stimuli perceived as incongruent increase theta power compared to congruent stimuli[10–12,17,20,21,28,35,36]. Past studies suggest that the location of the theta activity indicates the type of process involved. For example, an increase in theta power over the posterior region (found for semantically incongruent words, though not for semantically congruent but unpredictable words) could simply reflect the detection of semantic incongruences[21]; whereas an increase in theta power over the midfrontal regions (found after presenting an incongruent word), possibly reflects an error-monitoring process[20]. Moreover, there is a relationship between theta power and memory[37], including working and long-term memory[17,28]. In addition, the strength of the theta power is positively related to working memory demand[28,38]. The investigation of the semantic processing of emojis (pictorial representations of emotions or ideas) revealed that incongruent emojis—those emojis inconsistent with a sentential context—generated higher theta power at midfrontal, temporal, and occipital brain regions, compared with congruent emojis[28]. This was attributed to an increase in working memory load for error monitoring—represented by the midfrontal theta, and the activation of the long-term memory for emoji recognition and concept retrieval—represented by the occipital and temporal theta. However, theta increase in anterior parts (frontal) was also associated with retrieval of lexical information from long-term memory[17].

Most of the aforementioned ERP and brain-oscillation studies of congruence effects focus on language (in verbal and non-verbal forms). Because brand logos can influence consumers' brand perceptions[39], investigation of the processing of brands by the brain can expand our understanding of how brands are represented in consumers' minds. We therefore use real brands to explore how the brain reacts to brand-logos, representing brands that are congruently associated with brand cues (e.g., products, store layout), compared to logos that are incongruently associated with such cues. If brand logos are clearly represented in the minds of consumers, this knowledge should be accessible for retrieval when consumers encounter cues related to the brand. Thus, based on previous findings from other fields, we postulate that an increase in both N400 and theta power will occur in response to incongruent as against congruent logos. We propose that the N400 ERP and theta power features could be valuable for understanding how consolidated brands are encoded in the minds of consumers. Given our study design and stimulus, we expect to find a theta increase that represents an error-monitoring process, which is linked to working memory, as well as an activation of long-term memory. If this occurs, it could be argued that brand logos induce semantic processing that is similar to other representations, such as those encoded deeply in language.

Results

This section describes the results of the ERP analysis focusing on the N400 component, followed by the results of the time–frequency (TF) analysis comparing congruent as against incongruent conditions in the theta band (4 to 7 Hz).

Event-related potential. ERPs for each condition (congruent and incongruent) were obtained by averaging the corresponding pre-processed trials, in each specific brain region (mid-frontal, central, parietal, and occipital). Figure 1a–d shows the grand ERPs, which were obtained from the ERP average for all subjects in each condition. In the mid-frontal region (Fig. 1a), and the range of 400 to 600 ms, there is a pronounced difference between conditions, where the incongruent condition has greater negative activity than the congruent condition. However, a permutation test on the averaged data for the 400 to 600 ms time window revealed that this difference is not statistically significant ($p = 0.19$, effect size = 0.34). In the central region (Fig. 1b), there is a difference between the conditions in the range of the 400 to 600 ms time window, where the oscillations in the incongruent condition have greater negativity than in the congruent condition, which is statistically significant ($p = 0.04$, effect size = 0.54). In the parietal (Fig. 1c) and occipital regions (Fig. 1d), there was no significant difference in the 400 to 600 ms range between the two conditions (parietal: $p = 0.84$, effect size = − 0.05, and occipital:

