ABSTRACT

Title of Dissertation:	ESSAYS ON THE IMPACT OF ELECTRONIC WORD-OF-MOUTH DYNAMICS ON CONSUMER BEHAVIOR
	Xindi Zhao
	Doctor of Philosophy Degree, 2022
Dissertation directed by:	Professor Michael Trusov Department of Marketing

Recognizing the importance of product reviews for product sales in online retail platforms, this dissertation studies the effect of electronic word-of-mouth (e-WOM) dynamics on consumer behavior, including information processing, review-reading behavior, product evaluation, purchase decision, and reviewing behavior. In the first essay, I focus on incentivized reviews, which are posted by reviewers who received economic incentives (e.g., free product) from the firm, and explore how their emergence in a reviewing system influences subsequent organic (i.e., nonincentivized) review contributions for the focal product. I find that the ratings of subsequent organic reviews decrease after the appearance of incentivized reviews and that the magnitude of this negative impact decreases over time and the ratings recover in the long run. This is because subsequent reviewers adjust their product evaluations downwards when faced with prior

incentivized reviews. In the second essay, I study the effect of a prevalence phenomenon—repetition in e-WOM—on consumer behavior. I demonstrate that high repetition in e-WOM could have a negative effect on persuasion and that this negative effect could be eliminated by modifying consumers' inferences about the cause of repetition. Furthermore, consumers' information-seeking behaviors are also affected by the share and type of repetition. Both essays provide an understanding of the impact of e-WOM on consumers' judgments and decisions and offer implications for firms and platforms on how to gather, manage, and display e-WOM effectively; they also provide interesting avenues for future research.

ESSAYS ON THE IMPACT OF ELECTRONIC WORD-OF-MOUTH DYNAMICS ON CONSUMER BEHAVIOR

by

Xindi Zhao

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2022

Advisory Committee:
Professor Michael Trusov, Chair
Professor Roland T. Rust
Professor David Godes
Professor Amna Kirmani
Associate Professor Nick Joyce, Dean's Representative

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1: Introduction

This dissertation studies the effect of electronic word-of-mouth (e-WOM) dynamics on consumer behavior, including information processing, review-reading behavior, product evaluation, purchase decision, and review-writing behavior. This is an important issue because consumers often utilize e-WOM to facilitate their decision-making on product choice, especially when they want to reduce cognitive effort and uncertainty, or they believe that the information provided by the firm is nondiagnostic or incomplete.

Recognizing the importance of product reviews for product sales in online retail platforms, practitioners employ various approaches to encourage consumers to leave product feedback. Focusing on one of these approaches—incentivized reviews—the first essay (Chapter 2) explores how their emergence in a reviewing system influences subsequent organic (i.e., nonincentivized) review contributions for the focal product. Analyzing a large set of product reviews from Amazon.com, I find that the ratings of subsequent organic reviews decrease after the appearance of incentivized reviews and that the magnitude of this negative impact decreases over time and so ratings recover in the long run. I explore underlying mechanisms of how incentivized reviews affect subsequent customers' reviewing behavior in terms of incidence (i.e., whether to post) and evaluation (i.e., what to post) decisions and test these mechanisms in lab experiments. I find that subsequent reviewers adjust their product evaluations downwards when faced with prior incentivized reviews; meanwhile, their motivations to post reviews are not affected by observing incentivized reviews. Moreover, the negative impact of incentivized reviews is consistently present when controlling for purchase decisions and manipulating the valence of customers' actual consumption experience. The results suggest that practitioners should be aware of the darkside of using incentives and exercise caution when engaging in these tactics.

Continuing with the investigation of the impact of e-WOM, in the second essay (Chapter 3), I study the effect of a prevalence phenomenon—repetition in e-WOM—on consumer behavior. The repetition effect has been investigated in many disciplines and domains, such as cognitive psychology, music appreciation, and advertisement. Surprisingly, there is no literature examining repetition in the e-WOM context, despite its prevalence in online product reviews, social media platforms, and other online forms of communication. I investigate the persuasiveness of repetition in review content. Prior literature typically focuses on the impact of features for a single review, such as source expertise. Here, I propose perceived repetitiveness as an integral feature of multiple reviews for the focal product and study how repeated reviews affect consumers' perceptions and purchase decisions. I also look at the impact of repetition on consumers' review-reading behaviors since consumers are self-determined and self-paced when they process online information from multiple sources. The repetition effect in e-WOM works through different mechanisms compared to the well-studied repetition effect of advertising. I argue that the level of repetition in e-WOM, as well as its type (verbatim vs. gist), could play a role in consumers' information processing and product judgment behaviors. The results revealed a negative effect of high repetition on persuasion through the lack of perceived information completeness and low perceived truthfulness of e-WOM. I also tested possible means to eliminate this negative impact, including endogenizing participants' information-seeking behavior and modifying their inferences about the cause of repetition. I provide managerial implications for marketing practitioners and platform designers regarding review management, platform design, and customer management strategies.

In both essays, I demonstrate the impact of e-WOM on consumers' judgments and decisions. The persuasiveness of e-WOM can be affected by both a firm's intervention and consumers' perceptions of multiple reviews regarding the focal product. I thus argue that firms, as well as platform designers, must carefully consider how to manage the performance of online reviews and how to display them appropriately in order to have optimal effectiveness on prospective consumers' decisions. In the next two chapters, I will describe my dissertation essays in detail. In each chapter, I will review relevant literature, construct the conceptual framework, provide empirical support, and discuss the implications for consumers and marketing practitioners.

Chapter 2: The Role of Incentivized Reviews: A Dynamic Perspective[1]

User-generated product reviews have become a vitally important factor contributing to firms' performance. User-generated content have been shown to attract greater consumer interest than firm-generated content (Bickart and Schindler 2001), influence consumers' attitudes toward the product (Hsu, Lin, and Chiang 2013), and affect purchase behaviors and sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). Appreciating the importance of user-generated reviews, firms from retailing, restaurant, hotel, and other industries employ various approaches to stimulate review contributions. One common approach practitioners use to stimulate consumer feedback is economic incentives, such as cash rewards, free products, and product discounts. Extant academic research has shown that economic incentives can effectively stimulate review contributions (Godes and Mayzlin 2009; Petrescu et al. 2018). However, little is known about how a reference to incentives, as disclosed by review contributors, affects subsequent consumers who do not receive incentives, including their postpurchase product evaluations and reviewing behavior. Specifically, we argue that the practice may carry some downsides to the business, such as an increase in lower product evaluations from nonincentivized buyers.

In this paper, we shed light on this phenomenon by investigating the effects of incentivized reviews on subsequent reviews in both the short and the long run and exploring potential underlying mechanisms that could explain the effect observed in our empirical data. We focus our study on reviews that follow Federal Trade Commission (FTC) guidelines and explicitly disclose any incentives received by the reviewer. Incentivized reviews without disclosure (which are noncompliant with FTC guidelines) are outside the scope of this study.

[1] This research is conducted with Michael Trusov.

Our intended contribution is twofold. Substantively, this research provides empirical evidence of the impact of incentivized reviews on product ratings. We show a temporary improvement in online product evaluations (i.e., an increase in average product ratings) coming mainly from more positively skewed incentivized reviews. Further analysis demonstrates that the effect is not persistent and vanishes shortly after the incentives end. Perhaps more surprisingly, we find that for several weeks following the incentive campaign, the valence of organic reviews goes down. This result is robust and holds across different empirical conditions and lab experiments that control for related factors, including purchase decision, actual consumption experience, and the valence of incentivized reviews. This finding also highlights an important tradeoff for managers who are considering adopting incentives to stimulate reviews—namely, the improvement in online evaluations during the incentive campaign comes at the cost of a decline in ratings in organic reviews after the campaign.

From a theoretical standpoint, the paper adds to our understanding of the mechanisms of incentive disclosures' impact on organic product evaluation and reviewing behavior. We propose a conceptual framework describing several consumer decisions that are potentially affected by incentive disclosures, including purchase decision, review contribution, and product evaluation. Using a mixed-method approach, we establish the most likely path of incentives' influence on evaluations through consumers' use of persuasion knowledge (Boerma, Van Reijmersdal, and Neijens 2012; Friestad and Wright 1994). Prior literature has demonstrated that sponsored disclosures influence the effectiveness of television ads, online advertisements (Wojdynski and Evans 2016), sponsored posts on social media (Boerman, Willemsen, and Van Der Aa 2017), and product recommendations (Carl 2008; Tuk et al. 2009) by activating consumers' persuasion knowledge (Campbell and Kirmani 2000; Friestad and Wright 1994). We contribute to this stream of literature by investigating the effects of incentive disclosures in an online context and by studying the persuasive outcomes, including consumer response and the impact on product review performance. We find that the effect of incentive disclosure holds when we manipulate the actual consumption experience and the valence of incentivized reviews.

The paper proceeds as follows: We begin with a review of the literature related to incentivized reviews and review dynamics. Then, we develop a conceptual framework of the consumer reviewing process in the presence of incentivized reviews. Next, we outline our model and describe the dataset we use. We present empirical results using various model specifications and estimate the average treatment effect (ATE) of incentivized reviews using the difference-in-difference model with propensity score matching. We then propose an underlying mechanism to explain the effects of incentivized reviews and present lab experiments that examine alternative theories. We conclude with managerial implications and directions for further research.

LITERATURE REVIEW

User-generated content is a prominent area in the digital marketing research domain commonly studied in the context of social influence, peer-to-peer communications, virality, consumer networks, and social media, among other related topics of academic inquiry. This paper focuses on one such topic: the impact of incentives on the rating environment. As such, we arrange our literature review into two related subareas: incentivized reviews and review dynamics.

Incentivized Reviews

Researchers from both marketing and information systems fields have examined various approaches to encouraging online word of mouth (WOM), such as employing reputational mechanisms (e.g., points, bandages, reviewer levels, status), stimulating altruistic motivations, or providing economic incentives (Carl 2008; Fradkin and Holtz 2022; Reimer and Benkenstein 2016; Ryu and Feick 2007; Zhang, Wei, and Zeng 2020). Among these approaches, economic incentives have been shown to effectively increase WOM transmission and contribution (Marinescu et al. 2021; Petrescu et al. 2018; Stephen et al. 2012). In this paper, we focus on a particular type of economic stimulation, in which a consumer is offered a free product in exchange for feedback on a public product review platform with the full disclosure of incentives (Figure 1).

Insert Figure 1 about here

While other forms of economic incentives (e.g., coupons, discounts, “buy-one-get-one” [BOGO] offers, cash rewards) are also common among marketing practitioners, we focus on a free product incentive for the following reasons. First, this form of incentive has been used by Amazon.com, the largest e-commerce platform, making the task of data collection and identification of incentivized reviews among organic reviews feasible. For example, our identification strategy for categorizing organic and incentivized reviews is based on disclosure, which usually contains keywords such as “for free” or “free product” within the review content. Second, offering a free product is one of the most commonly used economic rewards and is a strong motivator for a review contribution. For example, Amazon.com launched its Vine program in 2007, which aimed to invite “the most trusted reviewers on Amazon.com to post opinions[2]" for new products. Invited reviewers received free products and then posted reviews labeled as "Vine Voice" on Amazon.com. The same strategy was also adopted by sellers and third-party companies, such as Anker's "Power Users" program and BzzAgent. Finally, prior research shows that the level of payment does not influence how consumers perceive incentivized reviews as long as incentivized reviewers receive payment from the firm (Steward et al. 2020). Therefore, we believe that our findings may also prove relevant to other types of economic incentives.

Prior research has also investigated immediate effect from reviewer incentive campaigns and found mixed results. For example, Park, Shin, and Xie (2021) compare different incentivized review mechanisms—namely, seller-initiated versus platform-initiated (e.g., Amazon Vine)—and find that reviewers contribute more positive reviews when they receive incentives from the seller compared with the incentives from the platform. Stephen et al. (2012) study the interaction between sellers and incentivized reviewers under the exchange theory framework: reviewers receive larger benefits in exchange for posting incentivized reviews, they feel obligated because they are getting "paid" by the seller, and therefore they are more likely to post incentivized reviews reflecting more positive opinions. On the other hand, Fradkin and Holtz (2022) conduct a field experiment on Airbnb and find negative impacts on the valence of incentivized reviews. They argue that providing incentives could encourage review contributions with low value or mediocre experience (vs. extreme experiences). We add to this stream of research by first, providing consistent results for the immediate gains from incentive campaigns and second, focusing on the consequences of incentivized reviews' emergence in the review environment for subsequent organic reviews.

[2] https://sellercentral.amazon.com/help/hub/reference/external/92T8UV339NZ98TN?amp%3Bld=SDUSSOADirect

The perceived credibility of incentivized reviews is potentially harmed by material connections with the seller, as shown in studies by Martin (2014), Reimer and Benkenstein (2016), and Steward et al. (2020). Consumers on the receiving end of incentivized WOM may doubt the authenticity of the information provided if they are aware of the incentives and thus may develop a less favorable attitude toward the company. Conversely, Abendroth and Heyman (2013) suggest that disclosing a material connection with the firm may carry less harm than in if consumers find out by themselves. This stream of research focuses on product/brand evaluation as the key dependent variable and does not differentiate the impact of incentives on consumers' decisions throughout the purchase journey. We go a step further to explore the effect on prospective consumers' purchase, incidence (i.e., whether to post), and evaluation (i.e., what to post) decisions. We also demonstrate consistency in the results by manipulating the consumption experience and review valence.

To date, most studies related to incentivized reviews have focused on exploring consumer attitudes in the lab context. One exception is Petrescu et al. (2018), who analyze incentivized reviews in qualitative and quantitative studies. They show that firms can increase review volume and valence by providing consumers with economic incentives. Our paper differs from theirs in several ways. First, while we also observe positive skewness in incentivized reviews, our main research objective is different, as we investigate the impact of incentivized reviews on subsequent organic reviews. Second, Petrescu et al. (2018) study one product and one incentivized campaign; we enlarge our dataset to the product category level and analyze multiple product categories for a robustness check. Finally, we explore the temporal dimension of changes in the review environment, which is not studied in Petrescu et al. (2018).

Dynamics in Product Reviews

Two customary components of a user-generated product reviews are textual content and star ratings representing the numerical measurement of product evaluation reflective of a customer's consumption experience with the product). Prior research has shown that online product reviews not only mirror customers' independent and unbiased evaluations but are also affected by previous reviews, product review performance, and other social influences (Ma et al. 2013; Moe and Schweidel 2012; Park, Shin, and Xie 2021; Srihar and Srinivasan 2012).

From a quantitative perspective, several researchers have identified a decreasing trend in product ratings using different model specifications, such as the hazard model (Moe and Trusov 2011) and the ordered logit model (Godes and Silva 2012). While several behavioral theories have been proposed to explain this pattern (Li and Hitt 2008; Wu and Huberman 2008), motivation theory has been identified as a likely underlying mechanism for the sequential process, as well as a macro-level negative trend in the review environment (Godes and Silva 2012). A customer's motivation to post a review is lower if the evaluation is positive (vs. negative) because the potential impact on the changes in average product rating is smaller when posting a positive review. As a result, more negative reviews are posted over time, leading to a declining trend commonly observed in product review environments. Godes and Silva (2012) specify two dynamic components that account for this decreasing trend: an increasing trend over time and a decreasing trend over order. They argue that both trends exist, but the sequential trend dominates, resulting in an overall decline of average ratings. Our paper follows Godes and Silva's (2012) empirical approach to capture both trends, and we expand on their model by introducing additional effects related to having incentivized reviews in the review system.

