Why are some reviews perceived as more helpful than others?

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Short Paper

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Abstract

User-generated reviews (UGR) are valuable in online markets, but not all reviews impact prospective customers equally. Reviews rated more helpful are more persuasive and valuable than others. Literature has examined how consumers evaluate the helpfulness of online reviews. We examine and demonstrate that content and non-content cues are important to driving the helpfulness of online reviews and that these two cues are incongruently influential to perceived helpfulness regarding salience stimuli readers' attention. Specifically, a high salience of content cues (acceptable long and concrete content) and a high salience of non-content cues draw readers' attention, subsequently influencing the higher perceived helpfulness compared with the low and the high content and non-content cues, respectively. Our findings provided evidence that information cues stemming from attributes of UGR can compensate interchangeably with information cues retrieved from the content of UGR.

Keywords: User-generated reviews, review helpfulness, information salience, review cues

Introduction

User-generated reviews (UGR) are considered a crucial source of word of mouth (Yin et al. 2014). Online customers thus have widely adopted online reviews to facilitate their purchase decision-making. Because of the vast amount of existing UGR, adopting UGR to assist online purchases challenges customers in selecting and sorting which reviews they can rely on. In other words, customers may face the problem of information overload (Eppler and Mengis 2004).

The problem of information overload can be solved to some extent by voting mechanisms that allow consumers to vote for reviews they find helpful (Cao et al. 2011). Since helpful reviews are quality information, they can assist potential customers, orienting them toward what they should read to save time and effort. The mechanism is indeed an optimization of information, assisting buyers and sellers in the online market. Subsequently, a helpful review becomes “a peer-generated product evaluation that facilitates the consumer’s purchase decision process” (Mudambi & Schuff, 2010, p.186).

Given the consensus on the importance of helpful reviews, scholars have attempted to investigate the customers’ evaluation of review helpfulness (Mudambi and Schuff 2010; Yin et al. 2021). The focus is mainly on identifying antecedents that affect the review helpfulness evaluation process. In other words, the “what” question has been well solved (e.g., see Filieri, 2015; Mudambi & Schuff (2010)). Nonetheless, the way customers perceive helpfulness (“how” question) (e.g., De Pelsmacker, Dens, & Kolomiiets (2018), Yin, Bond, & Zhang (2017), Zhanfei Lei, Yin, & Zhang, (2021)) and particularly if there are any differences regarding impactful power between them ("why" question) or their relative importance have not been fully explored yet (Eslami, Ghasemaghaei, & Hassanein, 2018; Q. Ben Liu & Karahanna, 2017).

In addition, research on the predictors of review helpfulness has drawn great attention regarding both non-content cues (Mudambi and Schuff 2010; Zhu et al. 2014) and content cues (Lei et al. 2021; Yin et al. 2014). Particularly, recent scholars have emphasized their investigations into the content of online reviews (content cues) that is reflected via different facets such as review sentiments (Hu et al. 2014), emotional expressions (Yin et al. 2017), content's abstractness (Li et al. 2013), reviewer's focus of attention (Zhanfei Lei et al. 2021). Despite a large stream of research, there is still a gap that needs to be fulfilled in terms of the relationship between these information cues (Thuy Nguyen and Tripathi 2022). For instance, several studies have shown that reviews with extreme ratings (a non-content cue) receive more helpful votes than those with neutral or moderate ratings (Cao et al. 2011; Forman, Ghose, and Wiesenfeld 2008; Pavlou and Dimoka 2006). In the meantime, an abstract review (a content cue) has been proven to be less influential and substantially less likely to draw the perceived review helpfulness (Li et al. 2013). Given these issues, one might question how consumers perceive reviews with lower-quality content (abstract reviews) but higher star ratings or vice versa. In addition, literature shows that the interaction between information cues (content cues and non-content/source cues (Forman, Ghose, and Wiese 2008)) can predict the helpfulness of a review (Pornpitakpan, 2004), and there is increasing research interest in how the online review helpfulness can be managed, understanding which basket of cues will serve the best, which has the least value, and if they complement or substitute in terms of providing information about the review. Therefore, we seek to examine the salient elements of cues that are integral to the helpfulness of online reviews.

