MIS Quarterly

RESEARCH NOTE

DELIBERATIVE OR AUTOMATIC: DISENTANGLING THE DUAL PROCESSES BEHIND THE PERSUASIVE POWER OF ONLINE WORD-OF-MOUTH [1]

Zhanfei Lei
Isenberg School of Management, University of Massachusetts Amherst
Amherst, MA U.S.A. {zlei@isenberg.umass.edu}

Dezhi Yin
Muma College of Business, University of South Florida
Tampa, FL U.S.A. {dezhiyin@usf.edu}

Han Zhang
Scheller College of Business, Georgia Institute of Technology, Atlanta, GA, U.S.A., and
School of Business, Hong Kong Baptist University, Hong Kong, CHINA {han.zhang@scheller.gatech.edu}

As online reviews become increasingly indispensable for consumers, they have attracted significant attention from both practitioners and researchers. It is a common belief that the persuasive effect of online reviews involves a deliberative and conscious process. Drawing on dual-process theories and the persuasion literature, we challenge this conventional wisdom, distinguish Type 2 processing (which requires deliberation) and Type 1 processing (which occurs automatically), and disentangle their relative impacts. With a focus on review elaborateness and review exposure, we propose that the automatic process of review exposure may play a greater role than elaborateness in changing consumers' attitudes and purchase intentions. In addition, in line with the negativity bias, we posit that the persuasive impact of review exposure (vs. elaborateness) is moderated by the valence of highly exposed reviews. The results of the two experiments provide consistent support for these predictions. Our findings complement and extend the emerging literature starting to explore the role of automatic Type 1 processing in consumers' use of online reviews, reveal the primary driver of persuasion and its boundary condition in online word-of-mouth, and provide important implications for review platforms, product manufacturers, and retailers.

Keywords: Review elaborateness, review exposure, review valence, deliberative process, automatic process, dual-process theories, persuasion

Introduction

Online reviews are increasingly important in consumers' purchase decisions (e.g., Jabr & Rahman, 2022; Lei et al., 2022). Review platforms often need to determine a subset of "best" reviews that should benefit prospective consumers the most. A common practice is to rely on the "wisdom of the crowd" to identify high-quality reviews (such as the most elaborate and detailed ones) and then display them first on product pages (Mudambi & Schuff, 2010). Such a practice is based on a predominant belief that helpful reviews are persuasive and that consumers employ a deliberative and conscious process in their use of online reviews (e.g., Yu et al., 2023). Guided by this belief, an important stream of research has investigated various deliberation-dependent ingredients of helpful reviews (e.g., Lei et al., 2021; Moore, 2015; Yin et al., 2014, 2017, 2023).

[1] Ron Cenfetelli was the accepting senior editor for this paper. Bo Xiao served as the associate editor.

However, recent works have started to question this belief. Yin et al. (2021) showed initial evidence that consumers' use of online reviews is not necessarily deliberative. Lei et al. (2022) and Lei et al. (2023) provided additional evidence that the persuasive effect of reviews might occur through an automatic and spontaneous process. Collectively, these two streams of literature suggest the existence of two distinct processes: one is deliberative, effortful, and slow, whereas the other is automatic and rapid. These two processes correspond to the Type 2 processing and Type 1 processing of dual-process theories in human judgment and decision-making (Evans & Stanovich, 2013; Kahneman, 2011).[2]

Despite the potential importance of automatic Type 1 processing in consumers' use of online reviews in their decision-making, no research, to our knowledge, has directly tested its impact or compared it with the impact of deliberative Type 2 processing. In this paper, we explore the primary source of persuasion in online word-of-mouth and disentangle the relative impacts of the two types of processing. To study deliberative Type 2 processing, we focused on review elaborateness (i.e., the extensiveness and depth of reviews), a key ingredient of helpful reviews that requires deliberative efforts (Hong et al., 2017). To study automatic Type 1 processing, we focused on review exposure (i.e., the extent to which reviews are visible to and read by consumers), which is rarely studied but potentially critical in consumer decision-making (Lei et al., 2023).

Our main proposal is that review exposure plays a greater role than review elaborateness in changing consumers' attitudes and purchase intentions. Based on the persuasion literature, information with greater exposure should become more familiar (Montoya et al., 2017; Zajonc, 1968). This greater familiarity can enhance the persuasive power of information through an automatic and effortless process that deliberation may not be able to override (e.g., Feldman & Lynch, 1988; Menon & Raghubir, 2003). In addition, in line with a negativity bias, which suggests that negative information is more influential than positive information (e.g., Baumeister et al., 2001), we posit that the persuasive effect of review exposure (vs. elaborateness) is stronger when the valence of highly exposed reviews is negative than when the valence is positive.[3] We used a novel trade-off design and conducted two experiments to test these hypotheses.

Our paper contributes to the online word-of-mouth literature by extending recent works that imply the potential importance of automatic Type 1 processing (Lei et al., 2022, 2023; Yin et al., 2021) and directly comparing its persuasive power with deliberative Type 2 processing. Our findings suggest that review exposure, an automatic process, is the primary driver of persuasion. Second, we propose a context-specific factor—the valence of highly exposed reviews—that moderates the persuasive effect of review exposure over review elaborateness, revealing a boundary condition for the automatic process. Our nuanced findings also offer important practical implications for review platforms, product manufacturers, and retailers on how to better deal with online reviews.

Literature Review and Theoretical Development

Attitude and Attitude Change

Attitude refers to one's general evaluation of other persons, objects, and issues (Petty & Cacioppo, 1986). People can form a positive or negative attitude about someone or something initially, and then they can change their attitude based on new information. Attitude change, which is also called "persuasion" (used interchangeably in earlier persuasion literature; see Petty & Cacioppo, 1981), results from communicated information (Petty & Wegener, 1998). Thus, a piece of information is persuasive to the extent that it changes a person's attitude.

Persuasion is relevant in our context. Before reading any reviews of a product, consumers should have already formed initial attitudes toward it based on its aggregated rating profiles (e.g., the average and the total number of ratings), which are often displayed prominently on both product listing pages and a particular product's page (Yin et al., 2016). Once the initial attitudes are formed, reading a few top-ranked reviews can change consumers' attitudes and purchase decisions (Lei et al., 2022). More persuasive reviews should change consumers' attitudes to a greater extent, and the direction of change is logically determined by the reviews' valence (Liu, 2006), becoming more positive (negative) if the reviews are overall more positive (negative) than the initial attitudes. In the following, we first describe the persuasive effect of review elaborateness through a deliberative process before discussing the effect of review exposure through an automatic process.

[2] We did not use the popular terms of System 1 and System 2 because they imply two singular systems; instead, the terms of Type 1 and 2 processing allow for multiple cognitive or neural systems to underlie each type of processing, and they also indicate qualitatively distinct forms of processing (Evans & Stanovich, 2013).

[3] "Highly exposed reviews" indicate reviews that receive more exposure. Similarly, "highly elaborate reviews" indicate reviews with more elaborate and detailed information.

Review Elaborateness and Persuasion

The traditional persuasion literature assumes that individuals carefully elaborate upon arguments about other persons, objects, and issues in a deliberative manner, and it is this deliberative process that results in attitude change (Petty & Cacioppo, 1986). Based on dual-process theories, this deliberation corresponds to Type 2 processing that involves reflective and analytic reasoning (Evans & Stanovich, 2013; Kahneman, 2011). In the context of online word-of-mouth, it is a common belief that the persuasive effect of reviews occurs through a deliberative process (e.g., Yu et al., 2023). For example, extensive research studied the key ingredients of helpful or diagnostic reviews (e.g., Lei et al., 2021; Moore, 2015; Yin et al., 2014, 2017), assuming consumers scrutinize such reviews via a deliberative process and then change their attitudes accordingly.

In this paper, we focus on the elaborateness of reviews. As a key determinant of review helpfulness, *review elaborateness* refers to the extensiveness and depth of online reviews (Hong et al., 2017; Mudambi & Schuff, 2010). Highly elaborate reviews include more detailed and concrete information. Such reviews help consumers reduce their uncertainty about product quality and envision what it would be like to use the product (Mudambi & Schuff, 2010). Therefore, the reading and subsequent use of an elaborate, in-depth review require a deliberative process on the part of consumers. Given the presumed importance of the deliberative process in the prior literature, highly elaborate reviews should be more persuasive in changing consumers' attitudes and purchase decisions.

