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

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Abstract

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

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

1 Introduction

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

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A diverse range of online review cues are available on e-commerce websites and social media sites, such as product evaluations (e.g., valence, star ratings), review verification (e.g., badges), or a combination of the two, and they help consumers make purchase decisions [6–8]. The increasing amount of research on OCRs reveals that, in addition to the volume, variance, or average star ratings of reviews [6], two additional cues influence prospective consumers' judgments and product sales [9]: the way in which comments are made (the text's linguistic style) [10, 11] and trust of an actual purchase (purchase verification) [12]. Linguistic style and purchase verification might influence consumers' assessments as seen in established knowledge in consumer research that is informed by cognitive and affective processing. However, despite extensive examination of the influence of OCRs on consumer behavior, studies on how consumers evaluate the influence of the content style (i.e., the linguistic style of the review) [6] and verified purchases in online reviews [13, 14] in terms of their product evaluations [6] remain inconclusive. In this view, we address two understudied gaps. Firstly, although content style is an integral part of online reviews as they disseminate information and persuade readers, their influence on purchase intention remains understudied. Content style in OCRs has been recently approached from different perspectives: (i) natural language processing for examining the content of featured words, such as nouns or adjectives, which then leads to sentiment analysis or assessing the affective content in order to detect emotions [15]; and (ii) the influence of the text type, such as the use of concrete versus abstract language or explicit versus implicit language [11, 16]. In recent years, the availability of digital text data and improvements in computational linguistics techniques has resulted in an incredible amount of studies using automated text analysis to provide understanding of psychological constructs of consumer behavior [17, 18]. Despite the high value of these studies, they do not provide answers on the persuasiveness of a limited number of online reviews. When consumers are looking for specific content instead of using other heuristics such as online ratings, they tend to read only a few comments [19]. Therefore, the analysis of the featured online reviews should be approached by searching for a specific type of content through other methodologies, such as an experimental design. Furthermore, the value of online reviews is driven by multiple factors, such as source credibility [20], which leads to the second point: Source credibility comprises both sender and platform issues. A mixed path for reducing uncertainty of a post's credibility is the verification of the comment by the platform. In a nutshell, certain platforms grant credibility to online reviews by certifying or verifying that the product in question was actually purchased. But the evidence for how verified purchases (VPs) translate into purchase intention remains inconclusive due to a lack of comparisons between either positive or negative valence of OCRs and the type of products analyzed. The literature shows varied online consumer behavior patterns between search and experiential product types [21, 22]. Based on these two research gaps of content style and VPs, this study aims to analyze the direct and interaction effects of these cues in both positive and negative online reviews in terms of consumers' purchase intentions for two distinct types of products: search and experiential products.

This study contributes to the growing amount of research on the effectiveness of online reviews in the following ways. Firstly, based on cue utilization theory, we account for the individual and interaction effects of content style, VPs, and valence on consumers' purchase intentions for two distinctive product categories. Cue utilization theory has been adopted in marketing, psychology, and consumer behavior studies to facilitate understanding of how products' quality perception is affected by cues [23–25]. As online product reviews consist of multiple cues that interact and impact consumers' decision making [5], understanding the effects of their interaction curbs the overestimation of a single cue's independent effect [4]. Consumers who judge products based on the cues contained within a single online review make incorrect inferences [26]. Secondly, the present work extends the sparse literature on review verification. Review verification is a platform-specific process that verifies that the reviews posted are indeed from the consumers that bought the product from the platform and that they are expressing their opinions [13, 14]. Due to concerns regarding reputation or fake review [27], review verification cue is critical for overcoming uncertainty for prospective consumers and is associated with helpfulness of the review to assist in decision making [28]. Therefore, examining main and interaction effects of review verification on subsequent purchase intention of consumers is critical for product sales on e-commerce platforms [9]. Using revealed preference theory, He et al. [12] analyze a dataset comprising a focal product's reviews obtained from a single source (Amazon), from which an established positive relationship between the proportion of verified reviews and sales was determined. In contrast, our study explores the effect of review verification across two distinctive product categories that are generally available on different platforms. Thirdly, for a comprehensive measurement of the effect of OCR cues on purchase intention, our analysis uses the Bayesian approach in addition to conventional frequentist analysis. Previous electronic word-of-mouth (eWOM) research has predominantly used a single methodology (e.g., fuzzy-set qualitative comparative analysis, analysis of variance, and structural equation modeling [SEM] to investigate the influence of online reviews on purchases [29], while Bayesian statistics has been rarely used. A Bayesian analysis provides direct inference about the probability of an effect occurring given a certain condition. In our study, it allows us to determine the probability of purchasing a product separately for each cue analyzed; hence, it provides additional, easy to interpret, information to the frequentist analysis [30].