From the theory of information salience (Hamilton and Fallot 1974) in impression formation, we are aware that customers' judgment can be predicted based on the descriptive information provided. As salience is a "capacity of a stimulus to attract attention," high salient cues may get greater attention (Hamilton and Fallot 1974). High salience cues (e.g., visual, auditory, or any sensory cue) are stimuli that stand out and draw individuals' focus in a given context or environment, playing a crucial role in directing attention and influencing cognitive processes in perception and decision-making. (Zhu et al. 2012). This study defines cues salience of online reviews (Huang et al. 2018) that draw the attention of potential customers and have implications for the evaluation of review helpfulness (Hamilton and Fallot 1974). Hence, we argue that review will be perceived less helpful when cue salience is low (e.g., a star rating shows a non-consistent rating with the content rather than a consistent valence) and vice versa. Further, different cues salience are incongruent in an explicit context to perceivers' schema (Albers 2007). We also postulate that the saliences of various cue groups (content vs. non-content cues) differently influence the perceived review helpfulness.

Grounded in a framework from information salience, we examine how cues salience affects individuals' perception of reviews and, ultimately, review helpfulness. This approach enables us to capture the complex nature of information cues through which individuals perceive the salience of information and cues to determine review helpfulness. Our work demonstrates that both content and non-content cues are important in driving the helpfulness of UGR and that these two types of cues are incongruently influential to perceived helpfulness regarding salience stimuli readers' attention. Specifically, a high content salience (acceptable long and concrete content rather than too short and abstract content) and a high non-content cue salience (jointly a salience of multiple non-content cues: rating consistency, reviewer reputation, and wisdom of crowds) draw greater attention of readers, subsequently influencing the higher perceived helpfulness compared with the low and the high content and non-content cues, respectively.

Our study offers fundamental contributions. Our research provided initial evidence that information stemming from non-content cues, however, can compensate interchangeably with information retrieved from review content. Specifically, this novel finding clarifies potential wherefore customers perceived a review as helpful though its content is inferior. In addition, to our best knowledge, this is the first paper exploring the perceived helpfulness from the angle of information salience in forming expression, which is believed to contribute greatly to the literature on review helpfulness. Salience of review cues are prone to drive the perception and behavior of review readers in terms of their signaling effects (Zhu et al. 2012). As such, weight of cue types in relation to review perceived helpfulness are comparable due to their varying salience embedded which can successfully explain and predict for the variation in review helpfulness voting behavior in a dynamic and mutable environment of a review system.

Theoretical Background

Prior literature on online review helpfulness

A growing stream of literature attempts to understand the influential factors driving customers' perceived review helpfulness. Recent studies have identified different aspects of information cues underlying UGRs as key factors of review helpfulness (Huang et al. 2018). Potential customers may use different information cues to diagnose the information and efficiently evaluate the helpfulness of the reviews.

Literature has suggested that prospective consumers rely on various sources of information cues to seek information such as star rating, review depth, review reputation, review readability, review recency (gaps between latest reviews and previous reviews), review sentiment, and review emotion (Huang et al. 2018; Mudambi and Schuff 2010; Yin et al. 2014; Zhanfei Lei et al. 2021). Previous studies have described how potential customers evaluate the cues and how they have used these cues to vote for review helpfulness. For instance, review content provides emotional arousal (Yin et al. 2014, 2017) or abstractness (Huang et al. 2018) to evaluate the helpfulness. More specifically, customers' evaluations are influenced by the content they read, which either shows emotions of anger or anxiety. Prospective customers consider reviews with content indicative of anxiety more helpful than those with content indicative of anger (Yin et al. 2014). Similarly, customers perceive an abstract review (a review that lacks detailed information on products' attributes) as less helpful than a concrete review (a review that provides detailed information about product features and functionalities) (Huang et al. 2018).