However, emerging research has started to question this "deliberation drives persuasion" assumption. Yin et al. (2021) found that while angry reviews are less helpful, they are, counterintuitively, more persuasive, likely due to an automatic process. This work provided an initial challenge by demonstrating an emotion-focused exception, but it did not explore the automatic process of persuasion in more general cases. In addition, Lei et al. (2022) demonstrated that consumers' purchase decisions can be swayed by a few top-ranked text reviews (despite contradicting average ratings), and Lei et al. (2023) found the greater exposure of negative (vs. positive) reviews to be a likely reason for their greater impact on product sales (i.e., a negativity bias); both papers pointed out the importance of studying the automatic process of exposure. However, none of these papers examined automaticity directly or explored the relative persuasive power of different processes. We extend these findings by disentangling the relative impacts of review elaborateness and review exposure, which we turn to next.

Review Exposure and Persuasion

According to the "mere exposure effect" initially demonstrated by Zajonc (1968), exposure refers to the extent to which a stimulus is perceptible to an individual. Repeated exposure to a stimulus enhances one's familiarity with the stimulus (Montoya et al., 2017). Beyond a single stimulus, the repeated-exposure effect can be more prominent with subliminal exposures particularly when one is exposed to different stimuli of the same category (Zajonc, 2001). In persuasion contexts, greater exposure to an object's information shapes attitudes toward the object because information that becomes more familiar can directly influence attitudes (e.g., Petty & Cacioppo, 1986; Weisbuch et al., 2003). Importantly, the repeated-exposure effect occurs via an automatic process outside one's awareness (Zajonc, 2001). Such a process aligns with Type 1 processing, defined by its autonomous nature (Evans & Stanovich, 2013).

In our context, *review exposure* reflects the extent to which a review or set of reviews is visible to (and read by) consumers in their decision-making. The reviews that receive more exposure should become more familiar to consumers and will thus likely be more persuasive due to the automatic and effortless process of exposure. Before consumers make purchase decisions about a product, they may be exposed to positive (negative) reviews more than negative (positive) ones. More exposure to reviews in the former valence can manifest either in the number of distinct reviews (e.g., three distinct positive reviews and two distinct negative reviews) or the display times of the same review(s) (e.g., two distinct reviews in each valence but one positive review appearing twice, in top reviews and in most recent reviews).[4] Regardless, the opinions contained in those positive (negative) reviews should receive more exposure and become more familiar, changing consumers' attitudes and purchase intentions in a positive (negative) direction.

Although both the deliberative Type 2 processing and the automatic Type 1 processing of dual-process theories can influence judgment and decision-making, Type 1 processing, which generates intuitive and default outcomes, may take priority over Type 2 processing (Kahneman, 2011). The

[4] In the rest of this paper, we will omit "distinct" from "the number of distinct reviews" for brevity. For example, a greater number of reviews means a greater number of distinct reviews.

persuasion literature also demonstrates that the automatic process alone might be sufficient (Lynch et al., 1988; MacKenzie, 1986), and the manifestation of the deliberative process can be overshadowed by the automatic process (Feldman & Lynch, 1988). The reason for this is that consumers are "cognitive misers" who tend to reduce the effort required for judgment and decision-making whenever possible (Fiske & Taylor, 1991). When different inputs vary in terms of how likely they can be automatically processed, consumers are less likely to engage in the effortful process of judging inputs deliberatively; instead, they are more likely to rely on inputs that can be processed automatically and effortlessly (Menon & Raghubir, 2003).

In our setting, *elaborate* reviews are often top-ranked because these longer reviews (with more details) are expected to be more helpful for consumers. Meanwhile, top reviews are more likely to be read by consumers, leading elaborate reviews to simultaneously receive more exposure. Accordingly, top reviews may be influential in changing consumer attitudes and purchase intentions (Jabr & Rahman, 2022; Liu et al., 2019), but the reason may not be review elaborateness (or helpfulness), which involves a deliberative process, but review exposure, which involves an automatic process. Integrating all the preceding arguments and evidence, we propose that highly exposed reviews should be more persuasive than highly elaborate reviews.

H1: *Review exposure influences consumers' **(a)** attitudes and **(b)** purchase intentions to a greater extent than review elaborateness.*

Negativity Bias and Persuasion

We next argue that the persuasive power of review exposure over review elaborateness may depend on the valence of highly exposed reviews.[5] Research in diverse domains has demonstrated that negative information is more influential than positive information (e.g., Baumeister et al., 2001). This negativity bias can be attributed to people's general tendency of risk aversion: People typically react more strongly to losses than to gains because they believe that the disutility of a loss will be greater than the utility of a gain (Kahneman & Tversky, 1979) and because people tend to be more concerned about negative outcomes than positive outcomes (Kahneman et al., 1991).

In our context, the negative reviews of a product are expected to contain unfavorable opinions of the product and indicate the potential risks of purchasing it. Therefore, consumers should be more sensitive to a product's negative reviews (versus its positive reviews) to avoid risk. Accordingly, when highly exposed reviews are negative in valence, the persuasive impact of review exposure (relative to elaborateness) is expected to be greater. Taken together, we propose the following.

H2: *The valence of highly exposed reviews moderates the impact of review exposure (vs. elaborateness) on consumers' **(a)** attitudes and **(b)** purchase intentions, such that the impact is stronger when the valence of highly exposed reviews is negative than when the valence is positive.*

To disentangle the relative impacts of review exposure and elaborateness, we used a trade-off design that aligns with the idea of testing competing theories. According to Leavitt et al. (2010), to disentangle different mechanisms or pit one theory against another, an ideal experiment should be designed such that competing theories would predict opposite outcomes. Thus, the final outcomes (e.g., if participants are forced to choose between options) can provide evidence supporting one mechanism or theory over another.

In our context, we varied review exposure and review elaborateness through a product's positive and negative reviews.[6] Our manipulation of the two factors through the (positive or negative) valence of reviews can lead to opposite directions of persuasion (i.e., opposite outcomes), with each direction (i.e., "forced choice" outcome) supporting a more persuasive impact of one factor over the other. As shown in Table 1, Column A represents cases in which positive reviews receive more exposure whereas negative reviews are more elaborate. In this condition, which we term the "positive condition" for parsimony, if consumers' attitudes become more positive (negative) after reading the reviews, review exposure (elaborateness) should be the primary source of persuasion. A similar logic applies to cases when negative reviews receive more exposure, whereas positive reviews are more elaborate (termed the "negative condition") (see Column B of Table 1). This trade-off design allowed us to infer the primary source of persuasion based on the direction of change in consumers' attitudes and purchase intentions.

[5] When examining the moderating role of the valence of highly exposed reviews, we focused on how it moderates the relative impact of review exposure versus review elaborateness rather than the individual impact of each factor.

[6] Note that the review valence per se is not our central focus (except as a moderator in H2), but it determines the direction of change in consumers' attitudes and purchase intentions (i.e., the persuasion direction).

Table 1. Trade-Off Design

	A. Positive condition		B. Negative condition	
	Positive reviews	**Negative reviews**	**Positive reviews**	**Negative reviews**
Exposure	High	Low	Low	High
Elaborateness	Low	High	High	Low
	Prediction: after reading the reviews, the attitudes or purchase intentions would become more positive (negative) if review exposure (elaborateness) is more persuasive.		Prediction: after reading the reviews, the attitudes or purchase intentions would become more negative (positive) if review exposure (elaborateness) is more persuasive.	

In addition, we drew on the previous literature to manipulate review exposure and review elaborateness. Based on the repeated exposure paradigm, exposure can be manipulated by varying exposure frequency in two ways: the frequency of exposure to (different) stimuli of the same type and the frequency of exposure to the same stimulus (Zajonc, 2001). These two ways of exposure manipulation have been used in diverse contexts; for example, advertising research has manipulated the exposure frequency of a brand's advertisements by varying the number of (different) advertisements of the brand or the times the same advertisement is exposed to consumers (e.g., Berger & Mitchell, 1989; Schumann et al., 1990). In our context, we manipulated review exposure in the first way by varying the exposure frequency of different reviews of a certain valence. Specifically, we varied the relative number of positive versus negative reviews (e.g., two positive reviews and one negative review) that consumers were exposed to such that the number of reviews in one (e.g., positive) valence was greater than that in the other (e.g., negative) valence. Accordingly, the exposure of reviews in the valence with more reviews (e.g., two positive reviews) was greater than the exposure of reviews in the opposite valence (e.g., one negative review). To manipulate review exposure in the second way by varying the exposure frequency of the same review, we kept the number of positive versus negative reviews identical but exposed a particular review in a certain valence to consumers multiple times, increasing the exposure frequency of reviews in that valence.