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

2 Literature review

2.1 Cue utilization framework

Previous research on OCR cues have pivoted around the signaling theory [31], heuristic-systematic model [32], elaboration likelihood model [33], and revealed preference theory [12]. Signaling theory (see Kirmani and Rao [34]) purports that there exists asymmetry of information between two parties i.e., seller has more information than buyer, and various 'signals' can reduce the gap [28]. Heuristic-systematic model and elaboration likelihood model follow dual theory perspective to examine OCR wherein consumers either put little cognitive effort and utilize heuristics, or expend much effort to build decision [35]. Cue utilization theory is consistently used to examine consumers evaluation of a product based on diverse cues, influence of product cues on consumer attitudes, and interaction between several cues to impact purchase intentions (see Table 1). The cue utilization theory informs that consumers evaluate product quality by utilizing a series of cues or information related to the products [36]. This array of product cues is classified into intrinsic and extrinsic cues [37]. Intrinsic cues are inherently related to the unalterable physical attributes of the focal product. Extrinsic cues are not inherently part of a product's characteristics and can be minimally altered [24]. The cue utilization theory states that prospective consumers might utilize intrinsic and extrinsic cues in e-commerce purchases before purchasing products. The intrinsic cue of the product refers to its inherent nature (e.g., search or experiential) while extrinsic cues are the varied forms of information regarding the product (e.g., online product reviews). For instance, when one is seeking to purchase a vacation or tablet, specifications regarding the tourism destination and tablet screen size can be considered intrinsic cues while reviews regarding the product or service can be considered extrinsic cues [31]. Consumers utilize extrinsic and intrinsic cues in parallel when evaluating products [37]. When intrinsic cues are difficult to access or are scarce, salient extrinsic cues help consumers make evaluations [38]. To investigate the independent and interactive effects of various cues on consumers' decisions, consumer researchers have adopted the cue utilization framework across a range of domains (see Table 1).

We searched for "cue utilization" in journal articles published from 2000 to 2022 in the Business, Management, and Accounting category in the Scopus database and found 92 articles in English. We then manually inspected each article and, after removing non-empirical studies and review papers, 64 articles were shortlisted for use in this study (see Appendix A). Figure 1 provides the keyword co-occurrence network [39] that was created from the 100 most common keywords obtained from the 64 papers' abstracts using VOSviewer software in order to identify the theme of each cluster, called the cluster identity [40]. Co-occurrence networks represent the intellectual structures of the topic, which indicates the conceptual relationship between keywords used in eWOM literature [41]. We derive two key takeaways from the co-occurrence network analysis. First, the red cluster dominantly represents the empirical investigation of consumer's cognitive processing (e.g., perceived value, perceived service quality) of products or brand (e.g., awareness, reputation) via different consumption channels (e.g., retailing, cross border e-commerce) using cue utilization theory. The green cluster highlights the use of cue utilization theory to examine influence of attributes (e.g., country of origin, third-party verification) pertaining to products available on e-commerce platforms on purchase (e.g., willingness to pay, purchase intention). The blue cluster represents consumers perception and attitudes of design cues available on products. Second, consumer's psychological mechanism involving attitude, perception or expectation towards the cues related

Table 1 Recent papers on cue utilization theory

Author (references)	Intrinsic cue (stimulus type)	Extrinsic cue	Findings
Roy and Attri [42]	Experiential (Destination)	Physimorphic and typographic brand logo	Physimorphic logos have a greater tendency to generate positive attitudes and intention to visit a destination than typographic logos do
Halkias et al. [43]	Search (16 assorted products)	Country of origin (COO)	COO labels influence behavioral intention depending on the duration and dwell time length
Gabriela et al. [44]	Experiential (Crowdfunding campaign)	Number of rewards	A campaign should be seen as neutral and conservative in style with an optimal range of pictures, videos, and record of rewards
Nie et al. [45]	Search (Packaging)	Food certification label	Consumers show differences in their willingness to pay based on labels caused by their purchase motivations
Konuk [46]	Experiential (Food taste)	Taste award	Using the Stimulus-Organism-Response model, SEM reveals a positive relationship between perceived taste, award, quality, and brand trust
Chi et al. [23]	Experiential (Accommodation listings)	Guest review and textual color cues	The textual cues related to color in pictures impact consumers' inclination to rent a property
Sun et al. [47]	Search (Giveaways value)	Cuteness and unexpectedness of meeting giveaways	High value giveaways render higher levels of word-of-mouth (WOM) intention. Cute and unexpected gifts moderate the value of gifts in terms of WOM intention
Yang et al. [48]	Search (Apparel)	Post popularity and quality	Both Instagram posts' popularity cues and argument quality cues reduce uncertainty in online apparel purchases
He and Oppewal [49]	Studies 1,2: Search (Book and chocolates)	Sales and stock levels	The effect of sales and stock level on subsequent choice is mediated by product popularity and quality. In addition, sales level supersedes stock level when both cues are available

Table 1 (continued)

Author (references)	Intrinsic cue (stimulus type)	Extrinsic cue	Findings
Konuk [50]	Experiential (Food quality)	Price fairness	A perceived food quality cue positively impacts price fairness and perceived value
Kinney and Xia [21]	Studies 1, 3, 4: Experiential (Local restaurant) Study 2: Search and Experiential (Hair dryer and hair styling)	Number of deals	Social extrinsic cues (the number of deals) impact evaluations and intentions when the intrinsic product, the deal cues (good versus service, discount size), and consumers' characteristics (familiarity with provider) are inadequate for determining deal attractiveness
Bruwer et al. [51]	Experiential (Wine)	Variety, wine style, and packaging	Product knowledge positively impacts products' intrinsic cues