Although review helpfulness used to determine a review quality is exhibited via the number of helpful votes of a review (Li 2018), it is inherent in two significant challenges. First, not all readers will use the review helpfulness mechanism to evaluate the review. Second, the evaluation of review helpfulness may become useless when reviews are helpful but less impactful or not persuasive, or vice versa (Yin et al. 2017, 2021). Thus a number of helpful votes on the mechanism sometimes cannot demonstrate the perceived review helpfulness regarding the review's quality (Mudambi and Schuff 2010). In order to overcome these challenges, recently, many studies have set up experimental settings to capture genuine perceived helpfulness. Since the design of an experiment with explicit purpose enables to capture real-time evaluation and true value of review helpfulness, such perceived review helpfulness measured may be liable to the reflection of quality of a review. For example, in an attempt to elucidate the effect of two aspects of content cues (discrete vs. abstract) on the review helpfulness, Huang et al. (2018) adopted an experimental setting to validate their proposed moderating model. The experimental design allowed authors to gauge the true value of perceived helpfulness by using the three reflective indicators (three measurement items) instead of using the number of helpful votes as a proxy and facilitating the estimation of the impact of review content on review helpfulness moderated by roles of temporal cues (the timespan when the review was posted) and social cues (original place of the post) both singly and jointly. Likewise, M. Li & Huang (2020) designed a controlled experiment to test the hypotheses regarding the relationship between review length and review helpfulness. In this paper, authors used a binomial question (yes/no) to capture the perceived review helpfulness. The study has ascertained that a medium-length review likely leads to a more helpful perception compared with a too-short or too length review. In this regards, a genuine value of review helpfulness would truly reflect whether the review is helpful, determining the quality of a review.

Given various critical cues shaping the perception of review helpfulness, two possible categories of information cues can be grouped: source and message cues (Chaiken 1980). The mentioned two groups of cues have already been appropriately employed in the context of UGR (Reinhard and Sporer 2010; Zhu et al. 2014) and are regarded as fundamental antecedents for credibility judgments (Reinhard and Sporer 2010). Although there seems to be a census on this categorization and also available extensive research on each category, no exploration of the total weight of impact for each cue and group of cues has been done. In the meantime, knowing the weighting impact of each cue/ and group of cues is believed to be practically beneficial to review sorting enhancement and eventually support better-informed decision-making. In addition, the vast majority of works in this domain have focused on the elaboration likelihood to explain how the review helpfulness is perceived. In brief, previous studies explain the perception of review helpfulness through impression formation and credibility attribution (Reinhard and Sporer 2010), which primarily rely on the dual-process theory assumptions for reasoning. The present study also anchors on impression formation to explain perceived review helpfulness. However, unlike prior studies, our current research examines impression formation from the angle of information salience, defined as the degree of implications that the content of the stimulus attributes have for the judgment being made. A high salience will indeed do a greater job of signaling than a low cue salience (Zhu et al. 2012). We investigate how online review cue salience impresses readers and influences their judgment and evaluation of review helpfulness.

Remarkably, in terms of information cues, the existing studies have focused only on a single cue or two at max. The examination was limited to investigating differential impact within the cues' dimensions. Those studies constrain the comparison within and between information cues so that further understanding and exploration of the evaluation toward the perception of review helpfulness can be revealed. For instance, what cues will the potential customers care for most when taking all the cues together? In other words, albeit so many factors have been found to impact forming the helpfulness significantly, what exactly groups of factors or combinations of factors make the review stand out? In which circumstance the content cues will be at best performance? We decided to go beyond examining the magnitude of the most critical cues from different sources as a group and individually. Our study, therefore, investigates the influence of multiple cues simultaneously. Our underlying theoretical argument is that the variances among multiple cue sources are due primarily to information salience, a vital facet of impression formation that has not yet been considered in prior studies. Indeed, evaluation outcomes may vary according to what the typical cue implies. Expectantly, the current study provides a more nuanced differentiation between impactful cues.

Information Salience and Impression Formation

Information salience is a social and psychological concept first introduced by Hamilton & Fallot (1974). It is considered as prominence given to an information attribute (Albers 2007). Information salience explains how perceivers utilize various information cues to make judgments and evaluations (Hamilton et al. 1978). Accordingly, each stimulus element (information cue) has corresponding informational salience for the judgment being made (Hamilton and Fallot 1974). Hamilton et al. (1978) confirmed that perceivers are undeniably sensitive to differential implications of content attributes for a given judgment. However, since individuals may face an issue of limited cognitive capacity in making judgments, they tend to pick the cues with the highest salience and focus their cognitive processing on those cues (Albers 2007).

Early research on impression formation posits the influential impact of primacy effects on impression, which suggests that earlier information is more convincing and has a higher weight than later information to form the impression (Hamilton et al. 1978). More recent studies have great attention to the perceiver's cognitive process, such as elaboration likelihood (Petty and Cacioppo 1986) and information salience (Albers 2007; Hamilton et al. 1978). These two foci allow the inference and explanation of impression formation without a sequence situation. While elaboration likelihood relies on an individual's involvement and motivation to evaluate the judgment, information salience counts on salient cues' implications for a specific judgment. Indeed, the formatted impression has been proven to be susceptible to the perceiver's involvement and the extent of the cue salience implying judgments (Hamilton and Fallot 1974).