In terms of elaborateness, given that more detailed and extensive reviews are more elaborate (Hong et al., 2017; Mudambi & Schuff, 2010), we manipulated this factor by varying the concreteness and extensiveness of the content contained in reviews. Using the above trade-off design and manipulations of exposure and elaborateness, we conducted two experimental studies involving a hypothetical online decision-making task.

Study 1

The first study deployed the trade-off design with the first form of exposure manipulation. Specifically, we manipulated review exposure (low vs. high) by varying the number of different reviews in a particular valence, and we manipulated review elaborateness (low vs. high) by varying the concreteness and extensiveness of reviews. In addition, to test H2, we manipulated the valence of high-exposed reviews between-subjects by incorporating two conditions: a "positive condition" in which the high-exposed reviews were positive and a "negative condition" in which the high-exposed reviews were negative.

Stimulus Materials

We selected a compact and foldable wireless mouse as the product because it is relevant and useful to undergraduate participants. To develop stimuli for this study and the subsequent study, we conducted two pretests. First, we prepared eight review titles that differed in valence but not in extremity (four positive titles: "Attractive," "Terrific," "Wise choice," and "Joyful experience"; and four negative titles: "It's worthless," "Depressing purchase," "Disturbing," and "Undesirable"). Second, we prepared four sets of high-elaborate reviews with two versions in each set (see Table 2). The positive and negative versions within each set were equivalent in extremity, and different review sets were equivalent in terms of information quantity, quality, and realism.

We then constructed stimuli based on the pretested titles and reviews. First, we selected the first three review titles of each valence listed in Table 2 for use in this study. Second, we selected the first three sets of high-elaborate reviews with extensive, in-depth comments about the product. For each high-elaborate review, we then created a corresponding low-elaborate version that contained fewer words and more abstract, general opinions (see Table 3). Within each set, we varied only the valence between the positive and negative versions, while we kept the substantial content nearly identical and the number of words similar (around 15).

Table 2. Four Sets of High-Elaborate Reviews

Set #	Positive version	Negative version
1	This is a great mouse and it works well. The mouse has the curved left side for the thumb, so it's very comfortable. Moreover, it allows me to change how quickly the cursor moves across my screen.	This is a worthless mouse and it doesn't work well. The mouse doesn't have the curved left side for the thumb, so it's very uncomfortable. Moreover, it doesn't allow me to change how quickly the cursor moves across my screen.
2	The mouse functions well. One feature that I found useful for saving battery life is the mouse turns off automatically after a long time of non-use. It is convenient for someone who walks away from their computer often.	The mouse functions poorly. One feature that I found harmful for saving battery life is the mouse doesn't turn off automatically after a long time of non-use. It isn't convenient for someone who walks away from their computer often.
3	Good value for the price. It includes a battery with the product, so you can use it immediately. It connects to my laptop very quickly. And it is responsive without any lag when I move it.	Poor value for the price. It doesn't include a battery with the product, so you cannot use it immediately. It connects to my laptop very slowly. And it isn't responsive with lags when I move it.
4	Very good wireless mouse. I like the side buttons, which are programmed to go back or forward on web browsers by default. The mouse has a setup software, so there is an easy way to reprogram the buttons.	Very bad wireless mouse. I don't like the side buttons, which are programmed to go back or forward on web browsers by default. The mouse has no setup software, so there is no easy way to reprogram the buttons.

Table 3. Three Sets of Low-Elaborate Reviews Used in Study 1

Set #	Positive version	Negative version
1	This is a great mouse and it works well. It is very comfortable to use.	This is a worthless mouse and it doesn't work well. It is very uncomfortable to use.
2	The mouse functions well. It turns off automatically after a long time of non-use.	The mouse functions poorly. It doesn't turn off automatically after a long time of non-use.
3	Good value for the price. It is responsive without any lag when I move it.	Poor value for the price. It isn't responsive with lags when I move it.

As a manipulation check of review elaborateness, we conducted a separate pretest and recruited 70 subjects from a U.S. university who participated for extra credit. Each subject was randomly assigned to read either the positive or negative version of the three sets of reviews (with a high-elaborate review and a low-elaborate review in each set), one review at a time. The order of the reviews was randomized. After reading each review, subjects were asked to report their evaluation of its elaborateness using a 9-point scale with three items adapted from Lei et al. (2021) and Lei et al. (2022) (e.g., "not at all detailed / very detailed"). The results of paired-sample t-tests showed that the elaborateness of the low-elaborate review was significantly lower than that of the high-elaborate review in each set, with a difference of at least 2.762, a t-value of at least 10.764, and a p-value of less than 0.001. Thus, our manipulation of review elaborateness was successful.

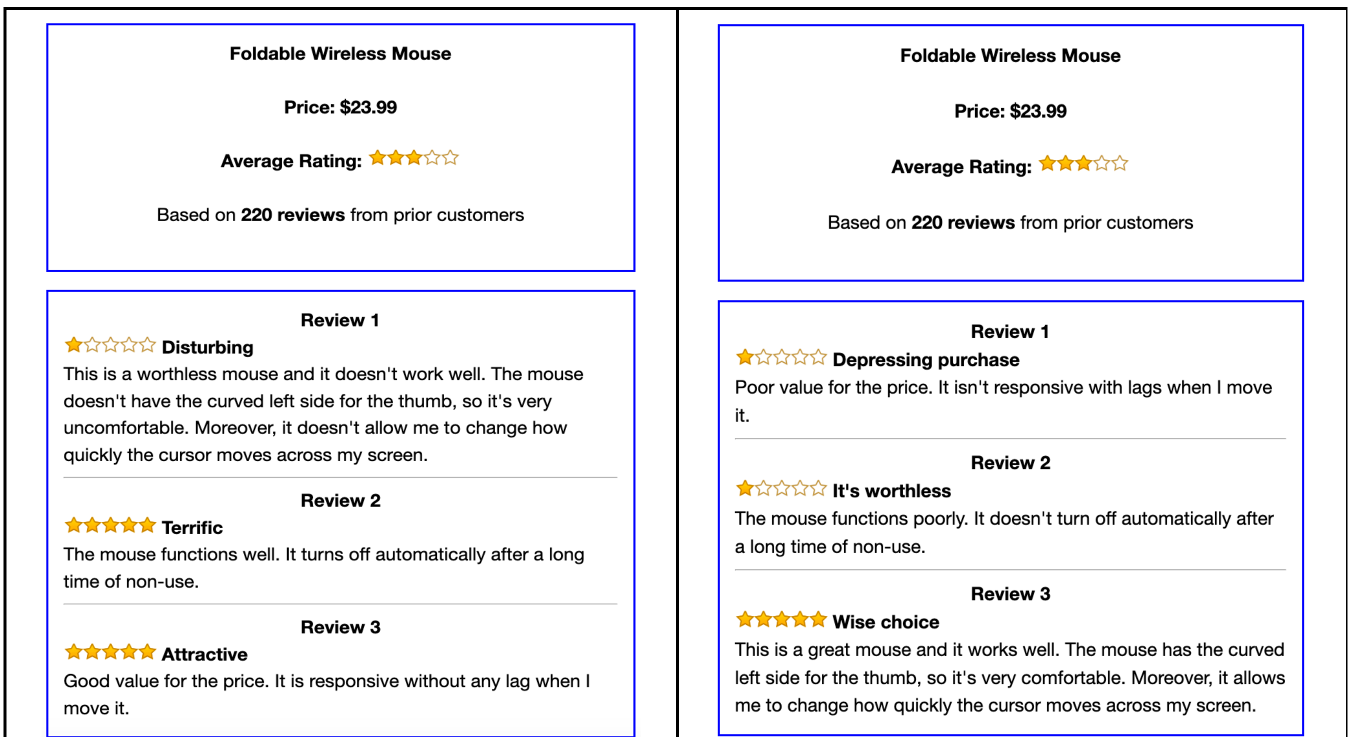
Procedure

In the main study, 95 undergraduate students (48 male) from a U.S. university participated for extra credit. Among them, 79% were originally from the U.S., 77% were juniors or above, and the average age was 23. In the cover story, participants were asked to imagine that they were planning to purchase a compact and foldable wireless mouse from Amazon.com, and their search returned one wireless mouse for $23.99. Then, they were asked to read the product's rating profile. The product had an average rating of 3 stars based on 220 reviews from prior consumers, ensuring that participants would develop a neutral attitude toward the product. After seeing the rating profile, participants were asked about their initial attitude toward the product using a 9-point scale with three items adapted from Darke and Ritchie (2007) (e.g., "very bad / very good"). They also reported their purchase intention using three items adapted from Dodds et al. (1991) and Goldberg and Gorn (1987) (e.g., "I would consider purchasing this mouse").