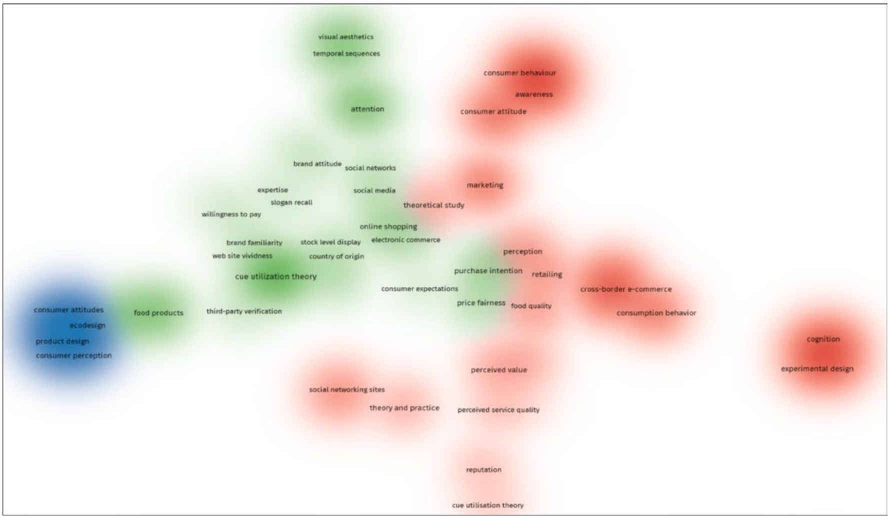

Fig. 1 Cluster identity of the keywords extracted from the database. This word map visualizes three interconnected clusters, with each color representing a theme

to product design or brands, has been a common feature across the three clusters using cue utilization theory.

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

2.2 Online reviews as extrinsic cues

In the digital marketplace, a product's perceived performance is gauged from OCRs of firms, brands, products, or services that are shared by consumers [52]. As a form of eWOM, OCRs have a significant influence on purchase intention [29]. However, previous studies have rarely used cue utilization theory to understand OCRs (see Table 1). Langan et al. [5] reveal that high review variance decreases purchase intention for utilitarian (versus hedonic) products. Additionally, they report that when brand equity is stronger, the impact of OCRs decreases. In their work, Sun et al. [47] sought to examine the perceived value of giveaways on word of mouth (WOM) intentions. They used cuteness of gifts and unexpectedness as extrinsic cues while manipulating the intrinsic cue, that is, the value of giveaways. High-value giveaways positively influenced attendees' WOM intention, while extrinsic cues moderated the effect of giveaways on WOM intentions. However, neither study used distinctive products to understand the interaction effects of extrinsic and intrinsic cues. Nevertheless, these studies facilitate an interesting discussion on the dynamics of extrinsic and intrinsic cues of products in the digital marketplace.

2.3 Search and experiential product categories as intrinsic cues

As demonstrated in Table 1, only a few studies address more than one product type in their analyses using the cue utilization framework. The search and experiential classification paradigm is useful for elucidating consumers' evaluations of OCRs [53, 54]. Nelson [55] demarcates products' characteristics based on the quality of attributes that can be evaluated prior to the purchase and the quality of those attributes that can only be determined post-purchase or during consumption. For search products (e.g., smartphones and dishwashers), the product cues (e.g., size and color) are easier to obtain before the purchase. Objective cues chiefly determine product evaluations of search products, limiting the role of sensory experiences in purchase decisions. On the contrary, consumers find it difficult to evaluate the subjective cues (e.g., flavor and pleasure) of experiential products (e.g., tourist destinations and movies) that are derived from sensory evaluation prior to making purchases [55]. While shopping online, consumers spend a relatively longer amount of time per webpage for experiential products than search products, but they view more webpages for search products than experiential products [56]. Researchers show that OCRs are important for influencing sales across search and experiential product categories, such as cellphones [53] and digital games [31].

3 Hypothesis development

3.1 Content style in online reviews

A growing stream of marketing literature has shown that the way in which OCRs are expressed (i.e., the content style) drives reviewers' credibility [57], reviews' helpfulness [58], and persuasion [11] and they have demonstrated that they are important for product or service evaluations [10]. These findings support the theoretical framework of heuristic and systematic information processing [59]. Researchers have examined the consequences of linguistic expression on purchase behavior and purchase intention, including the use of implicit or explicit endorsement language [16], tentative wordings [60], action or reaction explanations [58], textual parawordings [61], specific or vague styles [62], language mimicry [63], benefits or attributes [64], assertiveness [11], divided or mixed narratives [65], powerful or powerless markers [66], and figurative or literal language [67].

In the present study, we extend the line of inquiry by exploring the persuasiveness of general or specific information in reviews. A review's content serves as a factor in the persuasion process because the evaluation contained therein may reduce consumers' uncertainty and ambiguous feelings regarding the product [62]. An OCR can describe the specific features of the focal product during the consumption experience without highlighting feelings associated with the consumption. Conversely, it can narrate general aspects of the consumption experience of the focal product but suppress specific information. For experiential products, consumers have limited product information to inspect that could help in decision-making. Understandably, consumers rely more on other consumers' subjective evaluations than objective reviews for experiential products [68]. Contextually, a general review will offer valuable expressions of subjective feelings experienced while using the focal product or service. OCRs are generally voluntarily written to express personal experiences, opinions, and recommendations [69]. Thus, specific details are expected less frequently for experiential products because subjective information cannot be provided for these products before consumption. Alternatively, for search products, consumers can verify the focal product's readily available information cues and form objective criteria for evaluation of the products [68]. In this regard, specific reviews include objective facts about the product from which consumers can scrutinize information more accurately than a general review, thereby aiding their subsequent purchase (see Fig. 2). Consequently, we expect the following:

H1a General (versus specific) review content increases purchase intention for experiential products.

H1b Specific (versus general) review content increases purchase intention for search products.