Information salience has been proposed to explain the evaluator's perception and behavior during their decision-making (Albers 2007; Hamilton et al. 1978). In the same vein, this study introduces the information salience concept to elaborate on the effects of information salience on online review helpfulness in the context of UGR. We predict and distinguish readers' perceptions when evaluating review helpfulness (RH). Under the lens of impression formation, cues of RH are differentiated and evaluated fundamentally on the same measurement unit of salience. Salience of non-content cues is constituted from a combination of the salience of consistency (rating and content valence), the salience of the content's writer reputation (reviewer reputation), and the salience from the peer-review assessment (wisdom of crowds). In the meantime, salience of content cue is prone to the attraction of the content itself (detailed concrete information vs. abstract information). A high salience will indeed do a greater job of signaling than a low cue salience (Zhu et al. 2012).

Additionally, the signaling effectiveness of cue salience (Zhu et al. 2012) enables the comparison and conclusion of the weight of each cue or the combination of pairs of cues. As every cue infers some range of possible values along an aspect of judgment, we assume that every stimulus cue implies possible specific judgment. Therefore, it is expected that UGR readers perceive the helpfulness differently due to the various judgments implied by salience from various information cues of review, which potentially respond to why some reviews are perceived as more helpful. Therefore, we construct the following hypotheses:

H1: Saliences from both content and non-content cues of UGR impact consumers' perceived RH. High cue salience results in a higher perceived RH and vice versa.

H2: The effect of non-content cues salience differs from that of content cues salience on consumers' perceived RH.

Method

We conducted an online experiment to investigate the salience effects of user-generated reviews on perceived helpfulness. The experiment employed real user-generated reviews that utilized the helpful vote mechanism and documented the fundamental phenomenon in an assemblage setting. We investigated the influential impact of information salience on helpfulness as a whole, considering content cues vs. non-content cues (source cues) as the two categories of primary antecedents of impression formation. Using the experimental design, we attempt to unveil a deeper understanding of the impact of each cue group, indicating more sophisticated scenarios of how information affects the judgment of review readers. The study was designed to set the four groups of prospective customers to assess the helpfulness of an online review when shopping on an e-commerce platform. We provided different levels of information for each group, assuring that each group distinctly perceives different review helpfulness. Accordingly, the salience of content cues and non-content cues was manipulated across two levels: high vs. low. Participants assessed the helpfulness of the review and reported their perceptions respectively.

Stimulus Materials

This study adapted the stimulus materials from Yin et al. (2014). The preparation of experimental treatments comprises three phases. First, we collected a dataset including 447 samples of online reviews associated with the number of helpful votes. Amazon.com was chosen as the target website because it is a well-known e-commerce platform leading in implementing personalization technologies (Zhang et al. 2011). We selected the smartwatch as the target product category as it belongs to the electronic category, which is the most popular Amazon product category. In addition, smartwatch is supposed to be an innovative digital product. Unlike the conventional physical product made up of the entire physical components, smartwatch combines digital technology with physical components to enhance the functionality, interactivity, and user experience. Finally, we used actual Amazon helpful votes for designing the experimental treatments.

Second, we sorted out and considered two-sided reviews from the sample pool to choose two typical reviews focusing on content quality. The use of only two-sided reviews ensures the omission of confounding impacts of the review's sidedness since two-sided reviews are believed to have a greater influence on perceived helpfulness than one-sided reviews (Mudambi and Schuff 2010; Zhanfei Lei et al. 2021). In our study, low vs. high-quality review is determined by content clarity (abstract vs. concreteness; see Huang et al. (2018)), content structure (e.g., review with pros and cons constructed clearly; see Zhanfei Lei et al. (2021)), and content length (Mudambi and Schuff 2010). For instance, a high salience review content is associated with clear and detailed ideas, displayed in a good structure and presented at a medium length. In more detail, we chose a review structured neatly with pros and cons, with the number of words (288 words) in the review greater than the average value (141 words). The content was carefully checked to ensure a concrete review, providing "detailed information about the products' attributes or characteristics with specific expressions" (Huang et al., 2018, p.507). On the opposite, we chose a short, general and vague content review with one paragraph structure (67 words), providing that it was a two-sided review to form the second condition for the low content cue.