Next, participants were presented with three reviews (including star rating, title, and content) and were told that the reviews were randomly selected from the first review page of the 3-star product. For each participant, to manipulate review exposure at two levels, we varied the number of reviews to be at a low level (=1) in one valence (as a low-exposed review) and at a high level (=2) in the other valence (as high-exposed reviews); thus, among the three reviews, one was a low-exposed review and two were high-exposed reviews. Meanwhile, for the same participant, we manipulated review elaborateness at two levels (low vs. high) following the criteria that reviews (in one valence) with more exposure are less elaborate and vice versa (see Table 1). In addition, to manipulate the valence of the high-exposed reviews between-subjects, each subject was randomly assigned to either the positive (i.e., two positive reviews and one negative review) or the negative condition (i.e., two negative reviews and one positive review). Thus, in the positive condition with high-exposed reviews being positive, participants were asked to read two positive, low-elaborate reviews and one negative, high-elaborate review; in the negative condition with high-exposed review being negative, participants were asked to read two negative, low-elaborate reviews and one positive, high-elaborate review.

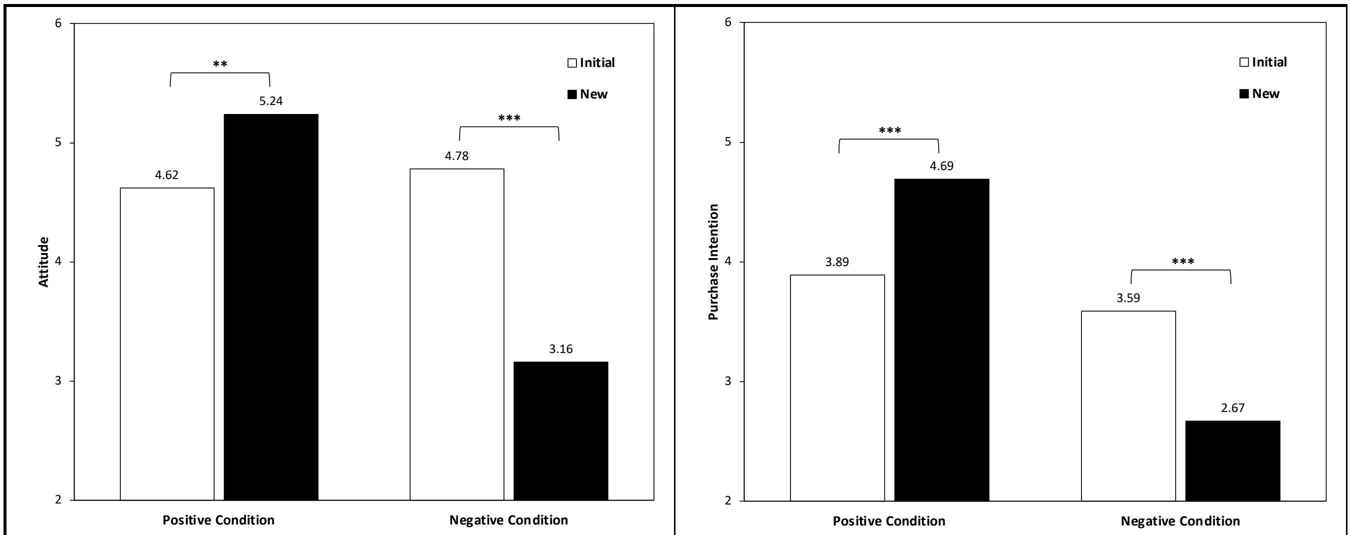
The review titles and content were selected according to the following criteria. First, for the positive (negative) condition, we randomly selected three review titles—two positive (negative) and one negative (positive)—from the six review titles used for this study. Second, the three text reviews were selected from the three sets of text reviews, one out of four versions from each set, so that multiple versions within the same set would not be displayed to the same participant. The valence version (positive or negative) in each review set was determined by the valence of review titles (matching it), whereas the elaborateness version (low or high) was determined by both the valence of review titles and the positive or negative condition that participants were assigned to (see the prior paragraph). Given the importance of valence in our manipulations, we displayed the star rating to go along with each review's title and textual content (see Figure 1 for two examples of the interface). We also randomized the order of reviews to mitigate order effects.

After reading the three reviews, participants reported their attitudes toward and purchase intentions of the product again. The twice-reported attitudes and purchase intentions (before and after reading the reviews) allowed us to capture persuasion—changes that result from reading the reviews. Finally, as a manipulation check for review exposure, participants were asked to recall the number of positive and negative reviews they read (e.g., "Can you recall the number of positive reviews based on what you read earlier?").



a. Positive Condition | b. Negative Condition

Figure 1. Two Examples of Rating Profiles and Individual Reviews Used in Study 1



a. Attitude Change **b. Purchase Intention Change**

Figure 2. Attitude Change and Purchase Intention Change in Study 1

Note: ** $p < 0.01$, *** $p < 0.001$

Results

We first conducted a manipulation check for review exposure. We found that most participants (87 out of 95) were able to correctly recall the number of positive and negative reviews.[7] We conducted an ANOVA analysis with participants' recalled number of reviews of a certain valence (corresponding to the exposure levels) entered as the dependent variable, (low vs. high) exposure entered as a within-subjects factor, and the valence of high-exposed reviews (i.e., positive vs. negative condition) entered as a between-subjects factor. The results revealed that the mean of subjects' recalled number of low-exposed reviews was significantly lower than that of the high-exposed reviews (M = 1.07 vs. 2.00, $F(1, 93) = 523.780$, $p < 0.001$). Thus, our manipulation of review exposure was deemed successful. Our manipulation of review elaborateness was also successful based on the pretest discussed earlier.

To compare the persuasive effects of review exposure and elaborateness on attitudes and purchase intentions, we conducted ANOVA analyses with one of the two outcomes entered as the dependent variable, the repeated (initial vs. new) measures of the outcome as a within-subjects factor, and the valence of high-exposed reviews (i.e., positive vs. negative condition) as a between-subjects factor. Results regarding attitudes revealed a significant interaction between the repeated measures and the valence of high-exposed reviews ($F(1, 93) = 55.350$, $p < 0.001$). Pairwise comparisons showed that in the positive condition, participants' attitudes became significantly more positive after reading the reviews (M = 4.62 vs. 5.24, $F(1, 93) = 8.349$, p = 0.005), in line with the direction of the high-exposed reviews. In the negative condition, participants' attitudes became significantly more negative (M = 4.78 vs. 3.16, $F(1, 93) = 58.634$, $p < 0.001$), again in line with the direction of the high-exposed reviews (see Figure 2a). These results show that review exposure dominated review elaborateness in changing consumers' attitudes, supporting H1a. Using consumers' purchase intentions as the dependent variable, we observed very similar patterns (see Figure 2b) and found evidence supporting H1b.

Finally, we examined whether the greater influence of review exposure (vs. elaborateness) on attitudes and purchase intentions was contingent on the valence of highly exposed reviews. We propose that the change in participants' attitudes (H2a) and purchase intentions (H2b) will be larger in the negative condition (when the high-exposed reviews are negative) than those in the positive condition. For each outcome, we captured its change by calculating the difference between participants' initial and new measures. Although the above findings reveal that participants' attitudes and purchase intentions became generally more positive (negative) in the positive (negative) condition (in line with H1a and H1b), there was no guarantee that the change of each participant was in our expected direction. To ensure that *a positive (negative) difference* between the two measures

[7] As a robustness check, we also conducted the main analyses based on the responses of 87 participants who correctly recalled the number of positive and negative reviews. The results were consistent.

indicated a greater influence of *review exposure (elaborateness)*, we calculated "change" variables differently for each condition: In the positive condition, we subtracted the initial measure from the new measure; in the negative condition, we subtracted the new measure from the initial measure. Then, we conducted *t*-tests to compare the exposure-driven change in participants' attitudes or purchase intentions between the positive and negative conditions. Results showed that the attitude change in the positive condition was significantly smaller than that in the negative condition ($M = 0.62$ vs. 1.62, $t(93) = 3.332$, $p = 0.001$), supporting H2a. However, the difference in purchase intention change between the positive and negative conditions did not reach significance ($M = 0.79$ vs. 0.92, $t(93) = 0.435$, $p = 0.665$); thus, we did not find evidence for H2b. We suspect that our exposure manipulation based on the number of reviews may have been more directly related to purchase decisions than attitude formation. Thus, the strong manipulation may have suppressed the effect of negativity bias in the case of purchase intentions but not attitudes.