3.2 Verification of a purchase in online reviews

Consumers make inferences not only about the review but also the cues associated with the reviewer [6, 70]. The review credibility system incorporates feature labels or badges in the reviews, indicating that reviews of VPs (e.g., Amazon Verified Purchase or Expedia Verified Reviews) are posted by reviewers who have purchased the

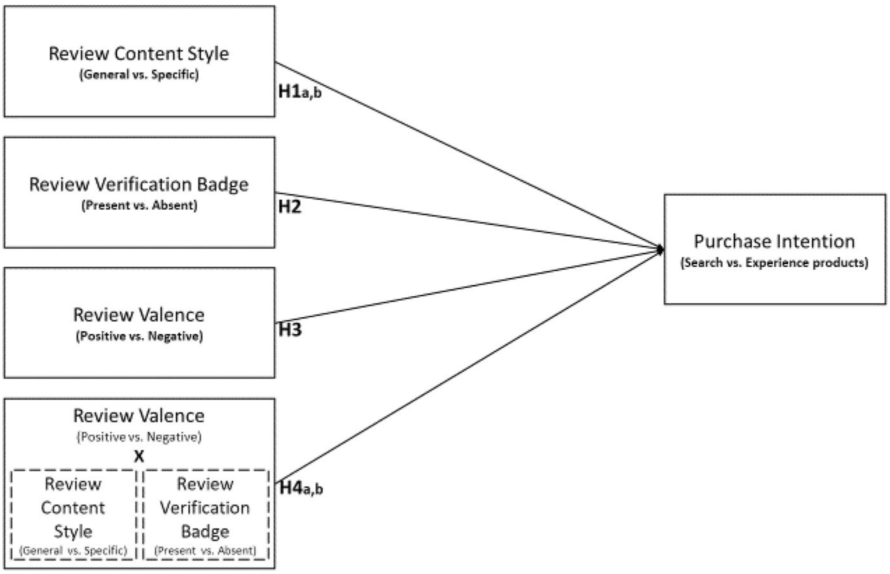

Fig. 2 Schematic representation of hypotheses

product from the platform in question [12]. However, not all platforms (e.g., TripAdvisor) have adopted such a system [13]. As a review cue, the VP label discloses purchase information by endorsing reviewers' genuine experiences with the focal product or service. The literature reveals that VP reviews increase product ranks compared to non-VP reviews [14, 71]. However, this effect has not been confirmed in other studies based on multiple tourism platforms [13], resulting in inconclusive findings. From another perspective, the related literature shows that a high percentage of VP reviews in a review set positively influences product sales and leads to the customer trusting the authenticity and credibility of reviews [9]. Figini et al. [14] studied review platforms for an experiential product (i.e., hotel ratings) and found that OCR ratings on open platforms that accept non-VP OCRs have relatively higher ratings than the OCR ratings of VPs, thereby endorsing the use of closed platforms. Additionally, the presence of unsolicited, fake, and deceptive reviews reduces credibility [72] and the helpfulness of OCRs [6], necessitating VP labels only being assigned to authentic reviews [27].

Source trustworthiness and expertise are acknowledged as determinants of persuasion in the source credibility scheme created by Hovland et al. [73]. The former dimension offers an adequate framework for supporting the influence of a VP as a relevant cue for assessing online reviews. Thus, VPs provide objective cues about the trustworthiness of the OCRs, which can result in the customer trusting the text. According to the trust transfer theory [74], it is expected that a VP (e.g., an object) will transfer customers' trust for the comment to the product itself (see Fig. 2). Based on these ideas, we propose the following hypothesis:

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

3.3 The persuasiveness of review valence

Review valence indicates the "evaluative direction" of the review and can be polarized (extremely positive or negative) or mixed (neutral) [75, 76]**.** Valence is regularly found to be one of the most helpful and persuasive cues in a review set [77], yet it yields mixed effects on subsequent purchase probability [8, 29]. Positive valence reviews have "pleasant, vivid and romanticized" explanations, whereas negative valence reviews contain complaints and unpleasant explanations [78]. The influence of positive ratings on purchase intention is greater than that of negative ratings [29]. Alternatively, when exposed to negative information, consumers become motivated to seek additional information through OCRs, and their purchase likelihood is reduced [79]. Additionally, studies have shown that search and experiential products have a moderating effect on OCR valence [80, 81].

Reviewers tend to post reviews only when they are extremely satisfied or dissatisfied, forming a J-shaped distribution [69]. As such, an improvement in positive ratings increases purchase intention over time [82]. We expect that prospective consumers will utilize valence to narrow their consideration set in order to ease the uncertainty experienced before purchase [83]. Arguably, a positive set of reviews will incentivize the consumer to make a purchase decision and vice versa [84]. Consequently, we anticipate a positive association between a set of positive OCRs and purchase intention across product categories, while negative OCRs will deter purchase intention (see Fig. 2). Hence, we propose the following hypothesis:

H3 Positive reviews lead to a higher purchase intention for experiential and search products than negative reviews.