In the third phase, we constructed two helpfulness voting systems with two corresponding addressed review contents and manipulated the non-content cues. Non-content cue signals are based on star rating, reviewer's reputation, and crowd wisdom; the manipulation of non-content cues varies due to the level of the three equivalent attributes. Consequently, the high salience of non-content cues is reflected by a consistent valence (between a star rating and the review content), a badged reviewer, and a large number of helpful votes (wisdom of crowds). In comparison, a low salience of non-content cues comprised a non-consistent valance, no badge for the reviewer, and a low level of helpful votes. As the two chosen contents were two-sided, a 3-star rating was selected for the high salience (a moderate rating is consistent with moderate/two-sided content) and a 1-star rating for the low salience of non-content cues (an extreme rating is not consistent with moderate/two-sided content).

On the shopping review page, an icon of orange stars was displayed next to the review title. Similarly, the level of review helpfulness was also manipulated as low and high. A review that receives thousands of helpful votes from past customers is believed to have a high level of helpfulness compared to a low level of helpfulness with just a few votes. We checked our secondary dataset and consulted it to manipulate this variate. The descriptive statistics showed a mean value of 99.22 and a median value of 29 for the number of helpful votes. Given that, we manipulated 6,258 and 1 for the high and low levels of helpfulness, respectively. In terms of reviewer reputation, the researchers used the reviewer badge to differentiate between a normal and an experienced reviewer. A review coupled with a badge showing a top reviewer symbol (e.g., top 1000 reviewer) placed next to the reviewer's name, indicating a review from the experienced reviewer. The badge authenticates the reviewer source, demonstrating a genuine reviewer. The four complementary treatments were established and presented in the table below.

	Low-salience content	**High-salience content**
Low salience of non-content cues + Non-consistent valence (1-star rating) + Low salience from the wisdom of crowds (1 helpful vote) + Low salience from reviewer reputation cue (Without a Hall of Fame badge)	35	35
High salience of non-content cues + Consistent valence (3-star rating) + High salience from the wisdom of crowds (6258 helpful votes) + High salience from reviewer reputation (With a Hall of Fame badge)	35	35

Table 1. Treatment conditions and number of samples

Experiment procedure

We tested our postulations using a 2 (Salience of the content: low vs. high) by 2 (Salience of non-content cues: low vs. high) full-factorial between-subjects design. Subjects were the Amazon Mechanical Turk (MTurk) workers and were randomly assigned to one of the four treatment groups. After passing the screening tests, subjects were presented with a mock-up shopping page[1]. Subjects were told to imagine that the review in a mock-up shopping page was real and read through it carefully. Afterward, subjects were instructed to complete a questionnaire that contained attention checks, manipulation checks (Yin et al. 2021), and measurement items of the research variables. Subsequently, they were allowed to vote (or not to vote) on the review published in the mock-up environment. Upon completing the task, subjects were directed to claim the reward.

Variables measured

Most of the variables in this study were measured on a 7-point Likert scale (1 - strongly disagree to 7 - strongly agree), using validated items adapted from prior published studies. In more detail, our dependent variable, perceived review helpfulness, was measured using four items from Huang et al. (2018) and M. Li et al. (2013). Two control variables: Product knowledge (PK) was measured using an existing instrument (Blair and Innis 1996), while shopping experience was measured with a three-item instrument (Khalifa and Liu 2007). And other control variables were: age, gender, Amazon Prime membership, and average annual spending.

[1] We followed the study of the online shopping setting in Huang et al. (2018) to simulate a mock-up shopping website. Accordingly, this webpage displayed comprehensive information about the product (i.e., product descriptions and its price), the review helpfulness cues (three studied cues), and a product review that was randomly taken from a sample pool of reviews. Besides, the date and place of posts presented are set consistently for all treatments to avoid the effects of social and temporal cues on the perceived review helpfulness (Huang et al. 2018). To mitigate the marginal effects, we selected the date for the review not to exceed three months from the experiment date. We also recorded each subject's time reading and comprehending the product review information. The work of gauging the time helped detect the nonserious workers who skipped the page within a very short time. The workers who completed the survey received a reward for their participation.