Discussion

Study 1 manipulated review exposure and elaborateness using a trade-off design and disentangled their relative impacts on consumers' attitudes and purchase intentions. We found that review exposure is more persuasive than elaborateness for both outcomes in line with H1a and H1b. Also, as proposed in H2a, we found that the greater impact of review exposure (versus elaborateness) on consumers' attitudes is dependent on the valence of highly exposed reviews.

Study 1 has two major limitations. First, our manipulation of the exposure of reviews in a certain valence relies on changing the exposure frequency of different reviews in that valence. This particular manipulation increased the likelihood of participants to mentally calculate the average valence of the three presented reviews, compare it with the product's average rating (3 stars), and then adjust their attitudes and purchase intentions accordingly. To rule out this alternative explanation, the next study kept the number of reviews in each valence identical, ensuring the average valence of displayed reviews was equivalent to the product's average rating. Instead, we manipulated exposure in an alternative, more subtle way through changing the exposure frequency of the same review. This more subtle manipulation of exposure also allowed us to more properly test the moderating role of the valence of highly exposed reviews in affecting consumers' purchase intentions as proposed in H2b. Second, although the low-elaborate reviews in Study 1 were significantly less elaborate than the high-elaborate reviews in the study, the low-elaborate ones still contained some details, which may have weakened the persuasive power of review elaborateness. We also addressed this limitation in the next experiment.

Study 2

Study 2 tested both hypotheses through a more conservative design in which the exposure manipulation was more subtle and the elaborateness manipulation was stronger. Specifically, we manipulated exposure by varying the frequency of exposing the same review in a certain valence while fixing the number of low-exposed vs. high-exposed reviews. Regarding elaborateness, we further reduced the concreteness and extensiveness of content in low-elaborate versions to strengthen the manipulation of this factor. Like Study 1, we manipulated the (positive vs. negative) valence of high-exposed reviews as a between-subjects factor.

Stimulus Materials

We developed stimuli for Study 2 based on the titles and reviews created in Study 1's pretests. First, we used the four positive and four negative titles validated in the first pretest. Second, we retained the four sets of high-elaborate reviews constructed in the second pretest (see Table 2). For each high-elaborate review, we created a low-elaborate review that contained only a few words (with the substantial content between the positive and negative versions kept nearly identical and the number of words kept similar) (see Table 4). Moreover, like in Study 1, we conducted another separate pretest as the manipulation check of review elaborateness in Study 2. We recruited 67 subjects from a U.S. university. The procedure was similar to that of Study 1's manipulation check pretest, with the exception that each subject was asked to read four pairs of reviews. Paired-sample *t*-tests showed that the elaborateness of the low-elaborate review was significantly lower than that of the high-elaborate review in each pair with a difference of at least 4.182, a *t*-value of at least 11.475, and a *p*-value of less than 0.001. Hence, our manipulation of review elaborateness was successful.

Table 4. Four Sets of Low-Elaborate Reviews Used in Study 2

Set #	Positive version	Negative version
1	Great mouse. Works well.	Worthless mouse. Doesn't work well.
2	The mouse functions well.	The mouse functions poorly.
3	Good value for the price.	Poor value for the price.
4	Very good wireless mouse.	Very bad wireless mouse.

Procedure

We recruited 152 undergraduate students (68 male) from a U.S. university for this experiment. Among the participants, 88% were originally from the U.S., 66% were juniors or above, and the average age was 20. The cover story and procedure were similar to those of Study 1, with several exceptions. First, after participants reported their initial attitudes and purchase intentions, they were presented with two top reviews (termed “first-screen reviews” during the rest of the study). Then, they were asked to imagine that they chose to read all reviews to know more about the product. Seeking more reviews after reading the top reviews is very common among consumers (Yin et al., 2023). After clicking the “see all reviews” button, participants were directed to a new screen and presented with three reviews (termed “second-screen reviews”). Following the repeated exposure paradigm (e.g., Berger & Mitchell, 1989; Zajonc, 2001), we manipulated review exposure more subtly such that in the positive (negative) condition, the first-screen, positive (negative) review was exposed to participants on the second screen again together with two other second-screen reviews that appeared for the first time, leading the high-exposed reviews to be positive (negative) in valence. Thus, each participant read four different reviews in total, and one of these reviews was displayed twice (once on each screen).

Moreover, the titles and content of the first-screen reviews were selected based on several criteria. First, we randomly selected one positive title and one negative title from the eight titles developed in the pretest and counterbalanced the order of the two titles to mitigate order effects. Second, we randomly selected two text reviews (one positive and one negative) from two out of the four sets of text reviews (one version from each set) so that no participant would see multiple versions from the same set. The selected version of each review set followed the same criteria as in Study 1. Thus, in the first screen, participants in the positive condition saw one positive, low-elaborate review and one negative, high-elaborate review. Those in the negative condition saw one negative, low-elaborate review and one positive, high-elaborate review.

In addition, we selected the titles and content of the second-screen reviews based on the following criteria. First, we randomly selected one positive title and one negative title from the eight pretested titles that were different from the first-screen review titles. We also randomly selected two text reviews (one positive and one negative) from the other two sets of text reviews that were different from the first-screen review sets. The selected version of each review set followed the same criteria used to select first-screen reviews. Second, based on participants’ assignment to the positive or negative condition, one of the first-screen reviews was displayed again on the second screen. Specifically, in the positive (negative) condition, the first-screen, positive (negative), low-elaborate review was displayed again on the second screen (as the high-exposed review). Therefore, in the second screen, participants in the positive (negative) condition read one positive (negative) review from the first screen again, one new, positive (negative), low-elaborate review, and one new, negative (positive), high-elaborate review. The order of the three second-screen reviews was also randomized.

Finally, we used a recall question to check the exposure manipulation. After reading all the reviews and reporting new attitudes and purchase intentions, participants were asked to recall the positive and negative text content they had read in all the reviews, using two questions adapted from Herr et al. (1991). For example, the recall question for the positive valence was: “Recall the positive content of all the reviews you just read (write down everything you can remember).” To mitigate order effects, we counterbalanced the sequence of the recall questions for the positive and negative review content. At the end of the study, to quantify the exposure of reviews in each valence based on recall accuracy (Biehal & Chakravarti, 1983), we displayed the original content of the two positive (negative) reviews and participants’ recalled positive (negative) review content side-by-side and asked them to evaluate the accuracy of their recalled (compared with the original) content using a 9-point scale with four items adapted from Berger and Herringer (1991) (e.g., “I remembered everything of the two positive reviews above.”).