The literature that investigates the dynamic effects of electronic WOM (e-WOM) shows that customers do not post their opinion independently. Instead, they are influenced by prior reviews. For example, drawing on social influence theory (Fromkin 1970), Sridhar and Srinivasan (2012) test the moderating effect of prior ratings, as a form of group consensus, on reviewers' online product ratings. Ma et al. (2013) study how reviewer characteristics and review characteristics can moderate the impact of prior reviews on subsequent reviews and find that expert (vs. nonexpert) reviewers are less likely to be affected by prior reviews as they tend to form their own ratings. Similar results have been reported for prior negative ratings. Schlosser (2005) finds that reviewers tend to rate products less favorably when they receive a negative (vs. positive) prior review. However, these studies do not account for the presence of incentives in the review environment. We argue that the effect of prior reviews can differ depending on the review type, and we propose that the type of prior review (incentivized vs. organic) is a potential factor that moderates the effect of product experience on reviewers' product evaluations.

CONCEPTUAL FRAMEWORK

Extant research defines several stages in the product review–generating process, each potentially affected by the state of the review environment: prepurchase product evaluation, purchase, postpurchase experience, the decision to contribute a review, and review creation (Moe and Schweidel 2012). Our work introduces yet another factor stemming from the review environment that may further shape this process: consumers' exposure to incentivized reviews. We depict our theorized effects in Figure 2.

Insert Figure 2 about here

When there are no incentivized reviews, shoppers make purchase decisions on the basis of their expectations about the product, which, in part, are formed by (organic) product reviews they have observed. If consumers purchase the product, they will form a private product evaluation that is based on their consumption experience. Subsequently, they will decide whether to post a review (incidence decision) and how to rate the product (evaluation decision), considering both their postpurchase evaluations and the prior reviews contributed by other consumers. However, when the review environment features some reviews that are identifiable by consumers as incentivized, an additional piece of information enters the decision-making process. First, the incentive disclosure suggests a material connection between the seller and the reviewer that could make the prospective buyer skeptical about the truthfulness of the review content and lower expectations about the product, which in turn may affect the consumer's purchase decision. Second, assuming the purchase is made, the review contribution decision could be negatively affected by a fairness perception, as the nonincentivized buyer would be extending the effort to write a review without having received any direct economic benefits, which stands in contrast to the observed incentivized reviewer. Finally, assuming the buyer chooses to contribute a review, that person's product evaluation may be affected. The direction of the effect could be either positive (if the actual product experience exceeds prior expectations, which were lowered by the incentive disclosure) or negative (if the incentivized reviews are perceived as the seller's persuasive attempt to attract buyers by inflating product ratings). In the latter case, even satisfied consumers may adjust their evaluation downward to correct for perceived bias in observed evaluations.

In the following sections, we explore the proposed effects using a combination of empirical analysis and lab experiments.

EMPIRICAL ANALYSIS

To study the effects of incentivized reviews on subsequent reviewing behavior (Figure 2), we start with the empirical exploration of a large set of product reviews collected on Amazon.com. Being the largest online retailer in the United States with millions of active users, the site is well-suited for the purposes of our research, and consumers are familiar with the site and accustomed to checking product reviews before making a purchase. Moreover, during our observation period, the practice of offering a free product in exchange for a review contribution on Amazon.com was used extensively by both independent sellers and the platform itself.[3]

We obtained the dataset from He and McAuley (2016),[4] and it contains approximately 142.8 million reviews from 24 product categories spanning May 1996 to July 2014. The data include both product (e.g., price, category, subcategory, brand name, sales rank) and review (e.g., ratings, review text, posting time, product, reviewer ID) information.

Identifying Incentivized Reviews

We identified incentivized reviews using the incentive disclosure statement within the review text. According to Amazon.com's then-current policy, full disclosure was required if

[3] In 2016, Amazon.com changed its policy and banned seller-initiated incentivized reviews. Currently, the only type of incentivized reviews officially supported by the platform are through the Amazon Vine program (https://www.amazon.com/vine/about).
[4] The dataset is available here: https://jmcauley.ucsd.edu/data/amazon/.

sellers had provided economic incentives (e.g., free products, discounts) in exchange for a review contribution. In line with this policy, incentivized reviews in our dataset contained a specific phrase such as "Disclosure: I received the product for free" or "Disclosure: I received the item at no cost from the manufacturer for purposes of a review" (see Figure 1). Thus, we identify incentivized reviews using key terms such as "disclosure" or "unbiased review."[5] The identification rule was designed and applied to each review to determine if it was incentivized. We also performed manual checking on a randomly selected sample to ensure accuracy of the identification rule. After that, we excluded all products that had no incentivized reviews and kept those with at least one incentivized review in the observation period as our focal dataset.

We identified incentivized reviews across product categories and found that categories receiving more than 600 incentivized reviews included beauty products, grocery and gourmet foods, health and personal care products, and toy and game products. Further, we focused on tangible products and did not consider digital ones, such as Kindle books or apps. Because we limit our scope to free product–incentivized reviews, we wanted to control for seller-incurred costs when conducting an incentivized campaign. There might be systematic differences for sellers that sell digital products and provide incentives to customers with no production cost, as well as potential differences in customers' responses to sellers' tactics. From the remaining product categories, we selected beauty products, as it has the largest number of products associated with incentivized reviews.

Incentivized Reviews Versus Organic Reviews

[5] The full list of match phrases used is available upon request.

Products with at least one incentivized review have higher average ratings than products without incentivized reviews (Ms = 4.26 vs. 4.15, $p < .000$). Moreover, incentivized reviews are generally more positive than organic reviews (Ms = 4.30 vs. 4.15, $p < .000$). In terms of the distribution of star ratings (see Figure 3), the distribution of organic reviews in our dataset is consistent with prior research reporting a J-shaped rating distribution, where 5-star and 1-star reviews were more popular than reviews with less extreme opinions (e.g., Hu, Pavlou, and Zhang 2006). Interestingly, for incentivized reviews, the ratings distribution does not follow a J shape. On the contrary, more than half of the incentivized reviews have five stars, and 86.17% of incentivized reviews show positive valence (5 or 4 stars) without a pronounced spike in 1-star reviews. In terms of review content, incentivized reviews, on average, are longer than organic ones, with more words and more sentences (see Table 1). Table 2 shows summary statistics for incentivized products only. Most of the products have very few incentivized reviews, and only a small fraction of products contain more than 20 incentivized reviews.[6]

Insert Table 1, Table 2, and Figure 3 about here

MODEL

In this section, we discuss the main inputs in our empirical analysis (Table 3), followed by the model formulation. As we noted in our discussion of the conceptual framework (see Figure 2), not all the stages of the consumer decision-making process are observable in the

[6] We also analyzed review content, comparing incentivized and organic reviews. The results appear in Appendix A.

secondary data. Thus, it is important to recognize that the outcome of interest that we explore empirically (i.e., pre- and postincentive product star ratings, labeled as “STARS”) is conditional on the individual’s purchase and incidence decisions. In subsequent sections, we address this limitation by adopting the experimental approach to shed light on these factors.

Insert Table 3 about here

With the incentivized reviews identified, we treat all the organic reviews posted *after* the first occurrence of an incentivized review for the respective product as potentially affected by incentive disclosure (in the subsequent analysis, we label these reviews with the dummy variable INC). Godes and Silva (2012) show that online reviews display dynamics evolution, which they further separate into two distinct trends: sequential and temporal processes. Following their work, we introduce two variables, ORDER and TIME, to account for effects related to review order and time since the first review appearance, respectively. For ORDER, we handle “ties” (i.e., same-day contributions) by allowing for the same ordinal value of this variable. To control for reviewer-level heterogeneity, we create a variable REVAVG, the average star rating of all reviews posted by the same reviewer except for the focal review. Following Godes and Silva’s (2012) approach, we treat REVAVG as a missing variable if the reviewer had posted only once in our dataset.

We also introduce the variable DIFFTIME, which measures the time difference between the focal review and the first incentivized review for the respective product. This variable helps account for the recency effect. We hypothesize that the more time that has passed since incentives were offered by the seller, the less relevant these may appear to the current decision maker i (i.e., potential buyer or review contributor). Thus, the incentive effect will diminish with increasing DIFFTIME. We also employ two control variables, CUMULMEAN and CUMULVAR, which represent cumulative average rating and cumulative variance, respectively, for all the reviews posted before the focal review. These variables allow us to account for product-specific rating environment effects on subsequent reviewers. Table 4 provides summary statistics for all variables discussed.

Insert Table 4 about here

To set up our model, we adopt Godes and Silva's (2012) approach, where $review_{ib}$ is the evaluation for product b written by consumer i and associated with a latent evaluation U_{ib}, which is a linear function of explanatory variables (Equation 1). We then use ordered logit formulation to map the latent utility to the observed star ratings (Equation 2). The model also includes product fixed effect (δ_b) and year fixed effects to capture product-level heterogeneity and macro time trend[7]:

$$U_{ib} = \beta_1 \cdot TIME_{ib} + \beta_2 \cdot ORDER_{ib} + \beta_3 \cdot REVAVG_{ib} + \delta_b + year_{ib} + \varepsilon_{ib} \quad (1)$$

$$STARS_{ib} = 1 \Leftrightarrow U_{ib} < \mu_1,$$

$$STARS_{ib} = k \in \{2,3,4\} \Leftrightarrow U_{ib} \in [\mu_{k-1}, \mu_k) \quad (2)$$

$$STARS_{ib} = 5 \Leftrightarrow U_{ib} \geq \mu_4.$$

Next, we expand the model by adding the indicator variable INC to account for the effect of incentivized reviews on subsequent reviews, as shown in Equation 3. INC takes the value of 1 if reviewer i posted after the first incentivized review for product b.

$$U_{ib} = \beta_1 \cdot TIME_{ib} + \beta_2 \cdot ORDER_{ib} + \beta_3 \cdot REVAVG_{ib} + \beta_4 \cdot INC_{ib} + \delta_b + year_{ib} + \varepsilon_{ib}. \quad (3)$$

[7] We included year fixed effects to capture the calendar year in which the review i, b, was written. Note that the year fixed effects are relative to 2009, which we chose because it was the first year in our main data set.

Finally, we want to explore if the effect of incentivized reviews changes over time. To do so, we include the variable DIFFTIME, which measures the time difference between reviewer i's post for product b and the first incentivized reviews for the product. We also include cumulative mean and variance of reviews in the model. Equation 4 is our final model:

$$U_{ib} = \beta_1 \cdot TIME_{ib} + \beta_2 \cdot ORDER_{ib} + \beta_3 \cdot REVAVG_{ib} + \beta_4 \cdot INC_{ib} + \beta_5 \cdot DIFFTIME_{ib} + CUMULMEAN_{ib} + CUMULVAR_{ib} + \delta_b + year_{ib} + \varepsilon_{ib}. \quad (4)$$

EMPIRICAL RESULTS

The appearance of incentivized reviews could affect subsequent reviewers' behavior in terms of both review ratings and review content. In this section, we focus on star ratings and identify whether incentivized reviews have a significant impact on ratings in subsequent organic reviews.

Effect on Star Ratings

We present the model estimation results in Table 5. Consistent with the findings of Godes and Silva (2012), the coefficient for TIME is positive, and the coefficient for ORDER is negative. Reviewer characteristics are also significant in our model, meaning that customers have their own reviewing habits and keep a similar evaluation approach for different products under the same product category. The negative coefficient for INC suggests that, after the appearance of an incentivized review, ratings for organic reviews significantly decrease.

Insert Table 5 about here

It is important to note that while the cumulative average star rating is predictive of subsequent evaluations being more positive (as captured by CUMULMEAN), the effect of incentives (INC) is negative. This result should be alerting to managers, as incentivized reviews can increase a running average product evaluation during the campaign, they can potentially erode the valence by inducing more subsequent negative organic ratings.

Next, we turn to variable DIFFTIME, which is significant and positive ($p < .0001$), suggesting that the negative impact of incentivized reviews may vanish over time. To investigate this temporal effect, we rerun our model using two dummy variables, BEFORE and AFTER, which denote whether the rating $STARS_{ib}$ is posted within or beyond a certain number of days (lag) after the incentivize campaign. We repeat this process to explore different lag values from 25 up to 70 days and report the results in Figure 4. We find that for all lags explored, our focal variable BEFORE remains significant and negative. However, the variable AFTER is positive and significant only before 50 days. The negative impact of incentivized reviews is persistent for up to 50 days and then starts to diminish after about two months.

Insert Figure 4 about here

We offer two potential explanations for why the negative impact of incentivized reviews vanishes over time. First, it is possible that incentivized reviews are being pushed out of view as new reviews are posted, so subsequent customers are less likely to notice these earlier ones and become aware of the past incentives. Depending on the sort order in use (e.g., “top reviews” vs. “most recent”), this may explain the observed pattern. Another explanation is rooted in consumer psychology and is related to the perception of time as an analogy of physical closeness: more recent reviews lead to higher customer involvement and, accordingly, a stronger effect.

Incentivized reviews posted a long time ago are perceived as less relevant and are discounted in decision making. Given the nature of the secondary data analysis, it is difficult to single out the exact underlying mechanism that leads to the diminishing effect of incentivized reviews.

Addressing Endogeneity

In the previous section, we analyzed products that received at least one incentivized review. One could argue that the decrease in star ratings following the incentivized review is the treatment effect on the treated (TOT), and the products with incentivized reviews are In the previous section, we analyzed products that received at least one incentivized review. One could argue that the decrease in star ratings following the incentivized review is the treatment effect on the treated, and the products with incentivized reviews are fundamentally different from the products not associated with incentives. Therefore, the observed decrease in star ratings may stem from product characteristics or related market conditions, which leads to the company's decision to offer incentives in the first place. For example, if the product's market performance is weak due to some inherent quality issues, the seller may be inclined to boost product ratings with incentives. In other words, we cannot conclude that the incentivized reviews affect the subsequent reviews negatively without considering that the decision to launch the incentive campaign could be related to some ongoing or expected dynamics in organic reviews (i.e., subject to endogeneity).

We address this potential issue using propensity score matching, which allows us to match treatment products with control products according to pretreatment characteristics. Controlling for propensity scores, we can estimate the average treatment effect using a difference-in-difference model.

Propensity Score Matching

Following the procedure outlined by Caliendo and Kopeinig (2008), we regard the incentive campaign as the *treatment*, which is not randomly assigned to every product. We consider all the products that received at least one incentivized review as the group (denoted by D = 1) and the rest as the control group (D = 0). We want to measure the average treatment effect τ_{ATT}, which is captured as the differences in product star ratings before and after an incentivized review has been posted:

$$\tau_{ATT} = E[Y(1)|D = 1] - E[Y(0)|D = 1], (5)$$

where Y(1) and Y(0) are potential outcomes for the treated and untreated products.

Because it is not possible to observe two potential outcomes for the same product at the same time, the unobserved potential outcome $[Y(0)|D = 1]$ (i.e., counterfactual) is replaced by the outcome of a matching product from a control group. The idea behind matching is to find products in the control group that are similar to the treatment group in terms of all relevant pretreatment characteristics X. Conditional on X, the treatment is considered randomly assigned, and a comparison of the difference in ratings yields the estimated treatment effect. To address the potential challenge of matching multidimensional data X, we follow Rosenbaum and Rubin's (1983) procedure and use a propensity score P(X), which is defined as the probability of a product receiving treatment given observed characteristics X.