Data Analysis and Preliminary Results

Sample Description

Our sample included 53% male and 47% female participants with an average age of 40. They had a minimum shopping experience on Amazon of 3.333 years and a mean value of 6.419 years, indicating that most participants have had a considerate experience shopping on this website. The mean value of product knowledge (4.016) is greater than the median value (3.5), reflecting the fair familiarity with the smartwatch product of the subjects on average. Besides, the majority of respondents were prime members of Amazon (mean = 0.836). The amount of money they spent was approximately US$500-US$1000 yearly.

Manipulation and Control Checks

Despite controlling for manipulation questions during experiments, we also conducted manipulation checks using a parametric summary to secure the successful manipulation of the salience of the product review content and the associated non-content cues. The results of one-way ANOVA for the salience of content cues and non-content cues separately revealed that low salient content was perceived differently from high salient content cues (F = 1141. p<0.001), and the high level of the salience of non-content cues is perceived consistently different from low-level of the salience of non-content cues (F=836.9, p<0.001). Moreover, the high and low levels variation is 4.39 and 4.19 for the salience of non-content cues and the review content, respectively.

We also inspected our four control variables for any systematic bias influencing the review helpfulness across the treatment groups. ANOVA outputs demonstrated a lack of significant difference at the level of significant 0.01 (F_age = 0.368, p=0.545; F_gender = 3.475, p=0.064; F_Prime.member = 1.902, p = 0.17; F_Spending = 0.551, p = 0.459). Therefore, control checks were deemed successful regarding participants' characteristics via randomization (Huang et al. 2018).

Results and Discussion

Our analysis demonstrated a significant major impact of the salience of content cues and non-content cues on perceived review helpfulness. In more detail, there is a statistically significant difference in perceived review helpfulness within groups of the salience of content cues (F(1,136)=20.624, p<0.001) and within groups of the salience of non-content cues (F(1,136)=14.703, p<0.001). The results posit that regardless of cues, the low and high salience of cues are associated with different perceived review helpfulness. This is likely the outcome of the distinct degree of salience implied in the reader's perception of judgment. The mean difference between low and high levels of content cue salience exceeds the gap between low and high non-content cue salience (-0.92 vs. -0.78, p<0.001).

ANOVA analysis results also revealed a statistically significant interaction effect between content cues and non-content cues (F=8.294, p <0.01), indicating the relationship between the type of content cues (high vs. low salience) and perceived review helpfulness depends on the salience of non-content cues. Further, when content cue salience is high, there is no significant difference in perceived helpfulness between low and high non-content cue salience (t = -1.095, p >0.1). However, when the salience of content is low, the difference in the salience of non-content cues matters. Tamhane's T2 test showed that a review with high salience of non-content cues would lead to a value of 3.730 (p<0.01) higher in perceived review helpfulness than a review with low salient non-content cues in a low salient content review. Likewise, the results demonstrated a non-significant effect for the low and high salient content difference in which the salience of non-content cues is high (t = -1.382, p <0.1). In contrast, when the salience of non-content cues is low, a review with high salient content significantly improves review helpfulness (t = 4.642, p <0.001).

Our findings from Study 1 support the two hypotheses, which demonstrate that the salience of both content and non-content cues is important in driving the helpfulness of UGR (H1). And that these two cue saliences are incongruently influential to perceived review helpfulness regarding salience stimuli readers' attention (H2). Interestingly, post-hoc test results postulate that information cues stemming from UGR can compensate interchangeably with information cues retrieved from the salience of review content. This novel finding clarifies potential wherefore customers perceived a review as helpful though its content is inferior. Similarly, while prominent information source cues of UGR are poorly presented simultaneously, customers still vote that the review is helpful. Our study reinforces the impact of both source cues and content cues of UGR; more importantly, one can compensate for another once one has a poor salience (Figure 1 supports the statistical inference of the interaction effects).