Results

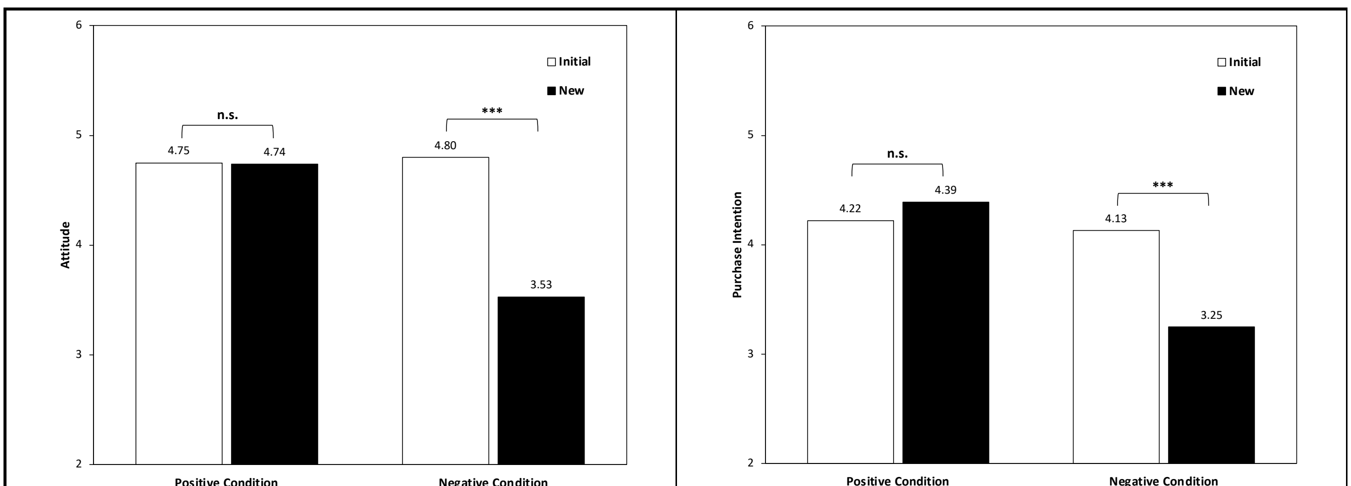
We first conducted a manipulation check for review exposure. To examine exposure based on consumers’ accuracy evaluation of their own recalled review content, we conducted an ANCOVA with their recall accuracy entered as the dependent variable, (low vs. high) exposure as a within-subjects factor, the (positive vs. negative) valence of high-exposed reviews as a between-subjects factor, and the sequence of recall questions as a covariate. Results showed that the self-perceived recall accuracy of the low-exposed reviews was significantly lower than that of the high-exposed reviews ($M = 4.64$ vs. 5.87, $F(1, 149) = 27.714$, $p < 0.001$). Because recall accuracy can also be captured by the similarity between the original and recalled content (Koriat et al., 2000), we created an alternative measure of review exposure based on an objective, text-mining method—cosine similarity, which has been widely used to compare the similarity of textual content (e.g., Huang et al., 2018). Specifically, the original review content and the recalled review content were treated as two documents, and the cosine similarity between the documents was calculated. In line with participants' subjective evaluations, a similar ANCOVA analysis based on the cosine similarity revealed that the exposure of the low-exposed reviews was significantly lower than that of the high-exposed reviews (M = 0.14 vs. 0.27, $F(1, 149) = 53.275$, $p < 0.001$). These results indicate that our manipulation of review exposure was successful. With regard to review elaborateness, its manipulation was also successful as verified by an additional pretest discussed earlier.

Next, we explored the relative impacts of review exposure and review elaborateness on consumers' attitudes and purchase intentions. In terms of attitudes, the ANOVA results revealed a significant interaction between the repeated measures and the valence of high-exposed reviews ($F(1, 150) = 21.578$, $p < 0.001$). Pairwise comparisons showed that participants' attitudes did not significantly change in the positive condition (M = 4.75 vs. 4.74, $F(1, 150) = 0.005$, $p = 0.945$), but the attitudes became significantly more negative in the negative condition (M = 4.80 vs. 3.53, $F(1, 150) = 44.065$, $p < 0.001$) (see Figure 3a). A similar ANVOA with purchase intentions as the dependent variable showed a significant interaction between the repeated measures and the valence of high-exposed reviews ($F(1, 150) = 13.862$, $p < 0.001$). Pairwise comparisons showed that the change in participants' purchase intentions was not significant in the positive condition (M = 4.22 vs. 4.39, $F(1, 150) = 0.770$, $p = 0.382$), but the purchase intentions significantly decreased in the negative condition (M = 4.13 vs. 3.25, $F(1, 150) = 19.252$, $p < 0.001$) (see Figure 3b). These results, taken together, provided additional evidence for H1a and H1b in the negative condition but not in the positive condition. The lack of evidence for the greater impact of review exposure (vs. elaborateness) in the positive condition was not unexpected. In line with H2, due to the negativity bias, the relative impact of review exposure (vs. elaborateness) should be weaker when the highly exposed reviews are positive; thus, it is possible that the relative impact was nonexistent in the positive condition.

To further examine whether the greater persuasive power of review exposure over review elaborateness depends on the valence of highly exposed reviews, we conducted several t-tests as in Study 1. The results of independent-sample t-tests revealed that participants' attitude change in the positive condition was significantly smaller than that in the negative condition (M = -0.01 vs. 1.27, $t(150) = 4.743$, $p < 0.001$), providing support for H2a. A similar pattern was observed for purchase intention change (M = 0.18 vs. 0.88, $t(150) = 2.482$, $p = 0.014$), supporting H2b.

Discussion

In this study, we disentangled the persuasive influences of review exposure and review elaborateness through a more conservative design. Consistent with H1a and H1b, our findings provide additional evidence for the greater impact of review exposure on attitudes and purchase intentions. Moreover, our results suggest that the valence of the highly exposed review is a boundary condition for the greater persuasive impact of exposure, not only on attitudes (H2a), as found in Study 1, but also on purchase intentions (H2b).



a. Attitude Change | b. Purchase Intention Change

Figure 3. Attitude Change and Purchase Intention Change in Study 2

Notes: n.s., not significant; *** $p < 0.001$

Table 5. Summary of Findings

Summary of design (Reviews of one valence that received more exposure were less elaborate, and vice versa.)		**Results**			
		H1a	**H1b**	**H2a**	**H2b**
Trade-off factors • Exposure: low vs. high (the frequency of exposure to different reviews of a certain valence in Study 1 and to the same review in Study 2) • Elaborateness: high vs. low Between-subjects factor • Valence of highly exposed reviews: positive vs. negative	Study 1	√	√	√	×
	Study 2	Supported in the negative condition only		√	√

General Discussion

It is widely assumed that the persuasive effect of online reviews is deliberative. Drawing on dual-process theories and the persuasion literature (e.g., Feldman & Lynch, 1988; Kahneman, 2011; Menon & Raghubir, 2003), we explore the validity of this assumption by disentangling the persuasive effect of review elaborateness (a deliberative Type 2 process) versus review exposure (an automatic Type 1 process). We propose that changes in consumers' attitudes and purchase intentions are driven more by exposure than by elaborateness and that the impact of review exposure (over review elaborateness) can be moderated by the valence of highly exposed reviews. We conducted two experiments and found converging evidence for the hypotheses. Our findings are summarized in Table 5.

Theoretical Implications

Our paper contributes to the online word-of-mouth literature in the following ways. First, although it is a common belief that deliberation drives the persuasive effect of online reviews, Yin et al. (2021) cast initial doubt on this assumption, demonstrating that the persuasive impact of reviews expressing anger could occur via an automatic and less deliberative process. Extending their demonstration of an emotion-focused exception, we explore the validity of this assumption in more general settings where consumers read a set of positive and negative reviews with varying levels of exposure (which activates an automatic Type 1 process) and elaborateness (which invokes a deliberative Type 2 process) to update their attitudes and purchase intentions. Our findings provide additional evidence countering this "deliberation drives persuasion" assumption.

Second, this paper represents an initial attempt to disentangle the persuasive impacts of the dual processes and uncover the primary driver of persuasion in online word-of-mouth. Although Lei et al. (2022) revealed that top text reviews could sway consumers' attitudes and purchase decisions, the effects of Type 2 and Type 1 processing were confounded in their studies. We uncovered the primary driver of persuasion by disentangling the relative impacts of the two types of processing via a focus on review elaborateness and exposure. Specifically, we used a trade-off design in which reviews of one valence (e.g., positive) that received more exposure were less elaborate, and reviews of the other valence (e.g., negative) that received less exposure were more elaborate, leading to persuasion in opposite directions. Our findings suggest that the persuasive impact of reviews can occur automatically and that Type 1 processing can overshadow Type 2 processing (Kahneman, 2011). Despite the critical role of Type 1 processing in consumer judgment and decision-making (Lei et al., 2022, 2023; Yin et al., 2021), it has been largely overlooked in the prior online word-of-mouth literature. Our paper opens up exciting opportunities for future research to examine the unique roles of Type 1 processing when people make use of information in diverse contexts (see also Lutz et al., 2023; Moravec et al., 2020; Turel & Kalhan, 2023).

In addition, the trade-off design represents a methodology contribution for testing competing theories or processes. Although most studies in IS and management tend to apply existing theories with no (or little) modification, there is a need and value in pursuing theory pruning (or failure) and pitting different theories or mechanisms against each other to better understand their boundaries (Gray & Cooper, 2010; Leavitt et al., 2010). A cleverly constructed trade-off design—a special case of conjoint analysis (Eggers et al., 2022)—is very effective for achieving this objective, and our research is among the first in information systems to deploy such a design and pit competing processes against each other (see also Lei et al., 2022). Future research in other contexts can leverage similar experiment designs to disentangle the relative impacts of distinct factors or test competing mechanisms.