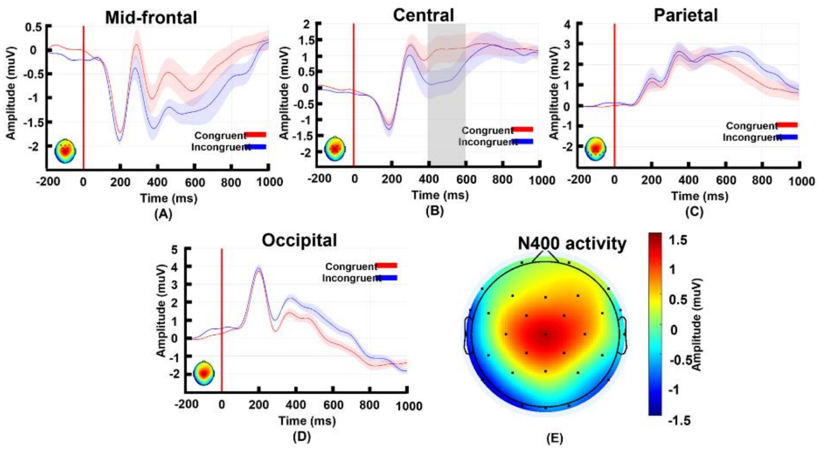

Figure 1. ERP obtained from average on trials of each condition and specific regions, and topo-map of N400 activity. Panels (**a**) to (**e**) show ERP activity for frontal, central, parietal, and occipital regions respectively. In all panels from (**a**) to (**d**), red curves show the ERP of congruent condition, and blue curve shows ERP of incongruent condition. The shaded area around each line indicates standard deviation of signals divided by square root of number of channels. In the same panels, the vertical red line in 0 ms indicates the start of the stimuli. The small topo-map at the bottom-left of each panel shows N400 activity and indicates the selected electrodes of each region. In panel (**c**), for the central region, the area highlighted in gray shows the significant difference between congruent and incongruent conditions ($p = 0.04$, effect size = 0.54), that occurs in N400. Panel (**e**) shows the difference of brain activity in two conditions (congruent-incongruent) in N400 (averaged from 400 to 600 ms). The hot colors show positive activity (i.e., congruent > incongruent) and the cold colors indicate negative activity (i.e., congruent < incongruent).

$p = 0.27$, effect size = − 0.29). Finally, Fig. 1e shows the averaged ERP amplitude differences (congruent minus incongruent) of each electrode in the 400 to 600 ms time window. The main difference occurred in the central region, which is consistent with a significant difference between the conditions occurring only in the central region.

Time–frequency. Figure 2a,c show the TF activity of congruent and incongruent conditions in the central region respectively. As shown, in the theta band frequency, and from 700 to 2300 ms, there is a negative relative power in both conditions, where the congruent condition is more negative. In addition, there is a negative relative power in alpha and beta frequencies for both conditions, starting from around 200 ms and lasting until the end of the stimulus. Figure 2b,d show the scalp power spectrum activity for the congruent and incongruent conditions respectively. There is negative relative power activity in the central region in both conditions, but the strength of this negativity is higher in the congruent condition. Moreover, there is positive relative power activity in the mid-frontal region only in the incongruent condition.

Figure 3a,c show the TF differences between the conditions (congruent minus incongruent) in the mid-frontal and central regions respectively. There is negative relative power in the theta band, and the 700 to 1200 ms time window (demarcated by the white rectangle), which occurs in both regions. We tested the statistical significance using a permutation test. The results showed that, in the mid-frontal region, activity is significantly higher for the incongruent condition compared with the congruent condition ($p = 0.03$, effect size = − 0.54), as well as in the central region ($p = 0.01$, effect size = − 0.69). Figure 3b,d show the differences in activity of the conditions in the mid-frontal and central regions respectively, obtained from averaging the same abovementioned frequencies and periods. The difference between conditions in the central and mid-frontal regions is noticeable. Finally, Fig. 3e,f show the power spectrum density of the mid-frontal and central regions respectively, which is the TF averaged over time. A significant difference occurs in the theta band, and it is specified by the gray area in the figures, where theta activity in the incongruent condition (blue line) is significantly higher than in the congruent condition (red line). Statistical analysis showed no significant difference between the two conditions in any other specified regions.

Discussion

In this study, we evaluated the ongoing, neuronal, semantic processing of brand logos, using ERP and Welch-based relative power analysis. Participants were exposed to 80 image sets, where the last image of each set included a brand logo preceded by a set of three images including brand-related cues (e.g., products or services).

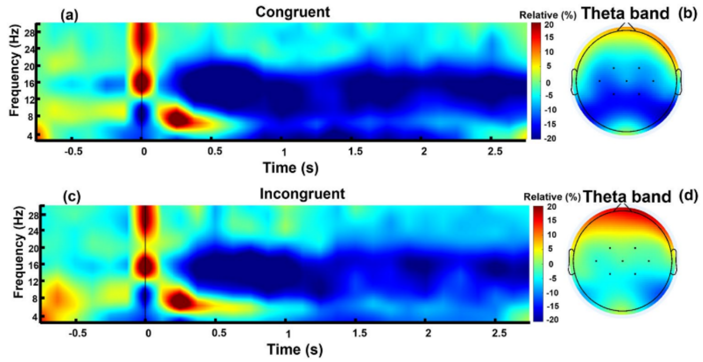

Figure 2. Time–frequency and topo-map (of theta band in central region) for congruent and incongruent conditions, calculated from brain activity of central region. Hot colors show positive relative power and cold colors show negative relative power. Panels (**a**) and (**c**) show time–frequency of congruent and incongruent conditions respectively. Both panels are plotted from − 0.75 to 2.75 s. The y-axis indicates frequency and the x-axis indicates time. The vertical black line in 0 s indicates the start of the stimuli. Panels (**b**) and (**d**) show topo-maps of brain activity in theta band of congruent and incongruent conditions respectively. The activity is averaged over theta (4 to 7 Hz) and time (0 to 2 s), and plotted as topo-maps.