Before calculating propensity scores as the matching criteria, we implemented preliminary filtering mechanisms to exclude the products with no incentivized reviews, which are strongly dissimilar from the incentivized products. First, to match the incentivized products group, we retained products with more than 20 reviews but less than 981 reviews (the maximum number of reviews for incentivized products). Second, because the first incentivized reviews did not occur until 2004, we dropped products that entered the market before this (proxied by the time stamp of the first review for the product posted on Amazon.com). Finally, we retained products with Amazon.com's sales rank that fell within the range observed in the treated group. After prescreening, we obtained a healthy sample of 16,142 control products.

Next, we derive pretreatment characteristics X (Table 6). We first divided all the products into subgroups based on the calendar month of entry time and calculated review system characteristics within each subgroup. The reason we do this is as follows: First, by controlling for the calendar month, we can rule out macro time changes in the review system and on the Amazon.com website. Second, subgroups reduce the computational strength required. Because organic products do not have real treatment time, we use the treatment time of the treated, which is the time stamp of the last organic review posted before the first incentivized review for incentivized products in the same subgroup, as the pseudo treatment time for organic products. To assign the treatment time to each control product, we reproduce the control pool by assigning each control product with all treatment dates within the subgroup and calculate the pretreatment characteristics using pretreatment variables. Note that we treat each control product–treatment time pair as separate observations and rule out pairs for which the control product received no reviews before the assigned treatment time. We ended up with 10,092 unique control products in our dataset and 36,623 control–treatment time pairs.

Insert Table 6 about here

We calculate propensity scores using a binary logit regression. We choose the nearest matching approach without replacement because the number of products in the control group is far more than the number of products in the treatment group. We performed the matching process in R using the MatchIt package, which resulted in 532 matched products. The treatment group and matched control groups are similar insofar as there is no significant difference between the pretreatment variables in the two groups. Table 7 provides summary statistics for pretreatment variables before preliminary filtering and matching, as well as the corresponding summary statistics for pretreatment variables after matching. Figure 5 shows the distributions of estimated propensity scores before and after matching.

Insert Table 7 and Figure 5 about here

Controlling for propensity scores, we use outcomes for the matched control group as the counterfactual outcomes for the treated group. We use a linear model in a panel setting to estimate the conditional average treatment effect of incentivized reviews (Equation 6), which follows the common modeling choice in the marketing literature (Proserpio and Zervas 2017). The additional benefit of using a linear difference-in-difference (DD) model is that the interaction term in the linear DD model can be easily interpreted as the ATE. In a nonlinear DD model, the treatment effect does not equal the estimation of the interaction term (Puhani 2012), and the interpretation of the interaction is not trivial (Ai and Norton 2003; Karaca-Mandic, Norton, and Dowd 2012): the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term, and more importantly, it can be of the opposite sign.

$$\mathrm{RATING}_{\mathrm{ib}} = \alpha_{\mathrm{b}} + \beta_1 \cdot \mathrm{TREAT}_{\mathrm{b}} + \beta_2 \cdot \mathrm{INC}_{\mathrm{ib}} + \gamma \cdot \mathrm{TREAT}_{\mathrm{b}} \cdot \mathrm{INC}_{\mathrm{ib}} + \beta_3 \cdot \mathrm{Z}_{\mathrm{ib}} + \varepsilon_{\mathrm{ib}}. \quad (6)$$

In Equation 6, the variable $\mathrm{RATING}_{\mathrm{ib}}$ is the rating posted by reviewer i for product b. The term α_{b} is a fixed effect for product b. $\mathrm{TREAT}_{\mathrm{b}}$ is a dummy variable indicating whether product b belongs to the treatment group or the control group. The variable INC equals 1 when reviewer i posts after the time of the first incentivized review (when receiving treatment). Z_{ib} is a set of control variables, including dummies for the calendar year and month, the aggregate level of order and time, and the average star rating of all reviews posted by the same reviewer. Finally, ε_{ib} captures the idiosyncratic random noise for each observation. Our focus is on γ, which captures the interaction effect between the treatment and treatment time dummies.

The estimation results reported in Table 8 show the interaction γ effect being significant and negative, suggesting that after matching the treatment products with similar control products, the negative effect of incentivized reviews on subsequent organic reviews still holds.[8]

Insert Table 8 about here

EXPLORING UNDERLYING MECHANISMS

A product review is an outcome of the customer's purchase journey. It can be affected by internal factors, such as product category and consumption experience, as well as external factors of the shopping environment, such as prior reviews. As Figure 2 suggests, incentivized reviews can affect different consumer decisions, including product purchase and review contributions, some of which are not directly observable in the secondary data. Therefore, to get further insights into what might underly the behavioral patterns in our data, in this section, we conduct a combination of additional empirical analyses and lab experiments.

[8] As an additional robustness check, we model the firm's decision to offer review incentives using a probit model and use the residuals as controls in the ratings model. The details of this analysis appear in Appendix B.

Impact of Review Characteristics on Subsequent Reviews

We start with a proposition that the negative impact of incentivized reviews on subsequent organic reviews may come from review characteristics other than incentive disclosure (e.g., star rating, review length, textual content). Because incentivized reviews tend to be more positive and contain more words than organic reviews, our proposition may have grounds. Accordingly, we should observe a similar decrease in ratings following the reviews that are structurally similar to the incentivized review but do not carry a disclosure statement.

To explore this possibility, we employ a placebo approach. For each incentivized product, we randomly choose one organic review with similar review characteristics (we call it a *pseudo*-incentivized review) and investigate its impact on subsequent organic reviews (for details, see Appendix C). We label the selected placebo reviews with an INC_placebo dummy variable and incorporate it in Equation 4 in the same way we used INC. For each review, INC_placebo takes a value of 1 if it is posted after the placebo-incentivized review and a value of 0 if it is posted before that. If the negative effect on subsequent organic reviews is due to review characteristics of incentivized reviews other than incentive disclosures, we should observe a significant and negative coefficient for INC_placebo.

To avoid a potential confounding effect of actual incentivized reviews, we removed actual incentivized reviews for each product. Moreover, the placebo reviews selected occur before the actual incentivized reviews. The results of the ordered logistic model estimation appear in Table 9. While the estimations of the sequential and temporal dynamics are consistent with our previous analysis, the estimated coefficient of INC_placebo is positive and insignificant. Thus, we conclude that in the absence of incentive disclosure, positive and detailed reviews alone do not have a negative impact on subsequent organic reviews.

Insert Table 9 about here

Purchase Error as an Alternative Mechanism

Another possible explanation for the observed decline in organic ratings following an incentivized review is the impact of incentives disclosure on the purchase decisions of subsequent shoppers. Being more positive on average, incentivized reviews drive product ratings up and lead to higher sales. Meanwhile, this may increase the chance of purchase errors, as customers make suboptimal purchase decisions based on inflated product ratings (Godes and Silva 2012). The observed decrease in ratings after incentivized reviews could then be explained by a higher share of dissatisfied customers among recent buyers.

To isolate the purchase decision from consumers' the incidence and evaluation decisions, we run a series of analyses that specifically examine the effect of incentivized reviews on organic reviews posted right after the incentivized review appears. We exploit the notion that if a customer posts an organic review shortly after the incentivized review, considering the product delivery time, it is possible that the customer made the purchase decision before exposure to the incentivized review. In this case, the incentivized review only affects that customer's review decision, not the purchase decision. According to Statista (2019), Amazon.com's click-to-door speed in 2015 was 5.9 days, which dropped to 3.07 days by 2018.[9] Thus, for data collected before 2015, we can assume that for a substantial number of reviews posted within a short time

[9] https://www.statista.com/statistics/957782/parcel-carriers-on-time-delivery-rate-peak-season/.

from the appearance of an incentivized review, corresponding purchase decisions were not affected.

To explore this scenario empirically, we replace the variable INC in our main model with two dummy variables, BEFORE and AFTER, which capture whether the review appeared before to the Xth day since the incentivized review (BEFORE set to 1) or beyond the Xth day since the incentivized review (AFTER set to 1). We then examined subsequent organic reviews posted within and beyond X days using 1, 2, 3, 4, 5, 7, and 14 days as cutoff values. The results appear in Figure 6. We find that incentivized reviews maintain a significant negative impact on subsequent organic reviews posted within 5 days after the treatment time.

Insert Figure 6 about here

From our two analyses, we conclude that incentivized reviews have a negative impact on subsequent product ratings after we control for the textual and numerical attributes of incentivized reviews and the purchase decision. Next, we investigate if incentive disclosures affect customers' reviewing behavior in terms of their decision to contribute a review and how to rate the product.

Impact of Incentive Disclosure on Reviewing Behavior

Following our conceptual framework (Figure 2), we envision two possible mechanisms of the negative impact of incentives on subsequent ratings. The first is through a selection process such that consumers exposed to incentivized reviews are more likely to contribute feedback when their private evaluation is negative than when it is positive. The second is through evaluation adjustment—that is, when consumers exposed to incentivized reviews adjust their private evaluation downward. Both scenarios would lead to the decrease in product ratings observed in our data, though for different reasons. We first discuss the theoretical motivation for the two mechanisms and then proceed to experiment-based testing in the next section.

Incidence decision (whether to post). This mechanism is based on the assumption that exposure to incentivized reviews may affect buyers' decisions to contribute their own feedback, depending on their private product evaluation. Exchange theory suggests that information transmission is conditioned on a communicator's cost–benefit analysis (Gatignon and Robertson 1986). As it applies to the consumer's decision to contribute a review, the associated costs (e.g., cognitive resources to systematically evaluate the product, time and effort to write the review) are compared with the expected utility (Petrescu et al. 2018; Proserpio and Zervas 2017). When consumers learn that earlier reviewers have received a free product as a reward for the effort, the perceived benefit from posting their own review may decrease as these reviewers would be receiving a lower reward than the incentivized reviewers. However, to yield a negative rating pattern, this effect must be asymmetric with respect to private product evaluation. Motivation theory (Wu and Huberman 2008) explains this asymmetry, as an overall positive evaluation (vs. a negative evaluation) constitutes a lesser deviation from the average rating hence is perceived by the potential contributor as less valuable. Note, however, that we do not find support for this mechanism in our placebo-based empirical study report. Nonetheless, we want to test this further in a controlled experimental setting.

Evaluation decision (what to post). This mechanism is based on the assumption that exposure to incentivized reviews affects buyers' persuasion knowledge (Friestad and Wright 1994). Specifically, incentivized reviews may be perceived by consumers as the firm's persuasive attempt to manipulate online review performance to attract buyers. Once customers consider incentivized reviews to be a part of this strategy, they may adjust their own evaluations.

Prior literature shows that by activating consumers' persuasion knowledge in the context of online and television advertising and social media posts, incentive disclosure affects the persuasive outcomes of the messages (e.g., the consumer's attitude toward the brand, brand recall, WOM usage, and engagement; Boerman, Van Reijmersdal, and Neijens 2012; Boerman, Willemsen, and Van Der Aa 2017; Campbell, Mohr, and Verlegh 2013; Wojdynski and Evans 2016). Disclosures also have a stronger impact when the commercial nature of the message is difficult to infer (Boerman, Willemsen, and Van Der Aa 2017). Given that incentivized reviews are integrated into the product web page so that they resemble organic product reviews posted by other buyers, we believe that when a consumer notices this, incentivized reviews may activate the consumer's cognitive persuasion knowledge. This, in turn may lead to the perception that the firm is attempting to inflate product ratings, thus resulting in a downward adjustment of the consumer's private evaluation (Campbell and Kirmani 2000; Friestad and Wright 1994).

EXPERIMENTS AND RESULTS

We designed this study with three objectives in mind. First, we aim to replicate the negative effect of incentivized reviews on subsequent organic reviews in controlled settings. Second, we examine two alternative explanations for the negative impact—adjustment and selection—by directly measuring participants' product evaluations and their motivations to contribute a review. Third, we test for a potential mediator: the perceived credibility of prior reviews that would be consistent with persuasion knowledge theory. The proposed selection theory and adjustment theory would have different predictions regarding to consumers' incidence decisions and evaluation decisions. Selection theory predicts an asymmetric impact on participants' motivation to post reviews, depending on their consumption experience: facing with prior incentivized reviews, participants would report a lower motivation to post reviews when they have negative consumption experiences but not for positive experiences. If that is the case, we should observe a significant interaction effect between consumption experience and the type of prior reviews on the motivation to post. On the other hand, adjustment theory predicts that prior incentivized reviews would influence participants' product evaluations regardless of their consumption experiences, so we should expect a significant main effect for the type of prior review on product evaluation. Consumption experience should only influence product evaluation through main effect rather than moderate the impact of prior incentivized reviews.

Design and Procedure

We employed a 2 (prior reviews: incentivized vs. organic) by 2 (consumption experience: positive vs. negative) between-subjects design, which allows us to examine the impact of incentivized reviews on consumers' incidence (i.e., whether to post) and evaluation (i.e., what to post) decisions under positive and negative private evaluation conditions. We recruited two hundred and fifty-seven participants (female = 42.02%, M_{age} = 41.8 years, $0.50 payment) from Amazon Mechanical Turk (MTurk) and randomly assigned them to one of four between-subjects conditions.

First, we primed participants with a scenario in which they purchased a product online with either satisfactory or unsatisfactory performance. Half the participants were assigned to the positive condition, and the other half were assigned to the negative condition. Participants were asked to imagine that they bought a V-tech Bluetooth speaker from Amazon.com as a birthday gift for a friend. The speaker either performed well with high sound quality and easy connectivity or was unsatisfying because it could not connect to the mobile phone and the sound low quality (Figure 7). We chose a speaker as the stimulus product because it is a search good for which customers commonly rely on online reviews to support purchase decisions and because customers evaluate speakers based on functionality rather than aesthetics or idiosyncratic preferences.

Insert Figure 7 about here

Next, participants were presented with a randomly selected review from the website (Figure 8). We used two reviews of similar length and positive valence (i.e., 4 to 5 stars) selected from the Amazon.com dataset and randomized presentation across participants. All other review characteristics, including reviewer name and posted time, were kept the same across all conditions. Under the incentivized prior review condition, the following incentive disclosure was added to the review text: “DISCLOSURE I received the item at no cost from the manufacturer for purposes of a review.” We obtained the disclosure from real incentivized reviews in the Amazon.com review dataset.[10]

Insert Figure 8 about here

Participants indicated their evaluations of the product using four questions (e.g., 1 = “very unfavorable,” 7 = “very favorable”; α = .993) and their motivations to post reviews using two items (e.g., 1 = “extremely unlikely,” 7 = “extremely likely”; α = .925).