Conclusion

Our study significantly contributes to understanding how prospective customers perceive user-generated reviews' helpfulness in assessing the two groups of saliences – content cues and non-content cues (or source cues) separately. The preliminary results showed the interplays of the salience of content and non-content cues to form impressions that implicitly impact review helpfulness. From a practical standpoint, our work

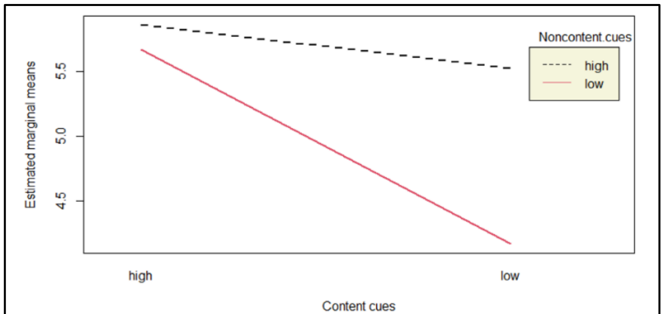

Figure 1. Interaction effect

underscores the critical role of managing information salience in the context of online reviews in which it is embedded, as it drives how reviews are interpreted and how they are perceived as helpful. However, this research in progress faces a constraint in offering a deeper explanation for the single salience effect of an individual cue. We are working on the study's second phase to provide complete and comprehensive knowledge to theorize information salience and seek the answers to why readers (prospective customers) evaluate some (non-content) cues as more salient and helpful than others.

References

Albers, Michael J. 2007. "Information Salience and Interpreting Information." *SIGDOC'07: Proceedings of the 25th ACM International Conference on Design of Communication* 80–86.

Blair, M. Elizabeth, and Daniel E. Innis. 1996. "The Effects of Product Knowledge on the Evaluation of Warranteed Brands." *Psychology and Marketing* 13(5):445–56.

Cao, Qing, Wenjing Duan, and Qiwei Gan. 2011. "Exploring Determinants of Voting for the 'Helpfulness' of Online User Reviews: A Text Mining Approach." *Decision Support Systems* 50(2):511–21. doi: 10.1016/j.dss.2010.11.009.

Chaiken, Shelly. 1980. "Heuristic versus Systematic Information Processing and the Use of Source versus Message Cues in Persuasion." *Journal of Personality and Social Psychology* 39(5).

Eppler, Martin J., and Jeanne Mengis. 2004. "The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines." *Information Society* 20(5):325–44. doi: 10.1080/01972240490507974.

Eslami, Seyed Pouyan, Maryam Ghasemaghaei, and Khaled Hassanein. 2018. "Which Online Reviews Do Consumers Find Most Helpful? A Multi-Method Investigation." *Decision Support Systems* 113(June):32–42. doi: 10.1016/j.dss.2018.06.012.

Filieri, Raffaele. 2015. "What Makes Online Reviews Helpful? A Diagnosticity-Adoption Framework to Explain Informational and Normative Influences in e-WOM." *Journal of Business Research* 68(6):1261–70. doi: 10.1016/j.jbusres.2014.11.006.

Forman, Chris, Anindya Ghose, and Batia Wiese. 2008. "Examining the Relationship Between Reviews and Sales: The Role of Social Information in Electronic Markets 1 Chris Forman." *Information System Research* 19(3):291–313. doi: 10.1287/isre.1080.0193.

Ghose, Anindya, and Panagiotis G. Ipeirotis. 2011. "Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics." *IEEE Transactions on Knowledge and Data Engineering* 23(10):1498–1512. doi: 10.1109/TKDE.2010.188.

Hamilton, David L., and Roger D. Fallot. 1974. "Information Salience as a Weighting Factor in Impression