The last image (i.e., the logo) could either be congruent or incongruent with the previous cues. We aimed to identify both time (ERP) and frequency (EEG power) changes that were anticipated as emerging because of semantic violation between brand cues and logos (hereafter, brand cues-logo). We therefore focused on N400 ERP activity and theta-band (4 to 7 Hz) power. In time-domain analysis, the results showed significantly larger negative N400 amplitude in the central electrode locations when incongruent logos were presented to participants, compared with congruent logos. In the frequency domain, incongruent logos led to significantly higher relative theta activity in the mid-frontal and central electrode locations compared with congruent logos, which can be further related to cognitive demands. The results suggest a neural distinction for semantic processing, between the congruent and incongruent semantic processing of brand logos. In the following paragraphs, we will first discuss the ERP and then the time frequency results.

Regarding the ERP, we found a significantly higher N400 peak in the central electrode locations for semantically incongruent brand cues-logo representations than semantically congruent ones. It is widely accepted that violations in semantic expectations result in larger higher N400 peaks in a wide variety of fields and tasks[9,25,29,40]. A review paper in the linguistic field suggested that the N400 reflects two main brain processes, unification and pre-activation, which are related to meaning integration. The authors declared that this activation is widely spread across brain electrode locations, but mostly focused in the frontal and temporal cortexes[8]. Studies using pictures as stimuli, which relate better to the present study, have also found a higher N400 for the incongruent than congruent condition. For example, Hamm et al. investigated brain responses to semantically congruent and incongruent images of different objects during an object-identification procedure[33]. Their results showed a greater N400 effect in the central-parietal electrode locations, and they concluded that N400 is responsible for semantic mismatch processing. In another study, Wu et al. showed a video-clip of a cartoon followed by an image of either a congruent or incongruent gesture[18]. They reported that the N400 is greater for the incongruent condition in the frontal electrodes, and claimed this is connected to semantic processing of gesture images. Moreover, many other image-based studies using picture series, line drawings, and videos as stimuli, reported greater N400 peaks in the frontal electrode locations[29,41–43]. Our results prove that, in line with previous studies, the N400 peak reflects the semantic processing of brand cues-logo associations. We argue that incongruence between brand logos and other brand cues represents a semantic violation that requires greater mental processing effort, to adjust to the violation, which is reflected by a high N400 peak. Although most previous image-based studies have reported frontal N400 (except Wu, Y. C. and Coulson, S.[18], that reported the effect in the central-frontal electrode locations), our results showed the N400 effect in the central electrode locations. This could be because of our type of stimulus (i.e., brand logos), whereas most other studies used ordinary objects, gestures, or images, shown within a context of sentences. Contrary to most forms of visual representation, such as those used in previous studies (mostly iconic), brand logos are not so open to interpretation due to their symbolic nature (note that we are not referring to the creative elements of a logo, instead to what they intrinsically represent). They provide a direct, unique, and unambiguous connection with a particular brand, while most other visual elements can have multiple associations. It is therefore reasonable to expect differences in the N400 effect compared with other types of stimuli. Finally, it is worth mentioning that studies including conflict tasks (such as the Stroop or flanker tasks) have consistently found greater N400 in the frontal-central electrode locations for incongruent as against congruent conditions[10,12–15]. Even though they emphasize more the response in the