Next, to make the reviewing process complete, we asked participants to write their own reviews (i.e., star rating and review text) regardless of their reported motivation. We then

[10] In other studies, we used a different paraphrasing of the disclosure and obtained the same results.

measured their perceptions of the prior review they read in terms of its perceived credibility. We measured perceived credibility using two groups of 7-point Likert scaled items capturing perceived expertise and trustworthiness (Ohanian 1990). For perceived expertise, we asked participants to rate the extent to which they agree with the statements that the review they read "shows knowledge about the product," "reflects the expertise of the reviewer," and "shows skills of the reviewer" (1 = "strongly disagree," 7 = "strongly agree"; $\alpha = .922$). For perceived trustworthiness, we asked participants to rate the extent to which the review is "honest," "sincere," and "trustworthy" (1 = "strongly disagree," 7 = "strongly agree"; $\alpha = .975$). Finally, participants completed a questionnaire about their online shopping behavior, reviewing behavior, and demographics.

Results

Product evaluation. A two-way analysis of variance (ANOVA) on product evaluation (see Figure 9) reveals a significant main effect of consumption experience ($F(1, 253) = 352.963$, $p < .001$) and incentivized prior review ($F(1, 253) = 9.20$, $p = .003$) on product evaluation. In terms of a two-way interaction, the interaction between consumption experience and type of prior review is not significant ($p = .140$), suggesting that consumption experience does not moderate the negative impact of incentivized reviews on customers' product evaluations.

Consistent with our intuition, participants in the positive experience condition had higher evaluations than those in the negative experience condition ($M_{positive} = 5.90$, $SD = 1.28$ vs. $M_{negative} = 2.57$, $SD = 1.71$). Furthermore, participants in the incentivized review condition had lower evaluations ($M_{inc} = 4.00$, $SD = 2.19$) than those in the organic review condition ($M_{org} = 4.44$, $SD = 2.32$). The results suggest that the negative impact of the incentivized prior review on subsequent customers' evaluations persists regardless of the customer's own experience. These results are consistent with the downward adjustment mechanism.

Insert Figure 9 about here

Star ratings. Because we asked participants to write a product review, we can also investigate the impact of incentivized reviews on star ratings. Similar to the results of product evaluation, a two-way ANOVA on star rating yielded a significant main effect of consumption experience ($F(1, 253) = 833.59$, $p < .001$) and a marginal negative significant main effect of prior incentivized review ($F(1, 253) = 3.42$, $p = .066$). Again, the interaction effect is not significant ($p = 0.97$). On average, participants rated the product .18 stars lower ($M_{inc} = 2.91$ vs. $M_{org} = 3.09$) when they read the incentivized prior review (vs. the prior organic review).

Motivation to post reviews. The selection mechanism predicts that consumers' motivation to post their own reviews might be affected by their own consumption experience with the product as well as the existence of incentive disclosure. Thus, we ran a 2 (consumption experience: positive vs. negative) by 2 (prior review: incentivized vs. organic) two-way ANOVA on participants' motivation to post reviews (Figure 10). The model is not significant ($F(3, 253) = 1.45$, $p = .228$). We only observed a marginally significant main effect of consumption experience ($F(1, 253) = 2.774$, $p = .097$), indicating that participants had a higher motivation to post reviews when they were not satisfied with the product ($M_{neg\_exp} = 5.08$, $SD = 1.81$ vs. $M_{pos\_exp} = 4.70$, $SD = 1.71$), which is consistent with prior research (Wu and Huberman 2008). Neither the main effect of type of prior reviews nor the interaction were significant (*p*s > .25). We conclude that incentive disclosure per se does not change participants' intention to contribute feedback.

Insert Figure 10 about here

Perceived credibility. Extant research suggests that expertise and trustworthiness are two source attributes that characterize credibility (Hovland, Janis, and Kelley 1953). It is worth noting the high correlation between perceived expertise and perceived trustworthiness ($r = .77$, $p < .000$), suggesting that in our study, they operationally do not represent distinct factors. Therefore, we combined these two variables and formed *perceived credibility* as a single variable to conduct the mediation analysis. An ANOVA on perceived credibility confirms that incentivized prior reviews are considered less credible ($M = 3.69$, $SD = 1.77$) than organic prior reviews ($M = 4.78$, $SD = 1.35$; $F(1, 254) = 86.79$, $p < .001$). To test whether the perceived credibility of prior reviews mediates the observed difference in product evaluation given a different type of prior reviews, we conducted a mediation analysis with 5,000 bootstrapped samples using the PROCESS Model 4 macro in SPSS (Hayes 2018). At a 95% confidence interval (CI), the indirect effect of the type of prior reviews through perceived credibility was significant ($b = .696$, 95% CI = [.430, 996]). The results suggest that perceived credibility mediates the effects of the type of prior reviews on participants' product evaluation (for the tested model and the mediation results, see Figure 11).

Insert Figure 11 about here

Discussion

Our findings provide insight into how consumers perceive incentivized reviews. Consistent with our empirical analysis, the results show that consumers produce reviews with a lower evaluation when they see prior incentivized reviews rather than organic ones. Overall, our results agree with the downward adjustment mechanism, and we do not find support for the selection mechanism as a driver for the negative impact. Conditional on purchase decision and consumption experience, participants made lower product evaluations when they were aware of the existence of a material connection between the reviewer and the seller (i.e., seeing the incentivized reviews). However, their motivation to contribute their own review did not change with knowledge about the incentives. Our mediation analysis suggests that consumers may perceive incentives as a manipulation tactic employed by the firm that affects the review's credibility. It is important to note that in this study, participants only saw positive prior reviews across all conditions. We deliberately chose to do so because this is consistent with our observation in the secondary data that most incentivized reviews have a positive valence. In an additional study, we explore a less common condition in which incentivized reviews are of a negative or neutral valence (see Appendix D). The result of this analysis still reveals a negative impact of incentives on subsequent product evaluation.

In summary, we demonstrate a consistently negative impact of incentivized reviews on customers' product evaluations. The effect is robust for both positive and negative consumption experiences. The findings provide evidence that although an incentivized campaign can improve product reviews in the short run by increasing contributions that also tend to be more positive, it can also have an adverse impact on review dynamics by leading subsequent reviewers to provide more negative opinions.

MANAGERIAL IMPLICATIONS

Our findings have economic and managerial implications for sellers and review platforms. It is generally acknowledged that incentives can be an effective tool to stimulate product feedback contributions, which in turn can be critical for a firm's performance, especially for lesser-known brands or new products entering market. Research has shown that the first review a product receives can significantly influence the product's future e-WOM performance (Park, Shin, and Xie 2021). Therefore, for new entrants, incentivized reviews can serve as a reputation management strategy to solve the "cold start" issue.

We also provide implications for the long-lasting discussion about incentivized review policies and whether incentive disclosures could protect consumer welfare. We found that, regardless of the authenticity and valence of incentivized reviews, incentivized disclosures trigger subsequent consumers' adjustment on their evaluations, which in turn biases the product's average rating. As a result, prospective buyers might make suboptimal purchase decisions because of the (negatively) biased online evaluation. In short, our results indicated that subsequent consumers who are exposed to those post-incentives organic reviews could be worse off.Our research shines a light on a potentially overlooked downside of this practice. We demonstrate that products associated with incentivized reviews may attract more negative reviews from consumers who purchase the product at a later time, after becoming aware of past incentives. This highlights an important trade-off for managers: receiving more positive and detailed incentivized reviews versus seeing a temporary decline in star ratings of subsequent organic reviews after the incentive campaign. Taking one hypothetical product as example, on the platform, the product has eight online reviews with a 4.15 average star rating. The valence and volume of e-WOM were chosen based on the calculations for the mean statistics for non-incentivized products in our empirical dataset. Assuming the seller sent free product to a potential reviewer and in return, the incentivized reviewer posted a detailed review with a five-star rating, the average rating would increase by 0.1. Based on our results for the negative impact on star ratings for subsequent organic reviews, such gain in average rating would be offset if the product receives five organic reviews after the incentivized review (i.e., the average star rating would drop to the original level). From an economic perspective, the task of resolving this trade-off is not trivial, and therefore, we hesitate to offer unequivocal recommendations.

Extant research points to complex dynamics in product review systems in which changes in product ratings affect sales and subsequent review contributions that, in turn, lead to changes in future ratings (Moe and Trusov 2011). These dynamics need to be taken into account when performing a cost–benefit analysis of offering review incentives. A related factor is the competitive standing of the focal product in the review system. Sometimes shoppers are faced with a choice scenario in which a less popular (in terms of review volume) but higher-rated product is compared with a more popular but lower-rated product. While incentives may help change the product standing on these dimensions, prior research has shown that the implications for consumers' choices are complex and that managers should take various additional factors into account to make sound predictions about economic outcomes (Watson, Ghosh, and Trusov 2018). Finally, the informational value of incentivized reviews needs to be considered. Although our results point to a temporary decline in product ratings, in the long run, the effect tends to dissipate, and the potentially high-quality incentivized feedback may serve its purpose of educating consumers about the product and (potentially) increasing its appeal (Wu et al. 2015).

In summary, while a comprehensive analysis of economic returns from incentive campaigns is complex and falls beyond the scope of this research, we can offer some practical advice to managers to help mitigate the negative impact of incentivized reviews on subsequent rating. Our findings point to perceived credibility as an important factor driving the observed decline in ratings. Thus, the firm may want to adopt tactics that directly address this issue. For example, some forms of incentive might be perceived by fellow shoppers as less likely to bias product feedback. One approach might be to use altruistic motivation (e.g., Reimer and Benkenstein 2016) or to employ a lottery mechanism in which each contributor is offered an equal chance of winning some monetary reward (e.g., Macy's "IT. rate IT. win BIG!"[11]). Another strategy might be to decouple the source of the incentive from the review beneficiary. Amazon.com's Vine program uses this approach, where invited reviewers are rewarded by the platform but not by the seller, thus reducing suspicions about the review's trustworthiness.

CONCLUSION

In this paper, we investigate the impact of incentivized reviews on subsequent product ratings. Specifically, we show that incentive campaigns can bring about unexpected adverse effects after the campaign. We provide a conceptual framework for illustrating the customer's reviewing behavior with the existence of economic incentives and investigate alternative mechanisms that might explain the negative effects observed in our data. On the basis of various analyses, we conclude that evaluation adjustment in which the incentivized disclosure activates customers' persuasion knowledge, thus causing customers to respond by adjusting their own evaluations downward, is the most plausible mechanism identified. Tactics aimed at diminishing

[11] https://www.sweepstakeslovers.com/unlimited-entry/macys-customer-product-review-sweepstakes/.

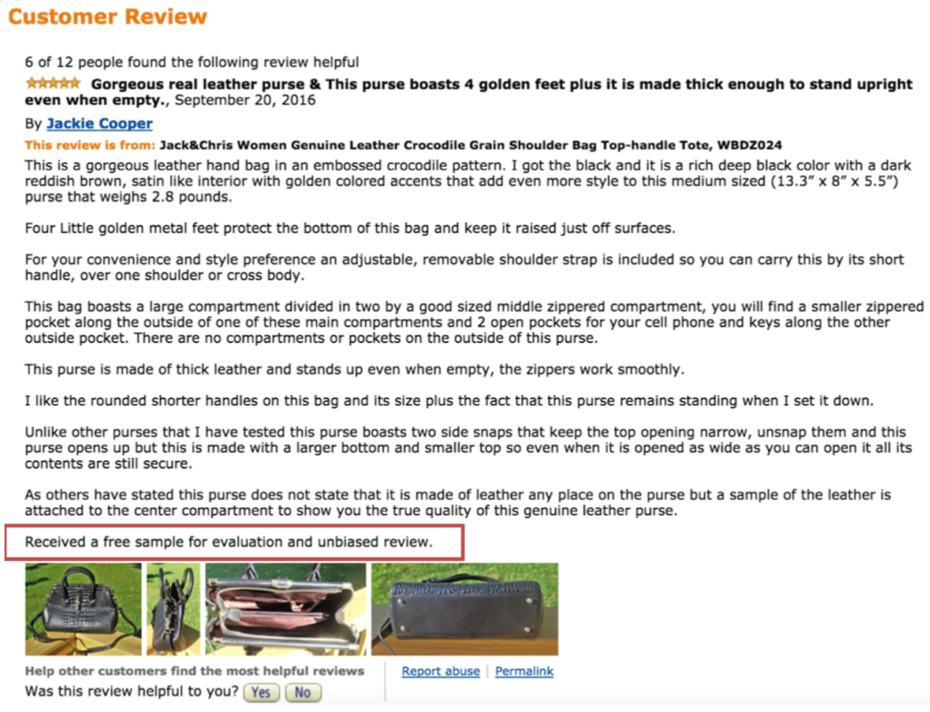
credibility concerns resulting from consumer awareness of incentives could mitigate these adverse effects.

In the paper, I designed lab experiments to test two competing theories by manipulating the type of prior reviews and valence of consumption experience. I found no significant evidence for the selection theory as the interaction effect on incidence decision was insignificant. However, such non-effect might subject to the experiment design or specific manipulation. Further analysis could include additional study to reject the competing theory. In addition, to increase the validity of the experiment, further analysis should consider using real product as stimuli and allowing participants to play with the product as opposed to using a vignette in the current study.

Further research could explore potential moderators for incentivized reviews, such as different types of rewards or the economic value of the incentive. In addition, the effects of incentivized content contribution on subsequent content contributions could be studied across a broader range of social media platforms, such as Reddit and Twitter. Future studies might also explore different schemes of providing incentives and how different seeding strategies affect content contribution and consumers' perceptions.

FIGURE 1

EXAMPLE OF AN INCENTIVIZED REVIEW (ESSAY I)



Customer Review

6 of 12 people found the following review helpful

Gorgeous real leather purse & This purse boasts 4 golden feet plus it is made thick enough to stand upright even when empty., September 20, 2016

By **Jackie Cooper**

This review is from: Jack&Chris Women Genuine Leather Crocodile Grain Shoulder Bag Top-handle Tote, WBDZ024

This is a gorgeous leather hand bag in an embossed crocodile pattern. I got the black and it is a rich deep black color with a dark reddish brown, satin like interior with golden colored accents that add even more style to this medium sized (13.3" x 8" x 5.5") purse that weighs 2.8 pounds.

Four Little golden metal feet protect the bottom of this bag and keep it raised just off surfaces.

For your convenience and style preference an adjustable, removable shoulder strap is included so you can carry this by its short handle, over one shoulder or cross body.

This bag boasts a large compartment divided in two by a good sized middle zippered compartment, you will find a smaller zippered pocket along the outside of one of these main compartments and 2 open pockets for your cell phone and keys along the other outside pocket. There are no compartments or pockets on the outside of this purse.

This purse is made of thick leather and stands up even when empty, the zippers work smoothly.

I like the rounded shorter handles on this bag and its size plus the fact that this purse remains standing when I set it down.

Unlike other purses that I have tested this purse boasts two side snaps that keep the top opening narrow, unsnap them and this purse opens up but this is made with a larger bottom and smaller top so even when it is opened as wide as you can open it all its contents are still secure.

As others have stated this purse does not state that it is made of leather any place on the purse but a sample of the leather is attached to the center compartment to show you the true quality of this genuine leather purse.