3.4 Interaction effects among extrinsic cues

Online reviews can be from a verified source or non-verified source, and they can use either specific or general content styles. The influence of content styles might vary depending on identification of the reviewer [66]. OCRs are viewed as diagnostic when consumers perceive information as credible [26]. To mitigate purchase uncertainty caused by unfamiliarity with the reviewer, consumers often look for other quality assessment cues, such as review credibility, before making purchases [29, 85]. Source credibility—an elementary feature that helps purchasers evaluate eWOM communication—refers to consumers' evaluations of a source in terms of expertise, trustworthiness, credentials, and attractiveness, and it has a positive influence on purchase intention [86]. A source is considered trustworthy when consumers perceive the information as genuine and accurate, leading to a positive impact on their purchase intention [29]. Filieri [87] reveals that consumers utilize cues such as valence, content, style, and review extremity to analyze trustworthiness. Building on the trust transfer theory [74], we argue that trust for an OCR based on a VP will be transferred to the content of the OCR. In addition to the direct effect of VPs on purchase intention (discussed in Sect. 3.2), further evidence on the interaction effects of VPs with content style and valence need further elaboration. The transferred trust of a VP on content style might be stronger depending on the type of text (either generic or specific). In line with hypotheses 1a and 1b, generic comments will have a stronger effect on purchase intention for experiential products, while specific comments will have a stronger impact on purchase intention for search products. Given the higher diagnosticity of VPs and general comments for experiential products, a stronger impact on purchase intention is expected. Similarly, a stronger impact of VPs and specific comments on purchase intention is expected in search products.

Regarding the effect of a review's polarity, its valence is perceived as less ambiguous, diagnostic, and helpful for the consumer than neutral reviews [26, 85], thereby ensuring that extreme valence—either positive or negative—is more credible than the valence of ambivalent reviews [88]. High variance in the review set diminishes the diagnosticity of information, leading to reduced source credibility [26]. The provision of visual information with a review that indicates that the reviewer has genuine experience with the product adds credibility to the review [87]. Certainly, a VP badge can function as a proxy for visual evidence that indicates a reviewer has genuine experience with a product, thereby enhancing the quality of the information and improving their review credibility. Because review cues can move jointly through central and peripheral processing [33], the interaction between OCR cues and purchase intention is compelling to explore (see Fig. 2). Therefore, we address these effects as follows:

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

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

4 Methodology

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

4.1 Design and participants

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

4.2 Stimulus

A pre-test with 44 consumers who did not participate in the main study was conducted online in order to select the comments for the products (see the Results and Discussion Section). For the main study, the stimulus resembled a webpage that contained online reviews from other consumers for two products in distinct categories:

a tablet, representing a search product, and a trip package, representing an experiential product. The artificial webpage consisted of a generic picture of the products (a tablet with no brand information and a beach landscape), a sentence that provided context, and four comments with a star rating and the badge (when applied) (see Appendix B). We presented four comments for three reasons: (i) For a consumer, it is difficult to read all the reviews for a product or service. Most platforms usually provide consumers with either a default setting to view only relevant reviews or filters for positive or negative reviews (e.g., five-star rating systems) or to organize the reviews by date posted (e.g., most recent or oldest), which assists in consumers' decision-making; (ii) Generally, consumers read approximately four reviews [89]; and (iii) To avoid participants' fatigue and lack of engagement when reading the comments. The reviews were manipulated in the following ways: (i) content (general or specific content); (ii) badge (the presence or absence of the VP badge); and (iii) valence (the valence of the star rating and comments' content). The positive (five-stars and positive wording) and negative (one-star and negative wording) comments had the same content but were framed accordingly. The comments were adapted from actual online reviews and comprised 37 to 40 words ($M = 38.25$). There were 8 conditions for both products (see Table 2). The composition of the reviews was mixed to make them seem genuine and to allow for comparison of the review cues. For each condition, one review among the four had the opposite condition. For example, in condition 1, three comments had positive valence, general content, and the verified badge, and one (always placed in the third position) had a negative valence, specific content, and no badge (see Appendix B).

4.3 Procedure and task

The participants answered the survey via the online platform Clickworker. Each participant was assigned to one of the eight conditions. The two products were presented in the same manipulation condition but in a randomized order. The procedure comprised the following: (i) a brief introduction; (ii) stimulus presentation (for the tablet, participants imagined finding the tablet's reviews on an e-commerce website and buying it, and, for the trip, they imagined planning their next vacation to Sri

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

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

Lanka and finding reviews for an online provider of packages for this destination); (iii) the purchase intention question of "What is the probability that you will purchase this tablet or purchase this trip?" being asked, for which the participants stated the probability in a percentage between 0 and 100%; and (v) demographics. The survey was self-paced.

4.4 Metrics and analysis

We used the continuous metric of purchase intention as a DV for the frequentist statistical analysis and a binary purchase intention metric for the Bayesian statistical analysis. The binary purchase intention variable was created based on the continuous metric. We assigned participants that scored $\geq 60\%$ to the "yes" group (i.e., a positive purchase intention) and $\leq 40\%$ to the "no" group (i.e., a negative purchase intention). Participants who scored between 45 and 54% were excluded from the binary analysis due to their indecisiveness. For ratings between 41 and 45% and 55% and 59%, a second metric that was not analyzed in this study was used in conjunction with the continuous metric in order to determine whether these participants would be included or excluded from the analysis. The final dataset for the binary variable consisted of 462 participants for the search product and 457 participants for the experiential product. The data were analyzed using IBM SPSS 26.0 for the frequentist inference analysis and R using the tidyverse, statsr, and Bayesian Adaptive Sampling packages for the Bayesian analysis. Each analysis is described in detail in the results and discussion section.