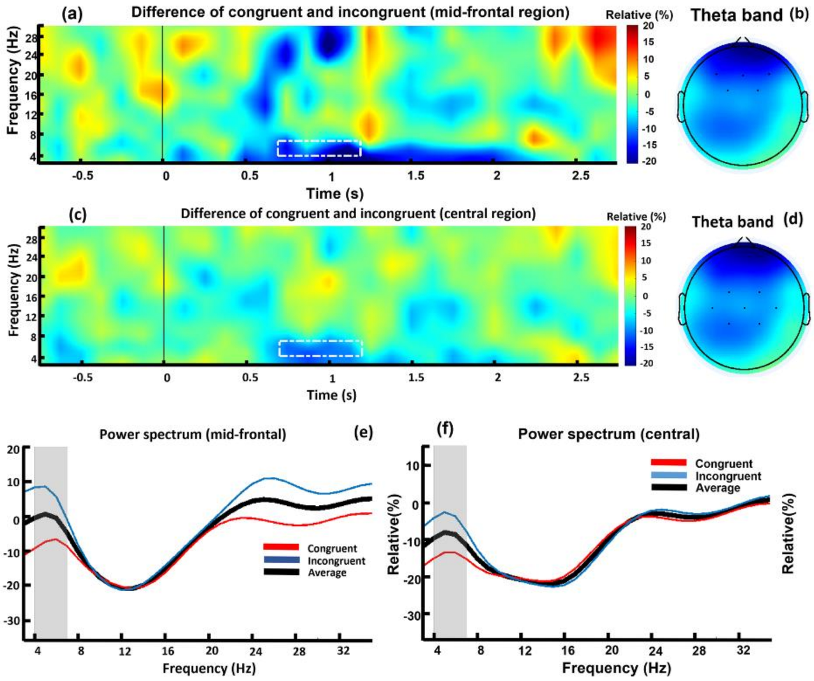

Figure 3. Time–frequency differences (congruent-incongruent), topo-maps (of theta band), and power spectrums. Hot colors show positive relative power and cold colors show negative relative power. Panels (**a**) and (**c**) show the subtracted TF of incongruent condition from congruent condition (congruent-incongruent). The white rectangle shows the region of theta frequency (4 to 7 Hz) and time (700 to 1200 ms), where the difference is maximum. The statistics, topo-maps, and power spectrum of this figure are all focused on this region. Panel (**a**) shows the TF difference in mid-frontal region and panel (**c**) shows the TF difference in central region. Panels (**b**) and (**d**) show topo-maps for mid-frontal and central regions respectively. They show brain activity averaged on the theta frequency and 700 to 1200 ms (the area of white rectangular). Panels (**e**) and (**f**) show the power spectrum activity of mid-frontal and central regions respectively. They show power spectrum of all frequencies averaged over time. The gray regions in both panels indicate the theta band, and there is significant difference between congruent and incongruent conditions both in mid-frontal ($p = 0.03$, effect size = − 0.54) and central ($p = 0.01$, effect size = − 0.69) regions. In both panels, the yellow curve shows the power spectrum of congruent, the red curve shows the power spectrum of incongruent, and the black curve shows the average power spectrum of congruent and incongruent conditions.

frontal than the central electrode locations, these studies provide evidence of the role of the central electrode locations in tasks concerning conflict (incongruence). The present study does not have a conflict-oriented task, therefore, the role of the central electrode locations in semantic violation processing needs further investigation.

Regarding the time frequency analysis, consistent with previous studies showing a theta power increase in the frontal/mid-frontal areas with higher cognitive processing, incongruence between brand cues and brand logo representations in the present study led to an increase in the theta band. Previous studies, which mainly focused on linguistic information, found that the theta band is connected to improved cognitive processing of language-related tasks[20,44–46], working memory demand[28,38], long-term memory[17,28], detection of semantic incongruences[21], increased task difficulty, and higher attention demands[47,48]. In a study of the pictorial aspects of cognitive processing, Tang et al. declared that cognitive processing of "paralanguage information", which is a category differentiated from linguistic processing, is also connected to theta oscillations[11]. Despite the fact that brand-related stimuli are neither linguistic nor emoji-based, the present findings showed that their cognitive processing is connected to theta oscillation. This suggests that theta oscillation indicates the neural activities occurring behind the detection of semantic violations.

In this study, we mitigated the influence of brand and picture (design differences) on brain responses by subtracting the responses to incongruent as against congruent brand logos. Semantic violations in incongruent brand cues-logo led to an increase in theta power in the mid-frontal electrode locations. Previous literature has declared that a theta power increase in the frontal and mid-frontal electrode locations is associated with difficulties in meaning integration, such as lexicon context and higher processing effort[28]. Moreover, mid-frontal theta increase possibly reflects an error-monitoring process[20], and theta power increase could indicate higher working memory load in error monitoring[28]. Considering our current results concerning theta power increase, and previous studies, we argue that the processing of violations between brand cues and brand logos needs greater effort in integrating mismatched brand representations (i.e., logos) with previous knowledge about the brand. Consequently, there is high working memory load in monitoring the manifested error during prediction, and this cognitive load is reflected in higher theta activity in the mid-frontal electrode locations.