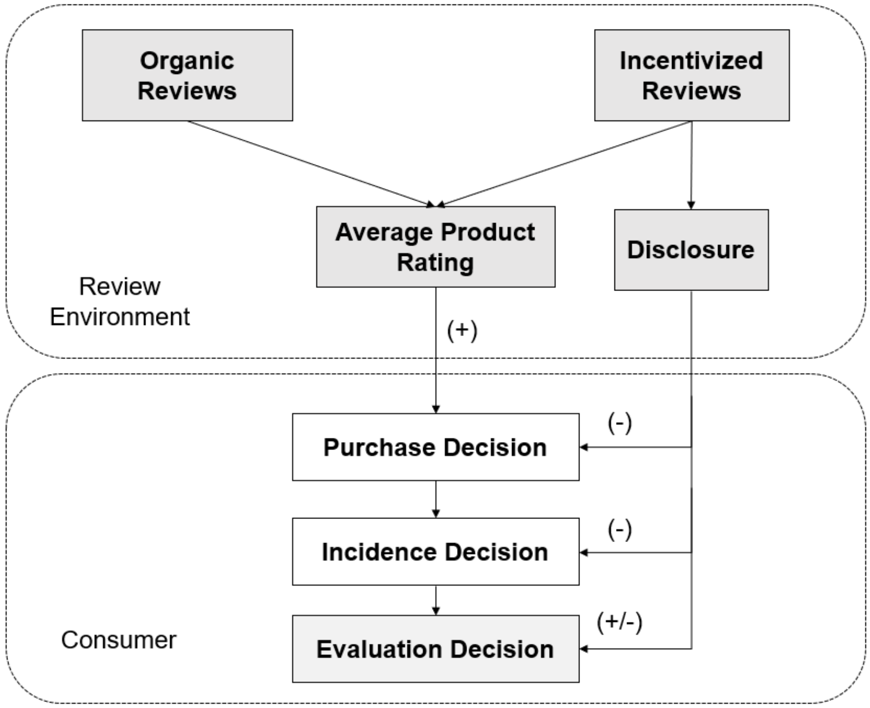
$\boxed{\text{Received a free sample for evaluation and unbiased review.}}$

Help other customers find the most helpful reviews | Report abuse | Permalink

Was this review helpful to you? Yes No

FIGURE 2

CONCEPTUAL MODEL (ESSAY I)



Notes. Gray boxes represent outcomes observed in secondary data.

FIGURE 3

DISTRIBUTION OF STAR RATINGS (INCENTIVIZED VS. ORGANIC REVIEWS)

(ESSAY I)

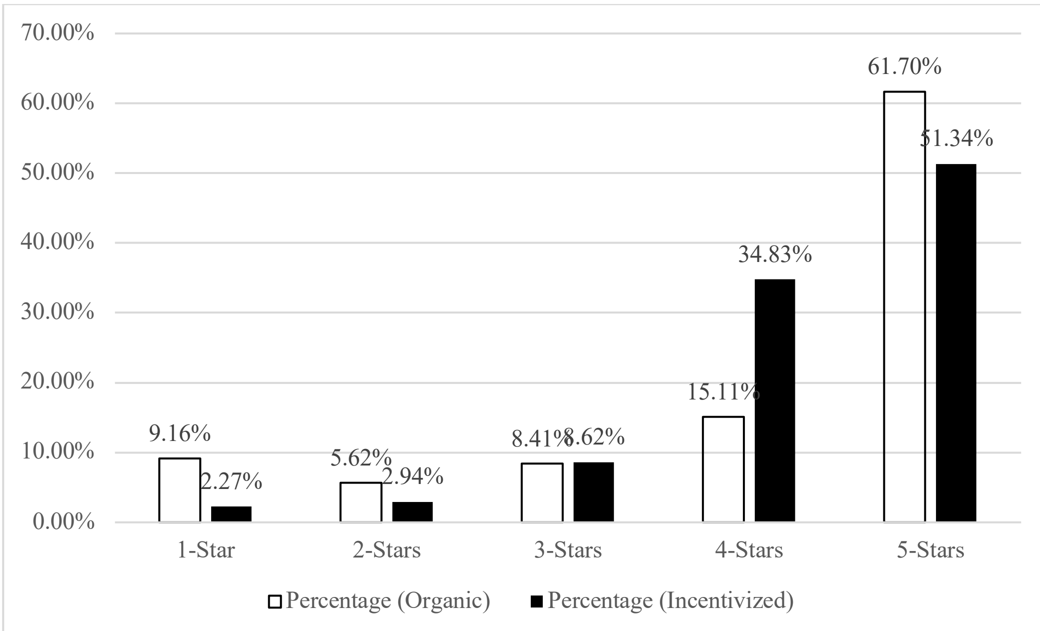
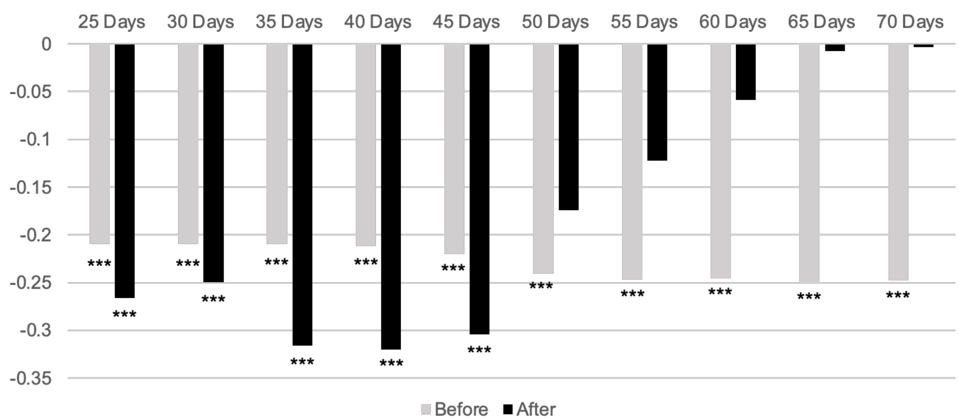


FIGURE 4

DYNAMIC IMPACT OF INCENTIVIZED REVIEWS (ESSAY I)



*p < .1.
**p < .01.
***p < .005.

Notes: The variables BEFORE and AFTER are dummy variable denoting whether the focal review is posted after the INC campaign either before or after a certain number of days.

FIGURE 5

DISTRIBUTION FOR PROPENSITY SCORES (ESSAY I)

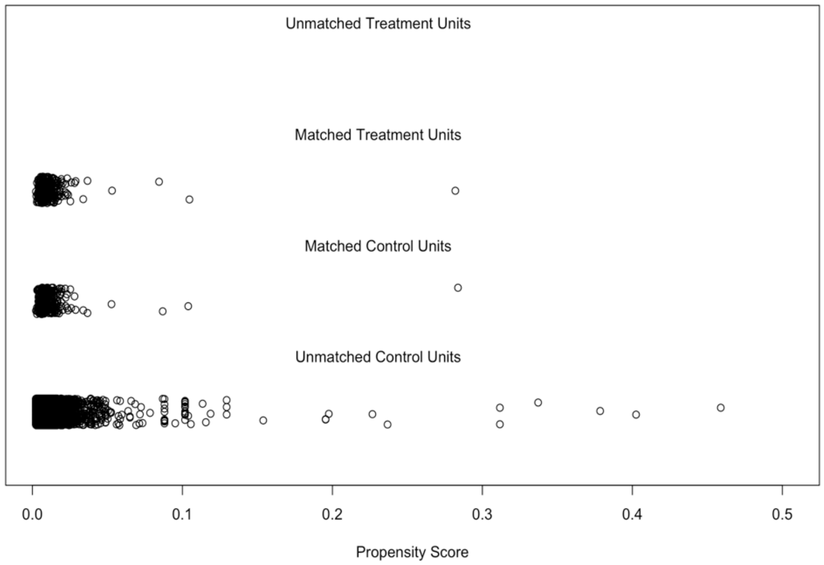
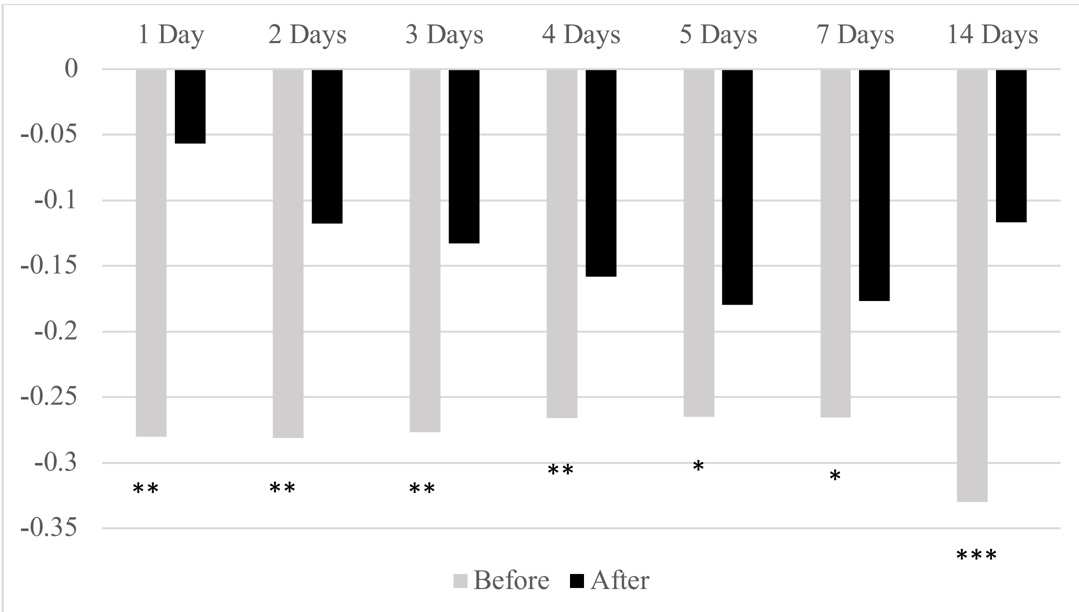


FIGURE 6

DYNAMIC EFFECT OF INCENTIVIZED REVIEWS ON SUBSEQUENT REVIEWS

(ESSAY I)



*p < .1.
**p < .01.
***p < .005.

Notes: The dummy variable BEFORE is set to 1 when the focal review is posted within X days after the first incentivized review. The dummy variable AFTER is set to 1 when the focal review is posted more than X days after the first incentivized review.

FIGURE 7

STIMULI FOR EXPERIMENT (CONSUMPTION EXPERIENCE) (ESSAY I)

Positive experience condition

Last week you bought a V-tech Bluetooth speaker from Amazon.com. It is for your friend Tom as a birthday gift. He decided to try this new speaker during his birthday party. The speaker connected with his cell phone without any difficulty. The speaker performed well with high sound quality. And Tom liked the simple design of the speaker as well.
You are very happy with this product.

Negative experience condition

Last week you bought a V-tech Bluetooth speaker from Amazon.com. It is for your friend Tom as a birthday gift. He decided to try this new speaker during his birthday party. The speaker connected with his cell phone with difficulty. The speaker performed poorly with low sound quality. And Tom disliked the simple design of the speaker as well.
You are very disappointed with this product.

FIGURE 8

STIMULI FOR THE PRIOR REVIEW (ESSAY I)

Prior organic review

Review 1:

By Richard Rust on December 12, 2020

This Bluetooth speaker is absolutely fantastic! The highs, mids and lows sounds are all very clear even at full volume. The build quality is very good albeit a bit simplistic in its styling. It's the Sound Cores function that matters more to me, in that regard it delivers on sound quality, battery life and its ability to quickly pair with my phone

Review 2:

By Richard Rust on December 12, 2020

It's the best speaker: solid design, long battery life, nice button placement, good response, nice sound, I do not use it much that way but good enough as a speaker phone, water resistant and feels like one, long range, easy connectivity and good reliability. We liked it so much that we decided to buy a second one so we did not have to share.

Prior incentivized review

Review 1:

By Richard Rust on December 12, 2020

#Disclosure# I received this V-tech speaker for free in exchange for a review. The opinions below are my own and no compensation was received.

This Bluetooth speaker is absolutely fantastic! The highs, mids and lows sounds are all very clear even at full volume. The build quality is very good albeit a bit simplistic in its styling. It's the Sound Cores function that matters more to me, in that regard it delivers on sound quality, battery life and its ability to quickly pair with my phone

Review 2:

By Richard Rust on December 12, 2020

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It's the best speaker: solid design, long battery life, nice button placement, good response, nice sound, I do not use it much that way but good enough as a speaker phone, water resistant and feels like one, long range, easy connectivity and good reliability. We liked it so much that we decided to buy a second one so we did not have to share.

FIGURE 9

PRODUCT EVALUATIONS (ESSAY I)

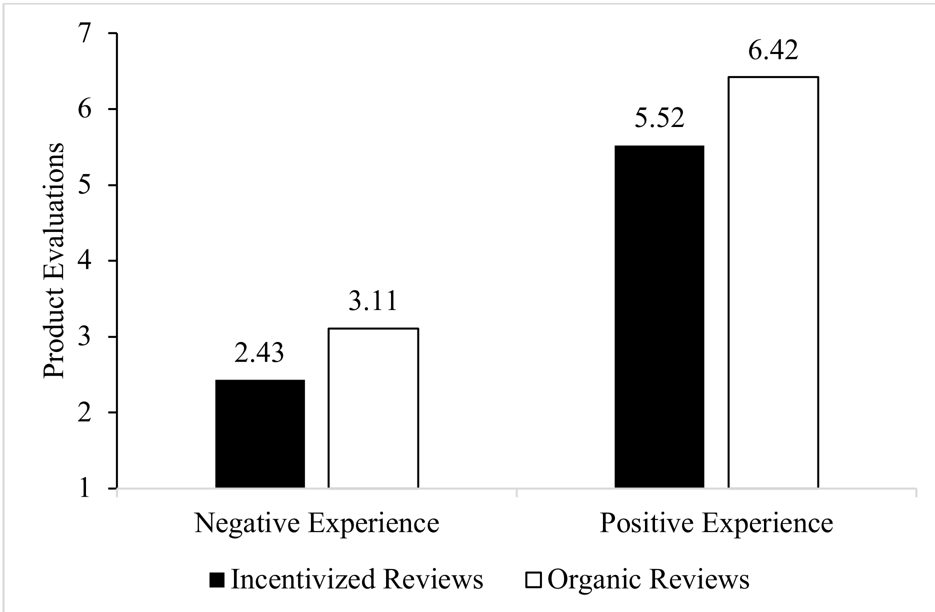


FIGURE 10

EXPERIMENT: MOTIVATION TO POST A REVIEW (ESSAY I)

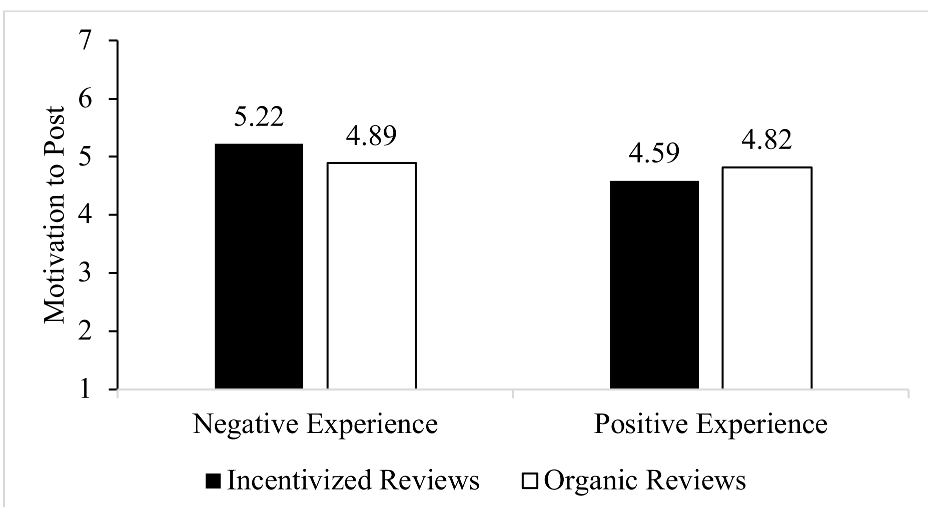
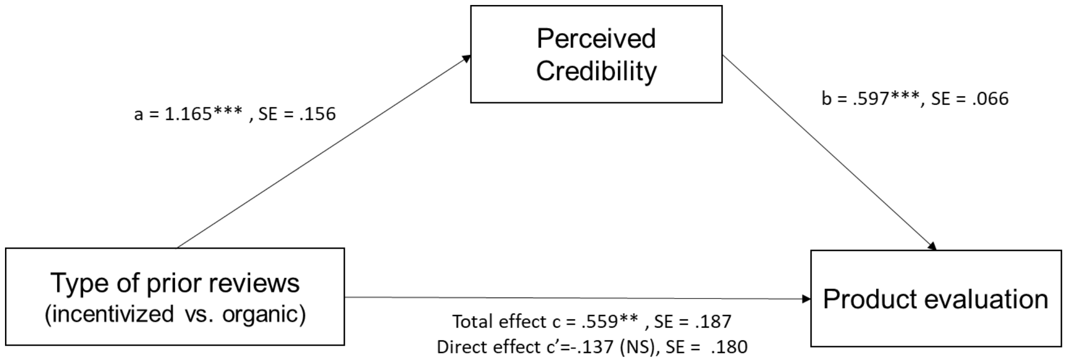


FIGURE 11

MEDIATION OF PERCEIVED CREDIBILITY ON PRODUCT EVALUATION (ESSAY I)



*p < .1.
**p < .01.
***p < .001.