5 Results and discussion

5.1 Pre-test

Participants rated the eight comments for each product from 1 (mostly general content) to *5* (mostly specific content), with the middle point as *neither general nor specific*. The chosen comments had individual means below three for general comments and means above three for specific comments. The results of a related-samples Wilcoxon signed-rank test showed significant differences between general and specific comments for the tablet ($Z = 975$, $p < 0.001$) and trip ($Z = 935$, $p < 0.001$). The mean values were: $M_{general\text{-}tablet} = 1.75$, $SD = 0.82$; $M_{specific\text{-}tablet} = 4.48$, $SD = 0.98$; $M_{general\text{-}trip} = 1.80$, $SD = 0.84$; $M_{specific\text{-}trip} = 3.92$, $SD = 0.92$.

5.2 Frequentist inference analysis

A chi-square test confirmed that the eight groups were homogeneous in all sociodemographic variables ($p > 0.100$). The group sizes ranged from 61 to 65 participants each. A generalized linear model with a robust estimation procedure was used to assess the influence of the three IVs (valence, content, and badge), and their two-way and three-way interactions with purchase intention (0–100%) for each product. In addition to a significant main effect of valence, the results reveal two significant two-way interactions: valence-content and valence-badge interaction. The other effects (three-way interaction, content-badge interaction, and content and badge main effects) were not statistically significant. The mean values for each condition and product are shown in Fig. 3, and the significant interactions are shown in Fig. 4.

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

We assessed whether the difference in purchase intention across the two conditions of content and badge was statistically significant within each valence condition (simple effects). A nonparametric independent-sample Mann–Whitney U test was conducted due to the violation of the normality assumption of the DV. For the negative valence, there was a significant difference in content style for both products ($U_{tablet}=5{,}530.5$, $p<0.001$; $U_{trip}=6{,}458.5$, $p=0.023$). For the badge variable, there was a significant difference only for the trip and not for the tablet ($U_{tablet}=7{,}236.5$, $p=0.366$; $U_{trip}=6{,}432.5$, $p=0.020$). For the positive valence, there was a significant difference in content style for both products ($U_{tablet}=10{,}641.0$, $p<0.001$; $U_{trip}=9{,}247.0$, $p=0.017$). For the badge variable, there was a marginally significant difference only for the tablet and not for the

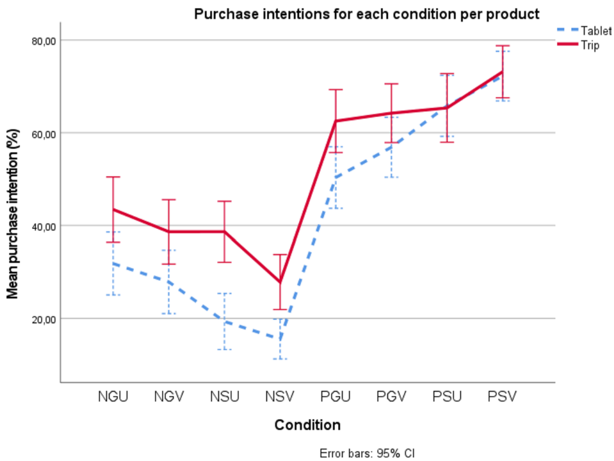

Fig. 3 Means of purchase intentions (%) for each product per condition. Key: The first letter represents the valence, with N = negative, P = positive; the second letter represents the content, with G = general, S = specific; and the third letter represents the badge, with U = unverified, V = verified

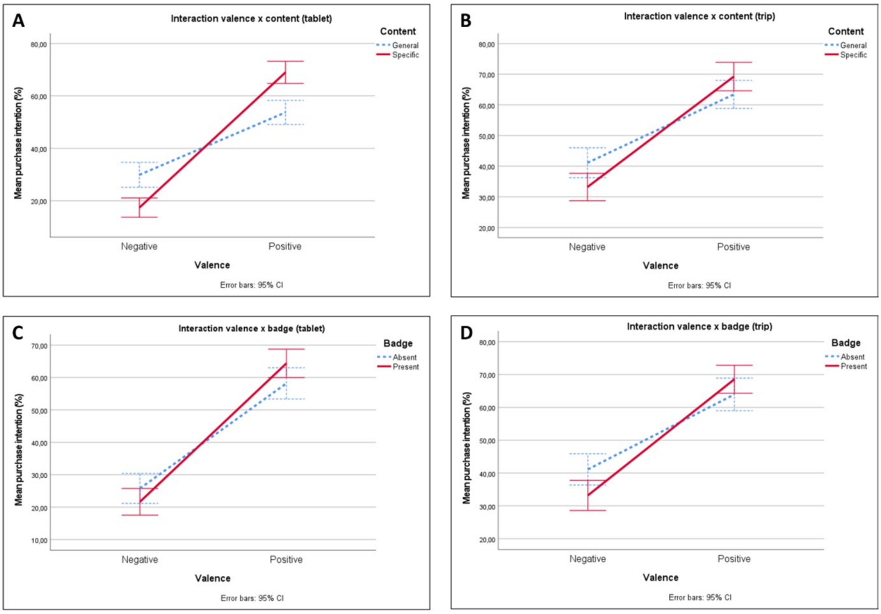

Fig. 4 Representation of the two-way interactions for the tablet (**A**, **C**) and trip (**B**, **D**)

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

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

trip (U_{tablet} = 8,975.5, p = 0.055; U_{trip} = 8,582.0, p = 0.218). The p-values are not corrected in order to allow for multiple comparisons.

The findings do not show a main effect of content style and the verification of reviews on purchase intention. Therefore, we reject H1a, H1b, and H2. However, the null main effects for those variables (i.e., content and badge) are explained by their significant interactions with valence. Depending on whether the valence is positive or negative, the effects of content style and badge on purchase intention is opposite (see Fig. 4). Moreover, the results demonstrate that the valence of OCRs is the main factor impacting purchase intention. Positive evaluations increase purchase intention

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

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

and vice versa. This confirms H3 and supports existing research on the impact of review valence on decision-making [84, 90, 91].