The findings also showed a significant theta power increase in the central electrode locations caused by semantic violation of incongruent brand cues-logo. To the best of our knowledge, there are not many studies investigating theta power responses to semantically incongruent image stimuli. Past results are mainly related to flanker and Stroop tasks, concluding that theta power increase is caused by conflict-related processing. Fernández et al. investigated theta activity in incongruent-vs-congruent trials in a Stroop task followed by a speech task[49]. They reported that the conflict caused by both tasks (especially the speech task), induced a theta power increase in the mid-central electrode locations. Using a flanker-type task, Pan et al. reported an increase of theta power for positive targets after incongruent rather than congruent primes in the central electrode locations[50]. They suggested that this theta increase was due to the integration of positive emotions with conflict resolution. Using an emotional conflict task, Ma et al. concluded that greater central theta activity in the incongruent (as against congruent) condition was due to a greater need for control in conflicting conditions[51]. Our results showed a significant increase in central theta. Because our task does not contain conflicting situations, it seems that this central theta increase reflects other kinds of processes. We found no previous EEG studies investigating brand logos or using related image stimuli. Therefore, further studies need to be done to have a better understanding of central theta increases in response to incongruent brand cues-logo.

Our data did not show a significant theta increase with incongruent processing, either in the occipital or the temporal electrode locations. Regarding the occipital electrode locations, a linguistic study stated that left-occipital theta power increase might be associated with visual form processing where longer and more complex words showed higher theta than shorter and simpler words[46]. Another study reported a theta power increase in the occipital lobe with emoji-processing compared to word-processing, which is possibly due to the complexity of the visual forms of emojis, which can be vague and difficult to retrieve[28]. One reason for dissimilar results might be because of our stimulus type. The abovementioned studies compared either two linguistic related stimuli together or a word/sentence stimulus with emoji, while we compared two different conditions for brand logos as stimuli. Therefore, we cannot expect to have differences in visual form retrieval. Another reason for this dissimilarity could be the fact that, in addition to visual form, language- or emoji-processing contains extra information such as phonetical, morphological, and lexical, potentially affecting visual form retrieval. Moreover, previous studies found significant theta increase in the temporal lobe with incongruent stimuli. They associate this increase with lexical retrieval[46,52] or the retrieval of pre-constructed concepts[28]. In our case, it could be that brand logos do not have actual lexical form. Although some brands use words (i.e., dictionary words) or letters in their logo, these elements are not necessarily related lexically to what the brand represents.

This is the first study using time and frequency domain EEG features to investigate how the brain reacts to a mismatch between brand-related cues and the expected brand, represented by its brand logo. In summary, two neuronal markers for semantic violation, the N400 effect and a pronounced theta oscillation, were found. The difference in theta oscillation occurred in the time window of 700–1200 ms, while the ERP difference occurred in the N400 component (i.e., approximately 400 ms). This finding suggests that these two methods capture different aspects of brain activity. Overall, our results were consistent with previous studies investigating semantic violations in other fields. However, specific to our study is the N400 effect present only in the central electrode locations, and pronounced theta in the frontal and central electrode locations. The presence of both markers, associated with the corresponding brain electrode locations, provide strong support for the view that brand logos are not only represented in consumers' minds but also that this representation differs from other forms of ordinary visual representations (e.g., objects, gestures, emojis). Regarding cognitive processes, we assume a working memory involvement during task performance, because information provided by the brand cues needs to be stored to confront it further with the brand logo information. Though our data did not show theta activation in regions related to long-term memory, as found in previous studies[28], we infer that this could be because of our stimulus type. We argue that long-term memory must have been present as well. As the task required inferring brand name from brand-related cues, when assessing those cues, participants had to retrieve previous formed associations with those cues from their long-term memory, especially which brand they represented. The same applies for the brand logo. When presented with the logos, it was again necessary to retrieve from memory brand-logo associations. Finally, some form of integration process must have taken place to link those elements (cues, logo, predicted brand name) and reach a decision (the name of the brand). Furthermore, the findings suggest that an error-monitoring process took place during task performance. We presume that the brand cues were in the working memory, together with the brand name information, and when an erroneous (i.e., incongruent) brand logo was shown, the brain engaged in a searching process, trying to find links between the cues and the mismatched brand logo, increasing cognitive load. In summary, our results suggest that brands and their representations (e.g., products and logos) can be deeply encoded in consumers' minds. Moreover, the data suggests that incongruence between brand cues and brand logos increases consumers' cognitive load due to the activation of an error-monitoring process.