TABLE 1

COMPARISON OF INCENTIVIZED REVIEWS AND ORGANIC REVIEWS (REVIEW TEXT) (ESSAY I)

		Organic Reviews	Incentivized Reviews	t-Test	*p*-Value
# of sentences	Mean	5.818	9.894	31.18	.000
	(SD)	(4.927)	(5.667)		
# of words	Mean	99.961	205.144	37.05	.000
	(SD)	(106.377)	(135.389)		

TABLE 2

DESCRIPTIVE STATISTICS FOR INCENTIVIZED BEAUTY PRODUCTS (ESSAY I)

Variable	Observations	SD	Mean	Min	p25	p50	p75	Max
Number of reviews (per product)	338	161.80	109.7	1.0	15.0	45.0	127.2	981.0
Number of incentivized reviews (per product)	338	10.33	4.43	1.0	1.0	1.0	3.0	102.0
Star rating of reviews	37,080	1.10	4.33	1.0	4.0	5.0	5.0	5.0
Star rating of incentivized reviews	1,496	0.91	4.30	1.0	4.0	5.0	5.0	5.0

TABLE 3

VARIABLE DESCRIPTIONS (ESSAY I)

Variable Name	Description
$STARS_{ib}$	Product b star rating posted by consumer i
$TIME_{ib}$	Time difference (number of days) between first review for product b and the review posted by consumer i
$ORDER_{ib}$	Order difference between first review for product b and the review posted by consumer i
$REVAVG_{ib}$	Average rating of all reviews posted by consumer i except the one posted for product b
INC_{ib}	Binary variable indicating whether the review posted by consumer i for product b appeared after (INC = 1) the first incentivized review
$DIFFTIME_{ib}$	Time difference (number of days) between first incentivized review and the review posted by consumer i for product b (0 if the review is posted before the first incentivized review)
$CUMULMEAN_{ib}$	Cumulative average rating for all the reviews of product b contributed before the review posted by consumer i
$CUMULVAR_{ib}$	Cumulative variance of all the reviews of product b contributed before the review posted by consumer i

TABLE 4

SUMMARY STATISTICS FOR VARIABLES (ESSAY I)

Variable	Mean	SD	Min	Max
$STARS_{ib}$	4.574	.874	1	5
$TIME_{ib}$	216.542	408.572	1.0	661
$ORDER_{ib}$	216.542	123.925	1	2,383
$REVAVG_{ib}$	4.563	.576	0	5
INC_{ib}	.605	.489	0	1
$DIFFTIME_{ib}$	43.271	154.273	0	1,458
CUMULMEAN	4.482	.849	0	5
CUMULVAR	.578	.581	0	4

TABLE 5

ORDERED LOGIT REGRESSION ESTIMATION RESULT (ORGANIC REVIEWS ONLY)

(ESSAY I)

Variables	Model 1	Model 2
REVAVG	1.33***	1.32***
	(.0629)	(.0628)
TIME	.0003*	.0004*
	(.0002)	(.0002)
ORDER	–.0022***	–.00161***
	(.0004)	(.0004)
INC		–2.56**
		(.0981)
DIFFTIME		.0010*
		(.0004)
CUMULMEAN		.234***
		(.0698)
CUMULVAR		–.409***
		(.1249)
YEAR fixed effect	Yes	Yes
LL	–3,503	–3,488
AIC	7031	7009
BIC	7116	7120

*$p < .1$.
**$p < .01$.
***$p < .005$.

Notes: LL = log-likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion.

TABLE 6

PRETREATMENT VARIABLE DESCRIPTIONS (ESSAY I)

Variable Name	Description
AVG_RATING_b	Average rating before the treatment for product b
SD_RATING_b	Standard deviation of star ratings before the treatment for product b
N_RATING_b	Number of reviews product b received before treatment time
FEQ_b	Average number of reviews product b received per week before treatment time

TABLE 7

DESCRIPTIVE STATISTICS FOR MATCHING DATA (PRE- AND POSTMATCHING)

(ESSAY I)

Variable		Prematching			Postmatching		
		Control	**Treatment**	***p*-Value**	**Control**	**Treatment**	***p*-Value**
N		36,623	266[a]		266	266	
AVG_RATING	Mean	4.26	4.28	.523	4.23	4.28	.420
	(SD)	(.64)	(.69)		(.74)	(.69)	
SD_RATING	Mean	.95	.86	.014	.89	.86	.456
	(SD)	(.60)	(.57)		(.58)	(.57)	
N_RATING	Mean	22.60	40.77	<.001	33.89	40.77	.251
	(SD)	(39.06)	(79.35)		(56.94)	(79.35)	
FEQ	Mean	1.45	4.14	<.001	2.88	4.14	.043
	(SD)	(3.55)	(6.92)		(7.36)	(6.92)	
Year[b]				<.001			.313

Notes: a. The products that had no organic reviews before the first incentivized review could not be matched and thus were excluded from the propensity score matching analysis. b. The variable Year is a categorical variable denoting entry year from 2004 to 2013.

TABLE 8

PROPENSITY SCORE MATCHING ESTIMATION (ESSAY I)

Variables	Model 1	Model 2
REVAVG	.977***	.975***
	(.004)	(.004)
TIME	.000	.000
	(.000)	(.000)
ORDER	–.0002***	–.0002**
	(.000)	(.000)
INC	.024	.050**
	(.012)	(.018)
TREATMENT	.108***	.130***
	(.023)	(.025)
TREATMENT × INC		–.044**
		(.022)

*$p < .1$.
**$p < .01$.
***$p < .005$.

TABLE 9

PLACEBO STUDY WITH PSEUDO-INCENTIVIZED REVIEW (ESSAY I)

Variables	Model 1
REVAVG	1.37***
	(.0641)
TIME	.0005**
	(.0002)
ORDER	–.0018***
	(.0005)
INC_PLACEBO	.0518
	(.0109)

**$p < .01$

***$p < .005$.

Chapter 3: How Much is Too Much? The Repetition Effect in e-WOM

With the development of 5G Internet, mobile and wearable devices, and other technology, consumers generate and consume e-WOM constantly to facilitate their purchase decisions. By the end of 2020, Yelp gained 220 million reviews and it continues to receive 26,830 reviews per minute[12]. Meanwhile, TripAdvisor reached one billion reviews in February 2022, with its most reviewed hotel having more than 48,000 reviews[13]. Firms and platforms have benefited from abundant user-generated content and still exert their skills to obtain more reviews. The question becomes whether having numerous consumer reviews is always a good thing. For example, information expansion resulting from abundant e-WOM might lead to higher decision difficulty for consumers (Broniarczyk and Griffin 2014). From a firm's perspective, too many reviews could be problematic if reading them is not enjoyable or is useless; for example, too much repetition in the review content could lead to negative perceptions of the product. In this paper, we focus on this prevalent phenomenon of repetition in e-WOM, and study its impact on consumers' information processing, product evaluation, and purchase behavior.

Repetition in e-WOM refers to the act of repeating something (i.e., an opinion or topic) that has already been mentioned by prior e-WOM. We categorize repetition in e-WOM into two types borrowed from linguistic topology: *verbatim* and *gist* (Dellarosa and Bourne 1885). Verbatim repetition refers to the act of repeating the exact same phrases or sentences, whereas gist repetition, also called paraphrasing in some literature (Silva, Garcia-Marques, and Mello 2017), refers to the action of expressing the same opinion or information using different phrases. Gist

[12] https://www.invespcro.com/blog/the-importance-of-online-customer-reviews-infographic/
[13] https://ir.tripadvisor.com/news-releases/news-release-details/travelers-push-tripadvisor-past-1-billion-reviews-opinions

repetition can be operationalized by synonym substitution, converse substitution, or change of voice, which should ensure that gist repetitions can widely overlap in the semantic features of the original message but differ in their surface structure. For example, if the focal message is "*the huge policeman halted the expensive automobile*," verbatim repetition means to repeat the exact sentence, and gist repetition means to express the meaning of the focal message in a meaning-preserving way (e.g., "*the large cop stopped the high-priced car*"). In the context of e-WOM, these two types of repetition are very identifiable from the readers' perspective, especially when the reviews are concise and brief (e.g., "*Great product*" or "*Excellent*").

Surprisingly, no existing research has investigated repetitiveness in e-WOM, even though repetition is such a prevalent phenomenon in online product reviews, social media, and other online communications. Figure 12 provides a screenshot of online reviews received by a Kindle seller on eBay, and we can see that the reviews are short, simple, and very similar to each other. In fact, eBay is only one of many platforms receiving high repeated e-WOM. Take one New York Airbnb room as another example. Among its one hundred and nine reviews, thirty-six reviewers used two words, "*great place,*" in their comments to describe their stay[14].

Insert Figure 12 about here

Why is repetition in e-WOM so prevalent? Several factors could contribute to high-level repetitiveness in our utterances. Consumers, consciously or unconsciously and due to endogenous or exogenous factors, repeat others' expressions to express themselves. People are always influenced by others' opinions when describing their own opinions online. In terms of exogenous factors, computer-facilitated functions may impact how people compose their public opinions,

[14] https://www.airbnb.com/rooms/19717723?check_in=2022-11-01&check_out=2022-11-04&federated_search_id=b4c674ef-30cc-46a8-9d06-ea7628320825&source_impression_id=p3_1666793911_DyFdABkrY%2FM3VowJ

such as auto-complete in Gmail and auto-suggestion in some search engines. These intelligent systems provide relevant keywords and alternatives to increase user productivity. These widely applied functions are designed to facilitate the efficient composition of text by human. Because of the limited options they offer to users, not only is content confined to a certain number of expressions, but consumer thinking is also limited. Hence, the level of repetitiveness in e-WOM then rises as the content becomes less and less diverse.

We also tend to express ourselves using briefer and simpler expressions for time-saving or effort-saving purposes. Research shows that consumers tend to post briefer reviews under physical or time constraints. For example, Melumad, Inman, and Pham (2019) found that consumers provided briefer content using mobile phones (vs. computers). Another example is comments on live streaming, which are generally shorter than forum comments due to the time constraints imposed by synchronous communication.

In addition, repetition can occur naturally due to the increasing volume of e-WOM; even reviewers generate their reviews independently. Imaging e-WOM is generated following the well-established LDA data-generating process. As the number of documents increases, the probability that documents will cover the same topic (or even phrases) also increases, which leads to a higher level of repetition. This is the case for online reviews, in which the number of topics per document, the number of potential words, and the length of documents are all limited. Therefore, the prevalent phenomenon of repetition in e-WOM, results from all these contributing factors, as we observe in our daily live. In the current paper, we aim to understand the consequences rather than the antecedent of repetition in e-WOM. We believe that consumers' perceptions of repetition in e-WOM could impact their product evaluations and behavioral intentions.

Unique Features of Repetition in e-WOM

Repetition is ubiquitous. Pop songs are played on the radio repeatedly, TV advertisements are on day and night, students memorize multiplication tables by reading them multiple times, and Catholics perform the Rosary, a Catholic set of prayers including five repeated decades. In contrast to all these examples in domains such as music appreciation, advertisement, cognitive processing, and ritual, in which people process the same piece of content multiple times, repetition in e-WOM can be differentiated. That is because repetition in e-WOM has unique features. First, manipulating the level of repetition in other contexts can never eliminate one cofounded factor: increased processing time. Usually, a higher level of repetition implies a more extended time for people to process the stimulus, and this is particularly true when the repeated sequence presented externally contains time intervals between repetitions. However, in the e-WOM context, the time dimension seems to collapse, and all repeated information is presented in one shot. Unlike other contexts in which participants retrieve the memory of prior exposures and may forget the stimuli as time goes by, here, participants form their opinions immediately after reading the repeated information, so there is very little or even no time for consumers to forget the repeated stimuli. Therefore, the results from previous research on repetition cannot be applied to the e-WOM context as the time dimension collapses and becomes endogenous. In fact, the level of the repetitiveness of e-WOM could affect how people process it (e.g., the processing time and the total amount of e-WOM read by the consumer). In this essay, we have one study in which participants were allowed to determine the time for information processing endogenously, and participants could stop reading the e-WOM content anytime they wanted.

The second feature comes from the nature of e-WOM, that is, e-WOM is generated from communications and interactions among multiple individuals. Regardless of whether the repeated advertisement is of the same version or varied versions, what is presented to consumers is produced and distributed by a single source—the advertised company. We believe multi-source repetition could be different from single-source repetition in terms of how receivers perceive it. Intuitively, it is more convincing when multiple individuals convey the same opinion, compared with a situation in which an opinion is repeated by a single source. Consumers usually adopt the "wisdom of the crowd" heuristic (Simmons et al. 2011), which predicts that independent judgments of a crowd of individuals are relatively more accurate than a judgment made by a single individual. In fact, repetition in e-WOM provides evidence not only for group judgment on the product level (i.e., general evaluation of the product usually depicted by star ratings) but also for group judgment on the product attribute level (e.g., repeatedly mentioning one product attribute). In addition to the impact of repeated information, repetition in e-WOM also exercises normative social influence (Cheung et al. 2009; Burnkrant and Cousineau 1975; Deutsch and Gerard 1955) which does not exist in other contexts.

The third feature is related to consumers' motivations to read e-WOM. Different from being exposed to an arbitrarily given, repeated sequence provided by researchers, firms, or other parties, consumers' review-reading behavior is essentially self-determined. Consumers seek user-generated content, such as online product reviews, to facilitate their decision-making. In other words, consumers would purposely decide what amount of WOM to look through and the amount of time to allocate processing such information. As a result, their decisions, such as whether to read more reviews, or search for more information, would depend on what they already read and how certain they feel about forming product evaluations or making purchase decisions. Accordingly, we would like to study the impact of repetition in e-WOM on consumers' information processing and review-reading behavior.