We answered H4a and H4b using the significant valence-content and valence-badge interactions. Reviews with general content led to a higher purchase intention than reviews with specific content when their valence was negative and vice versa for both products. An explanation for this is that specific content evokes more critical evaluations of the product than general content. The description of a product's specific qualities enhances positive and negative perceptions thereof (as inferred from the revealed purchase intention), depending on positive or negative framing, respectively. Our findings contradict those of Bigné et al. [62], who analyzes the effects of this interaction on the visit intention and digital destination image in a different country with a larger sample size and a sole focus on tourism destinations. However, we agree with the authors that "specific content is more trustworthy and thus more persuasive than general content" [62]. Moreover, we posit that this persuasiveness effect follows the valence of the comment. When a review is negative, specific comments reinforce the negative aspects of the product and decreases the purchase intention, whereas, when a review is positive, the specificity strengthens the positive perceptions of the product and increases the purchase intention.

Concerning the valence-badge interaction, our data show a tendency of higher purchase intention when the badge is absent in negative comments and present in positive comments. This tendency is seen in both products, but the differences in purchase intentions are statistically significant in the negative condition only for the trip package and in the positive condition only for the tablet. It seems that, when the comments are negative for search products (i.e., the tablet), participants give them equal weight, regardless of the presence of the badge, indicating that they have low purchase intention. However, when encountering positive comments, they find the verified comments more persuasive than the unverified ones. These effects are the opposite for experiential products (i.e., the trip). Therefore, we infer that search versus experiential products induce different judgment mechanisms depending on the type of information presented. He et al. [12] investigate whether verified online reviews on Amazon's website impact tablet sales. The authors find a positive correlation between the proportion of verified comments and sales rankings. However, they also find that the ratings of the VP reviews do not impact sales. Our data support the positive effect of the badge on purchase intention, albeit only when the review is positive.

5.3 Bayesian analysis

To produce a comprehensive analysis of the effects of each variable (valence, content style, and verification badge) on purchase intention, we conducted a Bayesian analysis (for details of its application in marketing settings, see Rossi and Allenby [30]. A Bayesian approach allows for direct inferences concerning the probability of success (i.e., a purchase) given a condition (e.g., positive valence). Moreover, prior knowledge about the effects of a variable in the outcome being investigated is incorporated in the analysis. When this knowledge is considered, it results in an informative prior. Therefore, the final probabilities, namely the posterior probabilities, incorporate the data obtained from the experimental condition as well as prior beliefs on the distribution of the data. This allows a better approximation of the true effect of one variable on another variable.

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

The plausible probability models took into account that conditions of the TG presumably lead to a lower purchase intention than the conditions of the CG. Due to the lack of information on the exact extent of the effect, the prior probabilities were distributed equally within probabilities greater than 50% and within probabilities less than 50%, but the lower probabilities had a larger weighting ($p=10\%$: 0.175, $p=20\%$: 0.175, $p=30\%$: 0.175, $p=40\%$: 0.175, $p=50\%$: 0.100, $p=60\%$: 0.050, $p=70\%$: 0.050, $p=80\%$: 0.050, $p=90\%$: 0.050). The posterior probabilities were derived from the prior probabilities and the likelihood probabilities were derived from the data.

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

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

Our observation of the point-mass probabilities is in line with and related to the previous analysis. The purchase probability with a specific comment present is slightly higher than if a general comment is shown for the search product but not for the experiential product. The presence of a badge leads to greater purchase levels for the search product. However, this effect is small, and it is null for the experiential product. The strongest effect was found in the valence of the OCR. A negative valence review powerfully impacts purchase intention. The purchase probability with negative reviews present is only 13.3% for the tablet and 30.6% for the trip (a noteworthy difference). This indicates that people are less willing to take the risk of purchasing search products than experiential products. Additionally, the reviews for the search products are perceived as more credible than those for the experiential products, thereby impacting the consumers' decision-making processes [53]. As expected, positive valence reviews have a strong effect on purchase intention. Sixty-eight percent of the participants reported an intention to buy the tablet and 77% reported an intention to buy the trip package under this condition. Moreover, different from the negative condition, the positive condition only had a 9% difference between product types.

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

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

6 Conclusion and implications

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

6.1 Theoretical implications

With the exponential rise in e-commerce, online information cues that influence purchase decisions have received great attention. Although the current study explores various previous findings, prior research neglects the joint effects caused by the linguistic component of product reviews and the presence or absence of VPs on consumers' purchase intention even though consumers are continuously exposed to these cues. Thus, the findings of this study extend our understanding regarding the effect intrinsic and extrinsic OCR cues have on consumers for different product types. We extend the marketing research on eWOM by adopting the cue utilization theory to examine how purchase intention is influenced by intrinsic cues (search and experiential products) and extrinsic cues (OCR cues). To the best of our knowledge, the present study is the first to examine the unique interplay between content style, purchase verification, and valence. Although search versus experiential product categories have received considerable attention across domains, research on the interactions among eWOM cues is sparse. In similar vein, examining the novel interactions between the heterogenous online review cues for purchase decisions can be useful to broaden other theoretical frameworks. Using information signaling theory, we can examine if presence of VP badge can signal trust and reduce information asymmetry in e-commerce as well as in online social media communities. Similarly, using elaboration likelihood model perspective can be utilized to examine interaction between the content style as central cue and VP badge as peripheral cue and their combined influence on consumer behavioral decision making, especially in tourism and hospitality sector (e.g., hotel choice, restaurant selection). In their work, Choi et al. [31] examined the effects of intrinsic cues (company reputation, newness, and retro features) and extrinsic cues (review valence, product popularity, price, and user engagement) on digital video game sales using signaling theory. They reported that the intrinsic cues of newness and retro features and the extrinsic cues of review valence, popularity, and price had a positive impact on sales, while company reputation had an insignificant effect. However, their findings were limited to a single product type. By contrast, we used two distinct product categories. The findings of this behavioral study, based on frequentist and Bayesian statistical analysis approaches, demonstrate that the effect of OCR valence of search and experiential products supersedes the effect of other review cues on purchase intention. Positive valence increases purchase intention and vice versa, as has been found in previous studies [84]. Yet, our main contribution lies in the interaction between the review cues.