Formation." *Journal of Personality and Social Psychology* 30(4):444–48.
Hamilton, David L., Roger D. Fallot, and Jack H. 1978. "Information Salience and Order Effects in Impression Formation." *Personality and Social Psychology Bulletin* 44–47(1):44-.
Hu, Nan, Noi Sian Koh, and Srinivas K. Reddy. 2014. "Ratings Lead You to the Product, Reviews Help You Clinch It? The Mediating Role of Online Review Sentiments on Product Sales." *Decision Support Systems* 57(1):42–53. doi: 10.1016/j.dss.2013.07.009.
Huang, Liqiang;, Chuan-Hoo; Tan, Weiling; Ke, and Kwok Kee Wei. 2018. "Helpfulness of Online Review Content: The Moderating Effects of Temporal and Social Cues." *Journal of the Association for Information Systems* 19(6):503–22. doi: 10.17705/1jais.00499.
Khalifa, Mohamed, and Vanessa Liu. 2007. "Online Consumer Retention: Contingent Effects of Online Shopping Habit and Online Shopping Experience." *European Journal of Information Systems* 16(6):780–92. doi: 10.1057/palgrave.ejis.3000711.
Lei, Zhanfei, Dezhi Yin, and Han Zhang. 2021. "Focus Within or On Others: The Impact of Reviewers' Attentional Focus on Review Helpfulness." *Information Systems Research* (May):1–19.
Li, Mengxiang, Liqiang Huang, Chuan Hoo Tan, and Kwok Kee Wei. 2013. "Helpfulness of Online Product Reviews as Seen by Consumers: Source and Content Features." *International Journal of Electronic Commerce* 17(4):101–36. doi: 10.2753/JEC1086-4415170404.
Li, Mengxiang, and Pu Huang. 2020. "Assessing the Product Review Helpfulness: Affective-Cognitive Evaluation and the Moderating Effect of Feedback Mechanism." *Information and Management* 57(7):103359. doi: 10.1016/j.im.2020.103359.
Li, Xitong. 2018. "Impact of Average Rating on Social Media Endorsement: The Moderating Role of Rating Dispersion and Discount Threshold." *Information Systems Research* 29(3):739–54.
Liu, Qianqian Ben, and Elena Karahanna. 2017. "The Dark Side of Reviews: The Swaying Effects of Online Product Reviews on Attribute Preference Construction." *MIS Quarterly: Management Information Systems* 41(2):427–48. doi: 10.25300/MISQ/2017/41.2.05.
Mudambi, Susan M., and David Schuff. 2010. "What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.Com." *MIS Quarterly* 34(1):185–200. doi: 10.2307/4132321.
Pavlou, Paul A., and Angelika Dimoka. 2006. "The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums and Seller Differentiation." *Information Systems Research* 17(4):392–414. doi: 10.1287/isre.1060.0106.
Pelsmacker, Patrick, Nathalie Dens, and Alona Kolomiiets. 2018. "The Impact of Text Valence, Star Rating and Rated Usefulness in Online Reviews." *International Journal of Advertising* 37(3):340–59. doi: 10.1080/02650487.2018.1424792.
Petty, Richard E., and John Cacioppo. 1986. "The Elaboration Likelihood Model of Persuasion." *Advances in Experimental Social Psychology* 19:123–205. doi: 10.1007/s12599-013-0259-3.
Reinhard, Marc André, and Siegfried L. Sporer. 2010. "Content versus Source Cue Information as a Basis for Credibility Judgments: The Impact of Task Involvement." *Social Psychology* 41(2).
Thuy Nguyen, Tien, and Arvind Tripathi. 2022. "How Is the Review Helpfulness Evaluated?" *ICIS 2022 Proceedings. 11.* (Association for Information Systems Association for Information Systems AIS Electronic Library (AISeL) AIS Electronic Library (AISeL)):1–9.
Yin, Dezhi, Samuel D. Bond, and Han Zhang. 2014. "Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews." *MIS Quarterly* 38(2):539–60.
Yin, Dezhi, Samuel D. Bond, and Han Zhang. 2017. "Keep Your Cool or Let It out: Nonlinear Effects of Expressed Arousal on Perceptions of Consumer Reviews." *Journal of Marketing Research* 54(3):447–63. doi: 10.1509/jmr.13.0379.
Yin, Dezhi, Samuel D. Bond, and Han Zhang. 2021. "Anger in Consumer Reviews: Unhelpful but Persuasive?" *MIS Quartely* 45(3a):1–74.
Zhanfei Lei, Dezhi Yin, and Han Zhang. 2021. "Focus Within or On Others: The Impact of Reviewers' Attentional Focus on Review Helpfulness." *Information System Research* 32(3):801–19.
Zhang, Tongxiao, Ritu Agarwal, and Henry C. Lucas. 2011. "The Value of It-Enabled Retailer Learning: Personalized Product Recommendations and Customer Store Loyalty in Electronic Markets." *MIS Quarterly: Management Information Systems* 35(4):859–81. doi: 10.2307/41409964.
Zhu, Ling, Guopeng Yin, and Wei He. 2014. "Is This Opinion Leader's Review Useful? Peripheral Cues for Online Review Helpfulness." *Journal of Electronic Commerce Research* 15(4):267–80.
Zhu, Meng, Darron M. Billeter, and J. Jeffrey Inman. 2012. "The Double-Edged Sword of Signaling Effectiveness: When Salient Cues Curb Postpurchase Consumption." *Journal of Marketing Research* 49(1):26–38. doi: 10.1509/jmr.09.0531.