In summary, we clearly define our research questions as follows:

- What is the impact of repetition in e-WOM on persuasion? Specifically, how does repetition in e-WOM affect consumers' purchase intentions and product evaluations? What is the underlying mechanism that drives these effects?
- What is the impact of repetition in e-WOM on consumers' review-reading behavior?
- How can we attenuate the negative repetition effect in e-WOM? For example, could the inferred cause of repetition eliminate the credibility issue of repeated e-WOM, thus eliminating the negative impact on persuasion? Does the type of repetition moderate the repetition effect?

By understanding these questions, we are able to answer the following managerial questions: whether the firm could benefit from repetition in its product's e-WOM, and if so, when and how? Under what conditions could the repetition in e-WOM be detrimental to the firm? Based on the findings in this paper, firms could design their product review platform and display formats to present repeated e-WOM effectively in such a way as to avoid the negative impact.

Our research aims to offer three main contributions. First, we fill the gap in the repetition effect literature by specifically studying the impact of repetition in the e-WOM context. To the best of our knowledge, there is no existing paper investigating repetition as an integral feature of e-WOM content and studying the impact of repetition in e-WOM on consumer's affect, cognition, and choice behavior. Our results indicate that repetition in e-WOM affects consumer's perceptions differently from the well-studied inverted-U shape repetition effect in the advertisements.

Second, we contribute to the literature on the persuasiveness of e-WOM, particularly the impact of e-WOM content on consumer behavior. Table 10 provides a summary of selected literature on the impact of e-WOM content since 2010. Although prior literature identified several key factors that can affect the persuasiveness of online reviews, they looked mainly at the effectiveness of specific features for a single review rather than the integral feature on the product level, despite the simultaneous presentation of multiple reviews to consumers. Although each review could produce a different effect on a consumer's decision-making process, consumers do not independently evaluate each review in the review set. The impact of reading multiple reviews does not equal the summation across every single review. In other words, multiple reviews jointly affect how consumers integrate multiple opinions and form their own product evaluations. The level of repetitiveness in e-WOM is one of the most salient and important features that consumers could derive from e-WOM and thus could have a profound impact on consumer behavior.

Insert Table 10 about here

Third, our findings also provide implications for consumers' review-reading behavior. To our knowledge, very few studies have investigated consumers' review-reading behavior. Liu, Lee, and Srinivasan (2019) utilized review-reading data and empirically studied the impact of review content on the conversion rate. However, they did not directly address the causal relationship between review content and review-reading behavior. As they noted, further research could examine the effect of reviews on consumer's information-searching behavior and investigate questions such as "Will reading consistent reviews reduce consumer search?" Our research aims to answer this question by directly measuring people's online review-reading behaviors and their perceptions of information completeness. Moreover, we look at one prominent feature, i.e., repetitiveness in review contents, and study the causal impact on consumer's information-seeking process.

From a managerial point of view, our research may help firms understand how consumers process and perceive repeated e-WOM and identify critical factors that affect the persuasiveness and credibility of e-WOM. Our findings could guide firms in designing an online interface to gather information, provide guidelines for prospect reviewers, and display repeated user-generated content.

THEORETICAL BACKGROUND AND HYPOTHESIS

Repetition Effect

The repetition effect has been studied starting with psycho-esthetics literature of the 1970s and then across many disciplines and domains, including music appreciation (Margulis 2014; Szpunar, Schellenberg, and Pliner 2004), ritual (Boyer and Linard 2006), and mother-infant communication (Gratier and Gisèle 2009). Zajonc (1968) first introduced the "mere exposure effect" and argued that "mere exposure is a sufficient condition for attitude enhancement" (p. 15). This refers to the condition when a stimulus is accessible to an individual's perception, and as a result, the individual has higher hedonic value and increased liking or preferences toward the stimulus. Then, a series of studies replicated this finding using different stimuli, including words, text, human faces, physical objects, and music excerpts, for both animal and human subjects (Kunst-Wilson and Zajonc 1980). In addition, other research has extended the repetition effect to include affect, from subliminal to supraliminal, and found that as repetition increases to a saturation point, the evaluation decreases (Berlyne 1970, 1971). Overall, an inverted-U-shaped relationship between repeated exposure and evaluation has been detected.

Generally, two theories account for this non-monotonical repetition effect: the two-factor theory (Berlyne 1971) and the perceptual fluency model (Bornstein and D'Agostino, 1994) (for a review, see Szpunar, Schellenberg, and Pliner, 2004). Fluency is a metacognitive cue that captures how ease or difficulty is associated with processing information (Alter and Oppenheimer 2009). An increase in perceptual fluency is induced by repeated exposure to a stimulus, and it can occur effortlessly and automatically. Although it is not a process per se, it can affect people's decision-making and changes in attitude. The perceptual fluency model argues that changes in liking are due to people's attribution. People first attribute the perceptual fluency effect to the liking of the stimulus, and then, realize that perceptual fluency is essentially due to familiarization rather than liking. As a result, their liking of the stimulus decreases.

Another theory that explains the wear-in and wear-out patterns of the repetition effect is the two-factor theory (Cacioppo and Petty 1979; Berlyne 1970, 1971). Berlyne argues that evaluation improves in the first stage because of the positive habituation resulting from a reduction in the uncertainty and conflict initially induced by the novel stimulus. Participants felt more familiar with and less threatened by the stimulus. However, the evaluation then decreases when the level of repetition passes a certain point, and the increasing boredom overrides the positive effect. As the boredom is caused by tedium, satiation drives decreases in liking and preferences.

Moreover, repeated exposure of an individual to a stimulus object may not enhance only liking. When the stimulus is a message, repetition can also affect subjects' memory and cognition (Dellarosa and Bourne 1985; Deutsch 1972), the illusion of truth (Silva, Garcia-Marques, and Mello 2017; Dechêne et al 2009), and changes in attitude (Cacioppo and Petty 1979). Prior literature identified an inverted-U-shaped relationship between the level of repeated communication and message persuasiveness. Cacioppo and Petty (1979) proposed cognitive response as the mediator by explicitly documenting subjects' cognitive responses (i.e., counterarguments, favorable thoughts, and neutral/irrelevant thoughts) elicited during the exposures to a stimulus (e.g., an advertisement). They found that in the wear-in stage, subjects learned the message content and generated thoughts consistent with the message argument. Later in the wear-out stage, the agreement with the message decreased due to the depletion of supporting arguments and the increase in counterargument generation. Thus, they concluded that a moderate level of repetition has an optimal effect on persuasion.

Repetition in advertisement

In the marketing literature, previous studies have explored the curvilinear relationship between advertising repetition and its effectiveness (Pechmann and Stewart 1988; Berlyne 1970, 1971). The main dependent variables shifted from hedonic value and liking toward repeated stimuli to the persuasiveness of the repeated message (i.e., ads) and its communication effectiveness. Researchers have studied the effect of repetition in ads on consumers' attention (Pieters, Rosbergen, and Wedel 1999), memory (Hawkins, Hoch, and Meyers-Levy 2001; Singh et al. 1994; Unnava and Burnkrant 1991), and ads evaluations, and more importantly, brand evaluation and purchase intention (Anand and Brian 1990; Cox and Cox 1988). This dynamic ad effectiveness has been found in both lab studies (Batra and Ray 1986) and empirical settings (Bruce, Foutz, and Kolsarici 2012) in both offline (e.g., printed ads and television commercial ads) (Tellis 1988; Calder and Sternthal 1980) and online environments (e.g., online banner ads) (Chae, Bruno, and Feinberg 2019; Chatterjee, Hoffman, and Novak 2003).

A great deal of research involves understanding the underlying mechanism that explains the diminishing and subsequently negative effect of ad repetition, including two-factor theory (Berlyne 1971) and perceptual fluency theory (Nordhielm 2002; Bornstein and D'Agostino, 1994), as discussed in the last section. Calder and Sternthal (1980) propose two explanations: *inattention* (Pieters, Rosbergen, and Wedel 1999; Unnava and Burnkrant 1991) and *active information processing* **(**Cacioppo and Petty 1979**)**. Inattention, or differential attention explanation, refers to the way in which the effectiveness of repetition in ads vanishes when subjects pay a lower level of attention to later exposures. However, inattention cannot account for the wear-out stage when the impact becomes negative. Active information processing argues that changes in effectiveness are mediated by the consumer's cognitive response (i.e., the number of supporting arguments and counterarguments generated by the consumer). As the generation of these two types of thoughts produces different patterns over time, the effectiveness of ad repetition decreases and eventually becomes negative when the number of counterarguments overrides the number of supporting arguments.

In addition, Chae, Bruno, and Feinberg (2019) argues that the key concern for marketers is not only the "wear-out" stage, in which additional ad exposure negatively affects persuasion, but also the "weariness" stage, in which additional exposure of advertisement would lead to a negative marginal effect. Recent research has begun to study possible solutions to postpone the wear-out or eliminate the negative impact of too much ad repetition. Several moderators have been proposed, such as the ease of processing the message (Anand and Sternthal 1990), brand familiarity (Campbell and Keller 2003), and message complexity (Cox and Cox 1988). For example, Anand and Sternthal (1990) argue that complex stimuli, compared with simple stimuli, could postpone the wear-out stage. The rationale is that complex stimuli require more time to process relative to the time available for information processing. As a result, consumers need more time in the learning stage (i.e., wear-in) and, compared to simple stimuli, they reach a saturation point at a higher level of repetition.

We argue that the repetition effect in e-WOM may work through different mechanisms, due to the essential differences between e-WOM and other contexts. Although reading repeated reviews leads to higher perceptual fluency and higher familiarity, consumers do not derive higher hedonic value or a more positive evaluation of repeated e-WOM. Rather, they integrate repeated opinions and form their own evaluations of the product. Moreover, varying the level of repetition in e-WOM does not necessarily change the time needed for information processing, so the cognitive responses generated during repeated exposure may not be displayed in the same fashion as in the advertisement context. Therefore, prescriptions for solving the negative effect of ad repetition are no longer effective in the e-WOM setting. Take message complexity as an example. From the seller's or platform's perspective, it's not easy to modify user-generated content, as asking consumers to contribute more thoughtful reviews might discourage their contributions. In the next session, we discuss the repetition effect in e-WOM and form our hypothesis.

Repetition in e-WOM

As discussed earlier, repetition in e-WOM has its own unique features that could differentiate it from the repetition effect in other domains. In this research, we examine the impact of repetition in e-WOM on consumer's review-reading behavior, evaluations, and purchase behavior. We argue that the level of repetition, as well as the type of repetition in review content, could play a role in consumer behavior, and theories developed for the well-established inverted-U-shaped pattern of repetition effect in the advertisement are not applicable in the e-WOM context.

Perceived repetitiveness in e-WOM

Before studying the impact of repetition on persuasion, we need to form a clear definition of repetition in e-WOM and understand its antecedents. Prior literature on advertising or cognitive psychology has usually manipulated the level of repetition by changing the number of instances of exposure to the stimuli (e.g., presented once, twice, or three times) without explicitly measuring subjects' perceptions. Similarly, the level of repetitiveness in e-WOM could be also manipulated by changing the frequency of keywords or phrases in the review content. Repetition in e-WOM refers to repeatedly mentioning the same opinion in multiple reviews, regardless of the expression they use in review content. Thus, *a higher level of repetition in e-WOM could lead to higher perceptions of repetitiveness among consumers*.

We argue that both absolute and relative levels of repetition in e-WOM could affect how consumers perceive the review set, the reasons for which are as follows. First, perceived repetitiveness is a feature of the review set as a whole, so it is a function of not only the absolute number of repeated reviews but also the number of non-repeated reviews. Consumers may perceive three identical reviews as very repetitive if they only see five reviews altogether, but they may also form a low level of perceived repetitiveness when they see twenty reviews, including only three identical ones. Second, as discussed earlier, online information-searching behavior is endogenously determined by consumers, so the number of reviews read for each product also varies across purchase occasions. Moreover, the perceived repetitiveness also depends on how the reviews are displayed online. Specifically, the number of reviews displayed per page varies across websites. In our study, we operationalize the level of repetition by changing the relative share of repeated reviews in the review set, since perceived repetitiveness is a subjective feature of multiple reviews regarding to the product. Focusing on the relative share of repeated reviews in the review set allows us to compare different conditions and draw more general implications of the repetition effect in e-WOM.

Furthermore, we argue that verbatim and gist repetition contribute to perceived repetitiveness with different magnitudes. Consumers can automatically detect verbatim repetition within review content upon first glance. The perceived repetitiveness occurs spontaneously, even before devoting cognitive effort to processing the information. Gist repetition affects perceived repetitiveness at a later stage, as consumers start to encode and comprehend the information and then realize reviewers are talking about the same thing and thus perceive the reviews as more similar to each other. Therefore, we believe that *consumers perceive verbatim (vs. gist) repetition in e-WOM as more repetitive, controlling for the share of repeated reviews in the review set.*

Repetition in e-WOM and Persuasiveness

Several studies have explored the impact of review characteristics on persuasiveness beyond the aggregate-level information of star ratings, such as valence, volume, and variance. Prior literature investigated the effect of several dimensions of review content, such as identity information for the reviewer (Forman, Ghose, and Wiesenfeld 2008), content rating congruency (Tsang and Prendergast 2009), level of detailed information within the content (Jiménez and Mendoza 2013), irrelevant negative information (Shoham, Moldovan, and Steinhart 2017), two-sided information (Eisend 2006; 2007), type of language (including action or reaction phrases) (Moore 2015), affective content (Ludwig et al. 2013), language abstraction (Schellekens, Verlegh, and Smidts 2010), and the combination of rating and review content (He and Bond 2013) on consumers' evaluations. However, most of them focused on features on the level of single reviews neglecting the fact that consumers do get influence from multiple sources.

In theory, the persuasiveness of e-WOM can be affected by helpfulness (Schlosser 2011) and several credibility dimensions, such as the level of detailed information, perceived truthfulness, perceived trustworthiness, and source expertise (Reichelt, Sievert and Jacob 2014; Cheung et al. 2009). All these contributing factors work independently and jointly to affect consumers' evaluations and choices. We propose that repetition in e-WOM could affect persuasiveness through multiple dimensions, including perceived truthfulness and perceived information completeness.

We argue that repetition in e-WOM means higher consistency in review content and thus increases the persuasiveness of e-WOM. Kelley (1967), in his attribution theory, suggests that product evaluations should be informative about that product to the extent that multiple evaluations from different reviewers are in agreement. If numerous reviewers mention that the same product attribute is good (e.g., the battery life is long), consumers will attribute the superior quality to the product itself rather than to the reviewer's own experience (Fiske and Taylor 1991). Higher repetition in e-WOM implies a higher level of agreement on choice, opinion, and product evaluation, as well as a higher level of persuasiveness, because consumers may simply follow the "wisdom of the crowd" heuristic (Jiménez and Mendoza 2013) and believe that "consensus implies correctness" (Areni, Ferrel, and Wilcox 2000).