The key findings of this study are summarized as follows. Firstly, the valence-content style interaction effect increases purchase intention when the reviews are specific and positive and decreases purchase intention when the reviews are general and positive for both product categories. Secondly, in terms of the valence-verification badge interaction, a positive review with a badge yields higher purchase intention, and a positive review without a badge yields lower purchase intention for the search products, with a weak tendency seen for the experiential products. Thirdly, when the valence of a review is negative, general content increases purchase intention and specific content decreases purchase intention. Fourthly, when a badge is present in a negative review, purchase intention decreases, and the absence of a badge in a negative review increases purchase intention. This last effect is noticeable for both experiential and search products. Fifthly, we do not find a significant effect of VPs on purchase intention. A conceivable explanation is that the badge does not influence a review's helpfulness. In this sense, He et al. [12] analyze 14,605 reviews for tablets from different brands and find that VP and non-VP reviews are perceived to be almost equally helpful. In summary, the content style and presence of VP badges are not important alone, especially for experiential products. These findings contribute to the debate on the influence of verified versus nonverified content, as discussed in the Literature Review. Moreover, content style and VP badges impact purchase intention differently according to the valence of the review. Lastly, the findings of the study show no asymmetric effect of review cues on the purchase intention for search and experiential products. We believe this is because e-commerce blurs the distinction between search and experiential products [92], which motivates consumers to use analogous strategies when purchasing them online, such as spending similar amounts of time online collecting information for both product types [56].

6.2 Managerial implications

Our findings offer several implications for e-commerce managers and designers. Specifically, this study highlights five key OCR-related factors: review valence, linguistic expression in reviews' content (i.e., specific or general content style), verification of the review (i.e., the presence of a VP badge), interactions of the cues, and their different impacts on consumers' purchase intention of search and experiential products. The impact of valence combined with content style and the verification of the reviews on product purchasing behavior has strategic implications for digital businesses. Because our study reveals the asymmetrical impact of the variables under consideration, information system designers should categorize and structure the features and presentation of OCRs for different product categories based on the type of extrinsic cue (see Liu et al. [93] on extracting OCR features from a designer's point of view). This will also simplify the evaluation process for consumers and assist them in information processing [94]. Firstly, e-commerce managers should focus on highlighting positive reviews on their platforms. For example, as a strategy for increasing sales, managers can display reviews in ascending order. In other words, instead of putting recent reviews first, reviews can be serialized according to valence. Also, managers can encourage consumers to leave specific comments about their products when they write positive evaluations. If reviews are negative, then general comments should be displayed. Secondly, digital commerce platforms can adopt the use of VP badges to indicate that a purchase is genuine. In doing so, the platform also endorses the reviewer by including a VP badge in their reviews, which can simultaneously create trustworthiness and positively impact sales [12]. Additionally, VP badges can be immediately applicable to e-commerce websites [13]. Highlighting high-quality reviews benefits consumers, sellers, and platforms [64]. Considering the current highly competitive business environment, "review fraud" is a usual occurrence that borders ethical infringement in eWOM communication [95]. Therefore, the indication of VPs could dilute the effects of fraudulent reviews.

6.3 Limitations and future directions

The present study has a few limitations that encourage new research prospects. Firstly, to control the number of words in each comment for the participants and measure their purchase intentions, this study presented modified versions of the actual reviews; however, the participants might not have considered the reviews thoroughly. Future researchers can use an incentive-compatible task and conduct field studies to gauge actual purchase behavior [96] or incorporate visual attention through eye-tracking studies [19]. Secondly, we sought to address search versus experiential product categories, but each category was represented by only one product. Hence, the use of caution is necessary when generalizing the findings, and future researchers should consider using more than one product. Thirdly, the stimulus presented was a simplified version of an online review. Actual reviews contain additional cues (e.g., average star ratings and the names of the reviewers) and have different formats (e.g., visual content). Fourthly, since neutral valence product reviews contain both the positive and negative aspects of the product, we did not include them in our study in order to clearly demonstrate the effects of review polarity (five-star versus one-star reviews) [97], thereby avoiding the diminishing of the diagnostic element of reviews [32]. Future studies can improve the framework by examining the effect of neutral valence (three-star ratings) on review credibility and subsequent consumer purchase behavior. Finally, future research can employ the cue utilization framework on various moderators of OCRs, such as cultural background, review platforms, consumers' knowledge, review length, product popularity, and so on, and measure their influence on purchase intentions.

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Declarations

Conflict of interest No conflict of interest has been declared by the authors.

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