Third, this work highlights a boundary condition of the persuasive effect of review exposure over elaborateness, suggesting that automatic Type 1 processing is also context dependent. Being a vital and probably the most critical aspect of online reviews, the valence of highly exposed reviews may moderate the impact of review exposure, and we found evidence supporting this prediction. These findings imply the greater persuasive power of negative (highly exposed) reviews compared to positive (highly exposed) reviews, extending our understanding of the negativity bias (e.g., Rozin & Royzman, 2001) to the automatic process of exposure in online word-of-mouth. Because consumers also seek out negative reviews more than positive reviews (Lei et al., 2023), these findings collectively point out the much greater power of negative reviews, which warrants future research attention.

Practical Implications

Our findings also offer practical implications for review platforms, product manufacturers, and retailers on how to better deal with online reviews. First, review platforms may need to reconsider the effectiveness of highlighting top and high-quality reviews. These platforms allow consumers to sort reviews based on metrics such as helpfulness, recency, etc. Moreover, they often highlight the most helpful reviews as top reviews in prominent places based on the intuitive belief that these top reviews are the most relevant for consumers and require their deliberative attention. Our findings suggest that the quality of reviews may not be the only factor that review platforms should incorporate to sort product reviews. Instead, reviews or certain content in reviews that receive more exposure can substantially and automatically shape consumers' purchase decisions. For example, review platforms such as Amazon display a few top reviews of a product on the first review page and then provide consumers an option to "see more reviews," supporting their desire to seek additional reviews (Yin et al., 2023). Amazon organizes additional reviews by first presenting the same set of top-ranked reviews again and then showing additional, less helpful reviews. These repeatedly exposed reviews can heighten the persuasive power of top-ranked reviews and unduly sway consumers' purchase decisions without their awareness. If the default criterion of ordering all the reviews is the same as that of top reviews, it may be more reasonable and defensible to show only *additional* reviews for consumers who click on "see more reviews" to reduce the unintended effects of repeatedly exposing the top reviews.

Review platforms should also put more thought into the ranking of reviews and how to display reviews based on consumers' preferences for reading reviews. In particular, Lei et al. (2023) revealed that consumers tend to search more for negative reviews than positive reviews, demonstrating a negativity bias in information seeking. Our findings further suggest that highly exposed negative reviews influence persuasion to a greater extent than highly exposed positive reviews. Integrating these insights, negative reviews can be extra powerful influencers because consumers actively seek them out, increasing the exposure of negative (relative to positive) reviews *across* consumers even if such reviews are not top-ranked or repeated. Review platforms could experiment with different ways of ordering reviews or deciding which kinds of reviews should be top-ranked to help consumers make better decisions with less undue influence (which may occur beyond their awareness).

Second, when product manufacturers and retailers establish their strategies for handling the tremendous number of online reviews (e.g., responding to reviewer comments), they should keep in mind that the influence of reviews often occurs automatically, such that the reviews receiving more exposure can sway consumers' purchase decisions. In practice, since high-quality reviews are often ranked as top reviews, a rational business may disregard other reviews and focus its attention and resources on the top ones. However, such a strategy may be misguided because reviews with greater exposure are more persuasive but are not necessarily top or high-quality reviews. Therefore, product manufacturers and retailers seeking to prioritize their efforts in dealing with a growing number of reviews should take a more balanced approach and consider the automatic influence of exposure and attention in addition to deliberation-related factors (Chen et al., 2024). For example, instead of focusing primarily on top reviews, a potentially more effective strategy might be to identify certain opinions that are repeatedly mentioned across many reviews, including short or low-quality reviews, and then come up with response strategies. This approach has become more feasible with the recent integration of AI-generated review summaries on some review platforms such as Amazon. By highlighting frequently mentioned opinions about certain product features from many consumers, these AI-generated summaries could allow product manufacturers and retailers to easily locate the opinions that receive more exposure *across* reviews and are thus likely to be more influential.

Limitations and Future Research

Our paper has a few limitations that are worthy of future exploration. First, although the results of two studies suggest that automatic Type 1 processing may be dominant in consumer decision-making, deliberative Type 2 processing can override the automatic process in certain situations (e.g., when reviews are deemed "fake" by consumers); future research should explore this possibility. Second, the lab experimental approach of our studies precluded us from examining more downstream outcomes, such as consumers' actual purchase behaviors, but they are worthy of future exploration using complementary methods (e.g., field experiments). Third, although our arguments are applicable to the general decision-making process of consumers involving other types of products, future work is needed to test the external validity of our findings in other contexts (e.g., when consumers differ in their goals or involvement). Finally, although the impact of AI-generated review summaries on consumer decision-making is outside the scope of the current paper, it is an emerging and critical topic for future research (e.g., how the availability and format of AI-generated review summaries may influence consumers' Type 2 and Type 1 processing of reviews).

Conclusion

In keeping with recent research challenging the common belief that the persuasive effect of online reviews is deliberative, we examine the validity of this conventional wisdom in a more general setting and further explore the primary driver of persuasion by disentangling the relative impacts of review elaborateness (a deliberative Type 2 process) and review exposure (an automatic Type 1 process) on persuasion. Drawing on dual-process theories and the persuasion literature, we propose that review exposure is more persuasive than review elaborateness and that the persuasive effect of review exposure (over elaborateness) depends on the valence of highly exposed reviews. Through two experimental studies, we found converging evidence for the hypotheses. These findings highlight the critical role of automatic Type 1 processing when consumers make decisions in the face of information overload and open up an exciting new area of inquiry for future research.

Acknowledgments

We sincerely appreciate the senior editor, Ron Cenfetelli, the associate editor, Bo Xiao, and the three anonymous reviewers for their insightful and constructive comments and suggestions throughout the review process. In addition, we are extremely grateful to Marius Florin Niculescu, Lizhen Xu, Michael Smith, Adrian Gardiner, and Katsiaryna Siamionava for their help in recruiting experiment participants.

References

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*(4), 323-370. https://doi.org/10.1037/1089-2680.5.4.323

Berger, I. E., & Mitchell, A. A. (1989). The effect of advertising on attitude accessibility, attitude confidence, and the attitude-behavior relationship. *Journal of Consumer Research*, *16*(3), 269-279. https://doi.org/10.1086/209213

Berger, J. D., & Herringer, L. G. (1991). Individual differences in eyewitness recall accuracy. *The Journal of Social Psychology*, *131*(6), 807-813. https://doi.org/10.1080/00224545.1991.9924667

Biehal, G., & Chakravarti, D. (1983). Information accessibility as a moderator of consumer choice. *Journal of Consumer Research*, *10*(1), 1-14. https://doi.org/10.1086/208941

Chen, G., Huang, L., Xiao, S., Zhang, C., & Zhao, H. (2024). Attending to customer attention: A novel deep learning method for leveraging multimodal online reviews to enhance sales prediction. *Information Systems Research*, *35*(2), 829-849. https://doi.org/10.1287/isre.2021.0292

Darke, P. R., & Ritchie, R. J. (2007). The defensive consumer: Advertising deception, defensive processing, and distrust. *Journal of Marketing Research*, *44*(1), 114-127. https://doi.org/10.1509/jmkr.44.1.114

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, *28*(3), 307-319. https://doi.org/10.2307/3172866

Eggers, F., Sattler, H., Teichert, T., & Völckner, F. (2022). Choice-based conjoint analysis. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 781-819). Springer. https://doi.org/10.1007/978-3-319-05542-8_23-1

Evans, J. S. B., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science*, *8*(3), 223-241. https://doi.org/10.1177/1745691612460685

Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology*, *73*(3), 421. https://doi.org/10.1037/0021-9010.73.3.421

Fiske, S. T., & Taylor, S. E. (1991). *Social cognition* (2nd ed.). Mcgraw-Hill.