Limitations and future studies. In this section, we consider this study's limitations and discuss suggestions for further research.

i. Our study design required the participants to think about the brand of the products or services that were going to be shown to them. The reminder of this requirement occurred just before the appearance of the target stimuli (and its silent answer) and was intended to reinforce the expectative state, which presupposes a semantic association at the precise moment before the incongruence/congruence appeared. This step was intended to ensure that the participant associated the target with the preceding images. The necessity of this reminder could itself be tested using a control group; this could validate our assumption that the question was implicit at the outset and that a reminder was necessary. In future studies, a comparison could be established between a group that is prompted by the reminder of the "silent question" and a group that is not. Nevertheless, if there were a difference between the two groups, it would remain a challenge to elucidate whether the difference was due to the presence or absence of the reminder question or to other confounding factors (e.g., if the task were unintelligible or lacked a clear goal).
ii. In the incongruent condition, the target brand logo was either a competitor of previously shown brand cues (i.e., from a related product category) or unrelated to the brand cues (i.e., from another product category). In the present study, we did not compare these two conditions due to the limited number of trials of each category. An interesting approach for future research would be to balance these two conditions in a 50–50 proportion in order to investigate this relationship.
iii. Our logos had a linguistic component (i.e., letters/words). To mitigate the possible influence of a reading process in the results, further studies could use either exclusively image-only logos or equally balance the logo types (linguistic and image-only).

Methodology

Participants. Thirty-two right-handed participants (13 female) living in Copenhagen of 16 nationalities. Demographics were as follows. Age: *M* 26.84, *SD* 4.33, age range 20–37. Occupation 69% students, 16% workers, 15% both. Highest educational level (completed or ongoing) 12% bachelor, 88% masters. The sample size was determined by a power analysis for the ERP and theta band effect with alpha = 0.05 and power = 80%. The highest sample size required by this analysis was chosen for the study (in this case, N = 32).

All participants signed an informed consent, were debriefed at the end of the experiment, and were paid for their time and effort. 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.

Design and stimuli. A within-subsects design with one independent variable called level of congruence (hereafter, "condition")—congruent as against incongruent—was conducted. There were 80 image sets in total (40 per condition), where each set was related to a well-known brand. Each image size was 1000 × 1000 px with a white background placed on a black background screen. The presentation order of the sets was randomized across participants. The task was divided into two blocks with 40 image sets each (50% incongruent).

Data collection and task procedure. Thirty-two channel EEG active electrodes were placed on the scalp of the participant according to the 10–20 system, based on the participant's head perimeter. The signals were recorded by Brain Products EEG system, using 500 Hz sampling rate. Conductive gel was applied to the electrodes to keep the impedance between the electrodes and the scalp below 25 KΩ (as required by the hardware). A virtual reality (VR) headset (HTC Vive Pro) was placed on top of the EEG cap. The VR headset was used for stimulus presentation because this study was part of a larger study.

The task comprised 80 image sets (40 incongruent sets). Before the task, participants were informed that they would see a sequence of three images related to a brand and subsequently would be asked to guess the brand. However, they were instructed to think of the answer but not say it aloud. Therefore, each set started by displaying a sequence of three images of a product or service from a specific brand for 2 s each. These three images could include explicit cues (e.g., name of the brand) or only implicit cues (e.g., products or store layout). After the third image, the question "What is the brand?" was displayed for another 2 s. Following this question, the logo was shown for 3 s (this is the target image of our analysis). The logo was either from the brand of the previous images (congruent) or from another brand (incongruent). All logos included a linguistic component (i.e., letters/words) in order to control for possible differences in information processing[39,53]. In the incongruent condition, the mismatched logos were randomized to be either from a competitor brand (20%) or an unrelated brand (80%). Thus, the mismatched logos would violate pre-encoded rules or previous knowledge at the semantic and/or pragmatic levels. Figure 4a shows an example for congruent and incongruent image sets, respectively. Next, a fixation cross appeared for 3 s, and the next image set started. Each block with 40 image sets lasted for almost 10 min (Fig. 4b shows the procedure of each block). The order of congruent and incongruent images was randomized across the participants in each block. The task was presented in the VR environment, using the desktop option of *Steam VR*. The images were therefore seen in 2D, but in a curved, big screen and with the "home" background of the software.