Goldberg, M. E., & Gorn, G. J. (1987). Happy and sad TV programs: How they affect reactions to commercials. *Journal of Consumer Research*, *14*(3), 387-403. https://doi.org/10.1086/209122

Gray, P. H., & Cooper, W. H. (2010). Pursuing failure. *Organizational Research Methods*, *13*(4), 620-643. https://doi.org/10.1177/1094428109356114

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research*, *17*(4), 454-462. https://doi.org/10.1086/208570

Hong, H., Xu, D., Wang, G. A., & Fan, W. (2017). Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decision Support Systems*, *102*, 1-11. https://doi.org/10.1016/j.dss.2017.06.007

Huang, A. H., Lehavy, R., Zang, A. Y., & Zheng, R. (2018). Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science*, *64*(6), 2833-2855. https://doi.org/10.1287/mnsc.2017.2751

Jabr, W., & Rahman, M. S. (2022). Online reviews and information overload: The role of selective, parsimonious, and concordant top reviews. *MIS Quarterly*, *46*(3), 1517-1550. https://doi.org/10.25300/MISQ/2022/16169

Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus & Giroux.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of*

Economic Perspectives, *5*(1), 193-206. https://doi.org/10.1257/jep.5.1.193

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291. https://doi.org/10.2307/1914185

Koriat, A., Goldsmith, M., & Pansky, A. (2000). Toward a psychology of memory accuracy. *Annual Review of Psychology*, *51*(1), 481-537. https://doi.org/10.1146/annurev.psych.51.1.481

Leavitt, K., Mitchell, T. R., & Peterson, J. (2010). Theory pruning: Strategies to reduce our dense theoretical landscape. *Organizational Research Methods*, *13*(4), 644-667. https://doi.org/10.1177/1094428109345156

Lei, Z., Yin, D., Mitra, S., & Zhang, H. (2022). Swayed by the reviews: Disentangling the effects of average ratings and individual reviews in online word-of-mouth. *Production and Operations Management*, *31*(6), 2393-2411. https://doi.org/10.1111/poms.13695

Lei, Z., Yin, D., & Zhang, H. (2021). Focus within or on others: The impact of reviewers' attentional focus on review helpfulness. *Information Systems Research*, *32*(3), 801-819. https://doi.org/10.1287/isre.2021.1007

Lei, Z., Yin, D., & Zhang, H. (2023). Positive or negative reviews? Consumers' selective exposure in seeking and evaluating online reviews. *Journal of the Association for Information Systems*, *24*(4), 1162-1183. https://doi.org/10.17705/1jais.00823

Liu, X., Lee, D., & Srinivasan, K. (2019). Large-scale cross-category analysis of consumer review content on sales conversion leveraging deep learning. *Journal of Marketing Research*, *56*(6), 918-943. https://doi.org/10.1177/0022243719866690

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74-89. https://doi.org/10.1509/jmkg.70.3.074

Lutz, B., Adam, M. T., Feuerriegel, S., Pröllochs, N., & Neumann, D. (2023). Affective information processing of fake news: Evidence from NeuroIS. *European Journal of Information Systems*, 1-20. https://doi.org/10.1080/0960085X.2023.2224973

Lynch, J. G., Marmorstein, H., & Weigold, M. F. (1988). Choices from sets including remembered brands: Use of recalled attributes and prior overall evaluations. *Journal of Consumer Research*, *15*(2), 169-184. https://doi.org/10.1086/209155

MacKenzie, S. B. (1986). The role of attention in mediating the effect of advertising on attribute importance. *Journal of Consumer Research*, *13*(2), 174-195. https://doi.org/10.1086/209059

Menon, G., & Raghubir, P. (2003). Ease-of-retrieval as an automatic input in judgments: A mere-accessibility framework? *Journal of Consumer Research*, *30*(2), 230-243. https://doi.org/10.1086/376804

Montoya, R. M., Horton, R. S., Vevea, J. L., Citkowicz, M., & Lauber, E. A. (2017). A re-examination of the mere exposure effect: The influence of repeated exposure on recognition, familiarity, and liking. *Psychological Bulletin*, *143*(5), 459-498. https://doi.org/10.1037/bul0000085

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

Moravec, P. L., Kim, A., & Dennis, A. R. (2020). Appealing to sense and sensibility: System 1 and System 2 interventions for fake news on social media. *Information Systems Research*, *31*(3), 987-1006. https://doi.org/10.1287/isre.2020.0927

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, *34*(1), 185-200. https://doi.org/10.2307/20721420

Petty, R. E., & Cacioppo, J. T. (1981). *Attitudes and persuasion: Classic and contemporary approaches*. Wm. C. Brown.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1-24). Springer. https://doi.org/10.1007/978-1-4612-4964-1_1

Petty, R. E., & Wegener, D. T. (1998). Attitude change: Multiple roles for persuasion variables. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology* (pp. 323-390). Boston: McGraw-Hill.

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review*, *5*(4), 296-320. https://doi.org/10.1207/S15327957PSPR0504_2

Schumann, D. W., Petty, R. E., & Scott Clemons, D. (1990). Predicting the effectiveness of different strategies of advertising variation: A test of the repetition-variation hypotheses. *Journal of Consumer Research*, *17*(2), 192-202. https://doi.org/10.1086/208549

Turel, O., & Kalhan, S. (2023). Prejudiced against the machine? Implicit associations and the transience of algorithm aversion. *MIS Quarterly*, *47*(4). https://doi.org/10.25300/MISQ/2022/17961

Weisbuch, M., Mackie, D. M., & Garcia-Marques, T. (2003). Prior source exposure and persuasion: Further evidence for misattributional processes. *Personality and Social Psychology Bulletin*, *29*(6), 691-700. https://doi.org/10.1177/0146167203029006002

Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS Quarterly*, *38*(2), 539-560. https://doi.org/10.25300/MISQ/2014/38.2.10

Yin, D., Bond, S. D., & Zhang, H. (2017). Keep your cool or let it out: Nonlinear effects of expressed arousal on perceptions of consumer reviews. *Journal of Marketing Research*, *54*(3), 447-463. https://doi.org/10.1509/jmr.13.0379

Yin, D., Bond, S. D., & Zhang, H. (2021). Anger in consumer reviews: Unhelpful but persuasive? *MIS Quarterly*, *45*(3), 1059-1086. https://doi.org/10.25300/MISQ/2021/15363

Yin, D., de Vreede, T., Steele, L. M., & de Vreede, G.-J. (2023). Decide now or later: Making sense of incoherence across online reviews. *Information Systems Research*, *34*(3), 1211-1227. https://doi.org/10.1287/isre.2022.1150

Yin, D., Mitra, S., & Zhang, H. (2016). Research note—When do consumers value positive vs. negative reviews? An empirical investigation of confirmation bias in online word of mouth. *Information Systems Research*, *27*(1), 131-144. https://doi.org/10.1287/isre.2015.0617

Yu, Y., Yang, Y., Huang, J., & Tan, Y. (2023). Unifying algorithmic and theoretical perspectives: Emotions in online reviews and sales. *MIS Quarterly*, *47*(1), 127-160. https://doi.org/10.25300/MISQ/2022/16600

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, *9*(2), 1-27. https://doi.org/10.1037/h0025848

Zajonc, R. B. (2001). Mere exposure: A gateway to the subliminal. *Current Directions in Psychological Science*, *10*(6), 224-228. https://doi.org/10.1111/1467-8721.00154

About the Authors

Zhanfei Lei is an assistant professor of operations and information management at the Isenberg School of Management, University of Massachusetts Amherst. She received her Ph.D. in information technology management from the Georgia Institute of Technology in 2019. Her research interests focus on user-generated content, biases and heuristics, and human-AI interaction. She has published in *Information Systems Research*, *Production and Operations Management*, and *Journal of the Association for Information Systems*.

Dezhi Yin is an associate professor of information systems and Muma Fellow at the Muma College of Business, University of South Florida. He received his Ph.D. in information technology management from the Georgia Institute of Technology in 2012. His research interests include feelings in online environments, user-generated content (e.g., online word-of-mouth), and AI-generated content (e.g., chatbots). He has published in *MIS Quarterly, Information Systems Research*, *Journal of the Association for Information Systems, Journal of Marketing Research, Academy of Management Journal, Production and Operations Management*, and other academic journals. He is a recipient of the 2024 AIS Mid-Career Award and the 2021 INFORMS ISS Sandra A. Slaughter Early Career Award.

Han Zhang is a chair professor of information systems at the School of Business, Hong Kong Baptist University. He is also a full professor of information technology management and Steven A. Denning professor of technology & management at the Scheller College of Business, Georgia Institute of Technology (on leave). He holds a Ph.D. in information systems from the University of Texas at Austin. His research focuses on online trust, user-generated content, online healthcare, and human-AI interaction. He has published in prominent journals such as *MIS Quarterly*, *Information Systems Research*, *Journal of Marketing Research*, and *Production and Operations Management*, and his research has been featured in the *Wall Street Journal*. He is a recipient of the 2023 AIS Fellow Award. He serves as editor-in-chief for *Information & Management* and Senior Editor for *MIS Quarterly*.