Data analysis. This section is divided into three sub-sections: (i) pre-processing, (ii) ERP analysis, and (iii) relative power calculation. The analyses were performed using Matlab R2020b (The Math Works, Inc) with

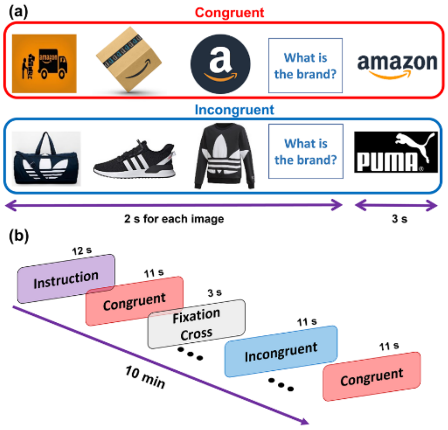

Figure 4. Example for stimuli and the task procedure. Panel (**a**) upper part shows an example for congruent set, where the last image (brand logo) matches the brand of the first three images. Panel (**a**) bottom part is an example for incongruent set where the last image and first three images do not match. Panel (**b**) shows the task procedure, which started with 12 s of instruction followed by congruent and incongruent image sets (randomized through the experiment). After each image set, there was a 3-s fixation cross.

in-house codes and tools from EEGLAB 2021.0 (https://eeglab.org/) and FieldTrip 20210128 (http://fieldtriptoolbox.org) toolboxes.

Pre-processing. The signals were filtered using a third order IIR Butterworth filter with 1 to 40 Hz cut-off frequencies to remove high and low frequency noises. Afterward, bad channels were detected using automated rejection procedure with voltage threshold of ± 500 µV, confirmed by an expert, and rejected from the channel list. All rejected channels were interpolated by spherical spline method using the information from six surrounding channels in FieldTrip toolbox. The average number of rejected channels per participant was 1.43 ± 1.42. One participant was excluded due to having more than four bad channels. Subsequently, considering the stationary assumption, the filtered data was segmented to 4 s epochs: 1 s before (pre-stimuli) and 3 s after (post stimuli) from the start of the stimulus for each condition (Fig. 5a). Noisy epochs were detected by a strict automatic rejection procedure with a voltage threshold of ± 120 µV, confirmed by an expert, and rejected from the data. The average number of rejected epochs per subject was 1.46 ± 2.2. Afterwards, the epochs were concatenated and fed into independent component analysis (ICA) to remove remaining artifacts. The Second-order Blind Identification (SOBI) method was used to estimate source activities. EOG (eye-related artifacts) and other artifact sources were detected by an expert and removed from the source list. For further ERP calculations, the same Butterworth filter, but with low cut-off frequency of 0.1 Hz, was applied to a copy of the raw data, and ERP-filtered data was obtained. The calculated coefficients of ICA part were then applied on the ERP-filtered data to estimate the sources, and the rest of the abovementioned procedure was identical for the ERP analysis. Finally, the de-noised data was re-referenced to the average activity of the electrodes. The preprocessing steps can be seen in Fig. 5b. For the following analyses, we divided the electrodes in four different regions: mid-frontal (Fz, F3, FC1, FC2, and F4), central (C3, CP1, CP2, Cz, and C4), parietal (CP5, CP1, Pz, P3, and P7), and occipital (O1, Oz, and O2).

ERP analysis. The ERP-filtered and de-noised data were used to calculate the ERPs. First, the baseline of all epochs was corrected by subtracting, from the entire signal, the signal average across a 200 ms pre-stimulus portion. Then, the epochs of the corresponding conditions (i.e., congruent and incongruent) of specific regions were averaged separately to obtain ERPs per condition and region. The steps are shown in Fig. 5c,c-1. Figure 1a–d shows grand ERP average (obtained from averaging all participants' ERPs) in different regions. For the purpose of this study, the N400 activity of each individual's ERP was calculated by averaging from 400 to 600 ms, and these values were then used for statistical analysis.

Relative power calculation. The relative power was calculated using the de-noised data. The TF information for each channel was estimated using the Welch method, including a Hanning window with 50% overlap. Then, the baseline-TFs (i.e., the TFs calculated from the one sec pre-stimulus portion of the signal) of all channels from a participant were averaged to obtain the averaged baseline-TF. This obtained average was used to calculate the relative power activity of each epoch as follows:

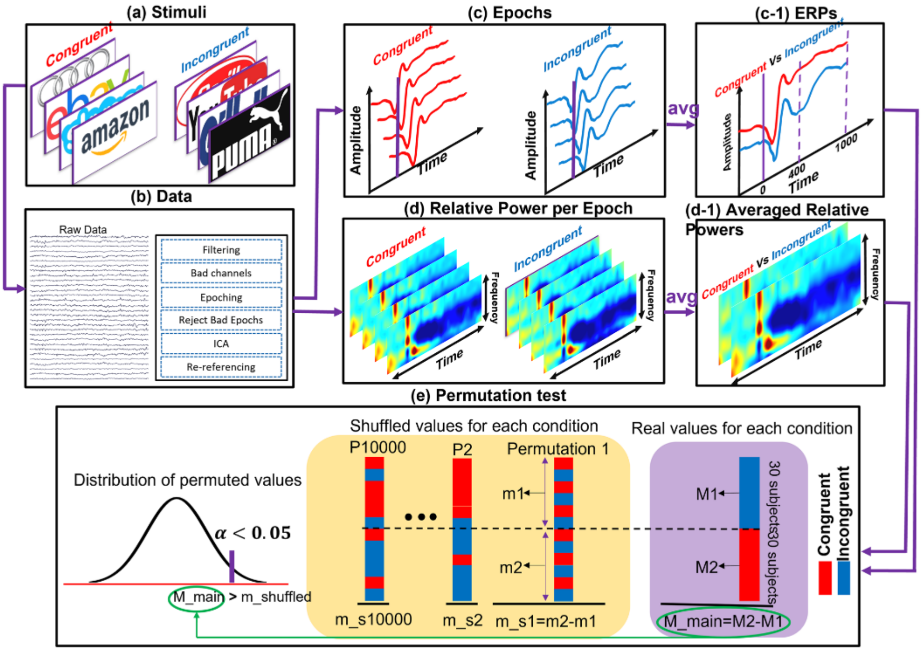

Figure 5. Shows the steps in our methodology. The plots related to congruent condition are indicated by red color, and incongruent condition by blue color. Panel (**a**) shows congruent and incongruent target brands (the last image of each set). Panel (**b**) shows an example of the EEG data followed by pre-processing steps. Panel (**c**) relates to pre-processed epochs corresponding to each condition. By averaging the epochs of each condition we reached panel (**c-1**), showing the ERP activity for each condition. Panel (**d**) shows the time–frequency activity of each epoch for two conditions separately (in each TF, hot colors indicate positive relative power and cold colors indicate negative relative power). By averaging of TF of each condition, panel (**d-1**) is obtained, showing the actual time–frequency activity of each condition. Panel (**e**) shows the statistical analysis using the permutation test—starting with actual difference calculation, then shuffling the extracted feature 10,000 times and calculating the difference in each iteration, and finally building up the random distribution and comparing it with the actual difference.

$$relative\ power = \frac{TF - averaged\ baseline\ TF}{averaged\ baseline\ TF}. \quad (1)$$

The calculation steps for relative power are shown in Fig. 5d,d-1. Finally, the relative powers of each condition and each region, for a participant, were obtained by averaging the corresponding TFs separately, and the values were used for statistical analysis. Figure 2 shows the overall TF activity for each condition in the central region.

To select the time window for further statistical analysis, we used a separate permutation test procedure for exploratory searching of power changes; this procedure was an adapted version of a method in the literature[20,54]. To do this, all subjects' TF in each condition were concatenated separately. Then, the resulting matrices were averaged across subjects. The difference between the two conditions was calculated by subtracting the average TF of the incongruent condition from that of the congruent condition (congruent–incongruent), this is the observed difference. Next, to generate the null distribution, the TFs of the two conditions were scrambled 1000 times, and the difference between the two conditions was calculated for each iteration. Finally, the observed difference was compared to the generated null distribution in order to calculate the p-value for each pixel of TF difference[55]. Then, the pixels that had a p-value lower than 0.01 were considered to show a significant difference between the two conditions. The result of this procedure in the central and mid-frontal region revealed that TF difference showed a significant pattern within the 700–1200 ms time window. Therefore, this interval was used for further statistical analysis.

Statistical analysis. The dependent variables are the N400 feature from ERP and the TFs, which are the averaged TF for each individual in the theta band (4 to 7 Hz) and from 700 to 1200 ms. We used a permutation test to evaluate the significant differences between the conditions. As shown in Fig. 5e, the actual difference (M_main) between extracted features for each condition was calculated. Then, the features corresponding to each condition were shuffled 10,000 times, and in each shuffled trial, the difference (m_s1 to m_s10000) between two newly generated groups was calculated. These differences were used to generate a random distribution, and the actual difference was tested on this distribution using significance level of 0.05.

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Author contributions
A.S. and H.D. designed the experiment, collected the data, and wrote the main manuscript text. H.D. analyzed the data and prepared the figures. All authors revised and approved the manuscript.

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Competing interests
The authors declare no competing interests.

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APPENDIX 3

DOES BANNER ADVERTISING STILL CAPTURE ATTENTION?

AN EYE-TRACKING STUDY

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