However, if the level of repetition is too high, the repetition effect in e-WOM would backfire and decrease the persuasiveness. This is because too much repetition could lead to credibility issues, as consumers may think that those repeated reviews are less truthful. The low level of perceived truthfulness of repetition could be due to the low level of perceived effort to craft and post repeated reviews (Grewal Stephen 2019; Kruger et al. 2004) or because consumers activate their persuasion knowledge (Campbell and Kirmani 2000), doubting the motivation to post identical reviews and postulating them to be fake reviews. The perceived truthfulness of e-WOM refers to consumers' perception of how honest the reviewer is and to what extent the review is telling the truth. Higher truthfulness means a review is more believable and leads to higher source credibility and higher persuasiveness (Priester and Petty 1995; Crowley and Hoyer 1994). Therefore, we expect perceived truthfulness to mediate the effect of repetition in e-WOM on persuasiveness. These hypotheses are stated formally below.

H_1: *When the level of repetition is not very high, consumers have higher product evaluation and purchase intention when facing high (vs. low or no) repetition in e-WOM. When the level of repetition is very high, the repetition effect in e-WOM backfires—high repetition in e-WOM leads to lower persuasiveness, lower product evaluations, and lower purchase intentions.*

H_2: *The effect of e-WOM repetition on persuasion is mediated by perceived truthfulness.*

Meanwhile, high repetition in e-WOM also means low variety in review content and few informative reviews, leading to low perceived information completeness. Perceived information completeness can lead to higher attitude certainty and greater confidence in decision-making (Rucker et al. 2014). When accompanied by overall positive valence, higher perceived information completeness can lead to higher purchase intentions (Shoham, Moldovan, and Steinhart 2017). In other word, the negative repetition effect in e-WOM could also be due to the lack of valuable information. Therefore, we also expect the perceived information completeness to mediate the relationship between repetition and persuasion.

H_3: *The effect of e-WOM repetition on persuasion is mediated by perceived information completeness.*

Type of repetition

In the advertisement literature, there is evidence suggesting that varying the content of the repeated message can eliminate the satiation stage of repetition, which is the so-called "repetition-variation hypothesis" (Schumann, Petty, and Clemons 1990). It has been found that the use of varied ads can forestall tedium and have a better impact on recall and attitude measures, which is consistent with the "encoding variability hypothesis" proposed by Madigan (1969). Similar to the repetition-variation hypothesis in an advertisement context (Appleton-Knapp, Bjork, and Wicken 2005; Haugtvedt et al. 1994; Schumann, Petty, and Clemons 1990) in which varied repeated exposures are proven to work better than repeated exposures to a single stimulus, in linguistic repetition, there are exact repetition (i.e., verbatim) and varied repetition (i.e., gist). We argue that the repetition variation-hypothesis can be applied to the e-WOM context, and the type of repetition could also moderate the effectiveness of e-WOM, although through different underlying mechanisms.

The difference between verbatim and gist repetition has been studied in other principles, such as cognitive psychology and learning (Glover and Corkill 1987; Dellarosa and Bourne 1985). Based on the accessibility hypothesis (Cuddy and Jacoby 1982), subjects require more effort and time to process gist repetition than verbatim repetition. In this view, subjects tend to retrieve the previous encoding of information when faced with repeated exposure. In verbatim repetition, full encoding occurs only on the first presentation, and all subsequent repetition is partially encoded. While gist repetitions are different in surface structure, the retrieval cues they offer are not sufficient for retrieval of the prior encoding. As a result, subjects must fully encode each gist repetition. This encoding variability explanation also prefers gist repetition in terms of its superior memorability (Unnava and Burnkrant 1991). However, there is no evidence to show that they have different impacts on the subject's judgment, such as the immediate illusion of truth (Silva, Garcia-Marques, and Mello 2017).

Although prior literature concludes that the impact of repetition on memory is independent of its impact on evaluations (Peretz, Gaudreau, and Bonnel 1998), we argue that different types of repetition (verbatim vs. gist) could impact not only how consumers encode and memorize information via semantic satiation but also the persuasiveness of the information. First, the level of cognitive effort required to process different types of repetition could influence consumer judgment based on both repeated and non-repeated information. Second, the identical surface structure of verbatim repetition leads consumers to generate negative tactic–related thoughts regarding the credibility of the information and subsequently affects the persuasiveness.

H_4: *The type of repetition affects the repetition effect in e-WOM on persuasion, in the sense that the negative effect would be eliminated by gist (vs. verbatim) repetition.*

Repetition in e-WOM and Review-reading Behavior

As we mentioned in the introduction, consumers seek user-generated content to facilitate their decision-making. Instead of passively receiving information from others, consumers' review-reading behavior is self-determined and self-paced, directly depending on the amount of information included in review content and its presentation format. Because reading product reviews requires cognitive effort, consumers are expected to stop reading additional reviews when they believe the additional benefit from reading more reviews is relatively low or they feel they have already grasped all the useful information and thus have higher perceived information completeness. On the contrary, if consumers are uncertain about product judgment and purchase decisions, they choose to read more reviews or seek information from additional sources.

Based on the research on attitude certainty and confidence, a sense of completeness can influence consumers' information-searching behavior in terms of the volume of reviews they read and the time they spend searching for additional information. When there is a high level of repetition in the review content, consumers may want to seek more information. That happens because the repeated reviews provide no additional useful information, which contradicts consumers' prior belief about the amount of information that they could obtain from reading online reviews. Therefore, facing high repetition in e-WOM may cause consumers to keep searching for and reading more reviews. As a result, the search time and the number of reviews read by consumers will be higher than in the lower level of repetition condition. Formally, we propose the following hypothesis:

H_5: *The repetition in e-WOM would affect participants' review-reading behavior through perceived information completeness; specifically, low information completeness leads to further information-seeking behavior.*

Moderating the Effect of Repetition on Persuasion

Earlier in the paper, we proposed that high repetition in e-WOM would have a negative impact on persuasion due to low perceived truthfulness, so one implication is that the negative effect of high repetition can be attenuated by resolving the credibility issue. E-commerce websites sometimes provide pre-defined content or auto-suggestions to reviewers to make the review writing process more fluent and less costly. Consequently, customers post reviews repeated verbatim without composing their own assessment of the product. The repetition takes place because of the computer-aided functions rather than the reviewers' deliberate intentions.

We argue that providing an exogenous cause of repetition should convince consumers that repetitive reviews are truthful and thus alleviate the negative effect of repetition on persuasion. If consumers believe that a high share of repeated e-WOM is generated by reviewers, the reviewers' credibility would be challenged, as we discussed previously, whereas if consumers believe the repetition is generated by a computer, the truthfulness of repetition could be maintained. Therefore, given the same level of repetition in e-WOM, consumers would have lower purchase intentions under the customer-generated condition than the computer-generated condition. The perceived credibility would mediate this process. On the other hand, we expect there to be no difference between customer-generated and computer-generated repetition when the amount of repetition is low.

H_6: *When customers infer that the cause of repetition in e-WOM is exogenously determined (i.e., computer-generated) rather than endogenously determined (i.e., consumer-generated), the truthfulness issues of a high (vs. low) share of repetition in e-WOM can be resolved, as can the negative effect of high repetition in e-WOM on persuasion.*

THE PRESENT RESEARCH

Overview of Studies

We test these hypotheses in a series of studies (see Table 11). Study 1 tests the main effect of repetition in e-WOM in a choice setting to see whether the relationship is curvilinear—meaning that repetition backfires when extremely high (H_1). Study 2 tests the negative effect of repetition by measuring product evaluation and purchase intention (H_1) and the mediation role of perceived truthfulness (H_2) and information completeness (H_3). Study 3 replicates Study 2 and tests additional hypotheses on the effect of the type of repetition (H_4). In addition, Study 3 also explores the repetition effect on consumers' review-reading behavior (H_5). Study 4 provides evidence for H_6 by directly manipulating the cause of repetition to be either endogenous (i.e., consumer-generated) or exogenous (i.e., computer-generated). Study 1 measures participants' absolute choice while the others measure participants' evaluation given the information about the product and a set of reviews. The sample size was decided based on the rule-of-thumb that each cell has about seventy-five (or more) participants and the same rule was applied to all studies in this paper. We also did power test to show the validity for the sample size.

Insert Table 11 about here

Study 1: Repetition in e-WOM and Product Choice

The first study tested how consumers perceive repetition in e-WOM in a choice setting. Participants were asked to choose between products with different review sets from different product categories. Study 1 focused on verbatim repetition and manipulated the level of repetition by including different numbers of repeated reviews in the review set. Study 1 also tested the potential boundary condition at which the impact of repetition backfires when the absolute level of repetition is exceedingly high. Our hypothesis suggests that participants will prefer the option with a higher level of repetition over the low repetition option, but a too-high level of repetition would be harmful, controlling for other product and review characteristics.

Four choice pairs were presented in the stimuli, including one filler task, and were designed to capture three different types of comparison in terms of the level of repetition—low repetition vs. moderately low repetition, low repetition vs. moderately high repetition, and low repetition vs. high repetition (described below). Meanwhile, it was ensured that product and review characteristics, such as product image, price, and aggregate product rating, were similar and indistinguishable in each choice pair.

Design, Stimuli, and Procedures

The design of Study 1 contained one within-subject factor—the share of repetition in the review set (three types, described below). The study was conducted online, and 224 MTurk workers (Mean age = 39.68, 61.36% female) were hired in exchange for a cash reward[15] ($.5). Participants were told that they would indicate their preferences over several choice pairs based on the information provided.

Four choice pairs were presented to each participant, covering four different product categories (headphones, Airbnb room, café, and microwave as filler). On each screen, two options were displayed side by side, and the provided information included the product image, product name, price, average product rating, and a set of customer reviews (see Figure 13). In all cases, the review set contained ten reviews, and ratings for single reviews were not included to avoid distraction. After examining the information, participants were asked to report their discrete choice between the two options (e.g., "If you were shopping for headphones, would you:" 1 = "Purchase option A" or 2 = "Purchase option B"?).

Insert Figure 13 about here

Four levels of repetition were examined in the study and manipulated by varying the number of repeated reviews in the review set. Each option contained a review set with 10 reviews presented in a random ordering. The *high*, *moderately high*, *moderately low*, and *low* repetition

[15] A post-hoc power test for within factor ANOVA test was conducted using G*Power and revealed 1.0 power which is greater than 80%, confirming the validity of the sample size.

options contained nine, seven, five, and three identical reviews, respectively (see Table 12). Three comparison types were designed in which participants compared the *low* repetition option with a higher repetition option (see Table 13). In the first type of comparison (*high–low* comparison), participants chose between the *low* repetition option and the *high* repetition option. In the second type of comparison (*moderately high–low* comparison), participants chose between the *low* repetition option and the *moderately high* repetition option. And finally, in the third type of comparison (*moderately low–low* comparison), participants chose between the *low* repetition option and the *moderately low* repetition option. Participants encountered all three types of comparison, as well as all product categories. Stimuli were designed based on a Latin square design, in which participants were randomly assigned to one of the three groups and saw all types of comparison and product categories (see Table 13). A filler choice pair (microwave) was also included to avoid repetition and disguise the manipulation of repetition, in which both options contained review sets with a *low* level of repetition, while one option had a higher average valence than the other. Finally, the product categories were randomly presented, and the left–right position of the two products was counterbalanced across choice pairs.

Insert Table 12 and Table 13 about here

Results

Our hypothesis indicates that participants will prefer the option with a *relatively higher* level of repetition than the *low* repetition option, but the preference decreases as the absolute level of repetition increases for the higher repeated option. Too much repetition hurts the evaluation and thus participants would prefer the option with a lower level of repetition. Table 14 presents participant’s choice for the relative share of the higher repetition option in the choice pairs. The first glance of the results indicates a pattern consistent with predictions: the higher repetition option was chosen by 53.4% of participants for the moderately low option and 47.8% of participants for the moderately high option, but the extremely high repetition option was chosen by only 41.3% of participants. Meanwhile, we also observed participants have a consistent pattern for their preferences on the product category level, indicating that the product information, other than customer reviews, have a significant impact on participants' choice.

Insert Table 14 about here

A binary logistic regression was conducted, in which the probability of choosing the low repetition option is predicted by the type of comparison, product category, and the position of the low repeated option. The overall logistic model was statistically significant, $\chi^2(5) = 43.2$, $p < .000$. We found a significant effect for the type of comparison (*Wald* = 6.71, *p* = .035), a significant effect for the product category (*Wald* = 32.27, *p* = .000), and a marginally significant effect for the position (*Wald* = 3.42, *p* = .065). Compared to the *moderately-low-low* comparison, there is a higher probability (around 1.7 times) for participants to choose the lower repeated option under the *high-low* comparison (β= 0.51, *p* = .01), while there is no significant difference between the *moderately-high-low* comparison and the *moderately-low-low* comparison (*p* = 0.25). In terms of the position, participants slightly preferred the option located on the right (β= 0.296, *p* = .065).

Discussion

Study 1 provided initial evidence for our hypothesis that the impact of repetition in e-WOM is not linear and depends on the level of repetition in the review set. For all types of comparisons, the probability of choosing the higher option is different. When the level of repetition is not too high (i.e., *moderately low–low* comparison), participants were more likely to select the option with a relatively higher level of repetition in the e-WOM, which differed from situations in which the repetition level was too high in the higher repetition option (i.e., *high–low comparison*). The pattern was consistent across multiple product categories and different comparison contexts.

Although outside the scope of our hypotheses, we found a significant main effect for the product category (i.e., preference for one set of product information over the other). For example, overall, participants preferred the Pioneer HDJ-X5 headphones compared to the Sennheiser-HD 4.40 headphones, regardless of the level of repetition in the review set (see Appendix E for the stimuli). We argue that plenty of variables could contribute to this consistent pattern, including brand name, price, and product image. We chose to use the product category fixed effect to capture the variation of product information in the choice pair because it is outside the focus of current research. To clearly identify the repetition effect on persuasion and avoid confounding effects from other factors, in the following studies, we presented only one product to participants and asked them to report their product evaluations and purchase intentions, as well as their perceptions of the repeated review set.

Study 2: Repetition in e-WOM and Persuasion

The objective of Study 2 is two-fold. First, we replicated the main effect of repetition in e-WOM on persuasion (i.e., the negative effect of high repetition) by measuring participants' product evaluation and purchase intentions (H_1). Second, we identified the mediation role of perceived truthfulness and perceived information completeness in the relationship between repetition in e-WOM and persuasion (H_2 and H_3). We employed a 2-cell (share of repetition: high vs. low) between–subject design. The level of repetition was manipulated by the number of repeated reviews included in the review set. Unlike in from Study 1, participants needed to examine only one product rather than choose from product pairs.

Design, Stimuli, and Procedures

One hundred and sixty-five participants (43.56% female; Mean age = 43.06) were recruited from MTurk (payoff $.60)[16]. Participants were randomly assigned to one of the two conditions and were asked to imagine that they were interested in choosing a one-night room from Airbnb. They were provided with a room webpage with both room information (see Appendix E) and a set of twenty online reviews. Each condition had the same room information, volume of reviews, star ratings, and reviewer information (avatar, reviewer's name, and date). The share of repetition was manipulated by the number of verbatim reviews in the review set. Specifically, under the high repetition condition, fourteen out of twenty reviews were identical (i.e., "*I really enjoyed my stay*"), while the same review was repeated only three times under the low repetition condition, coupled with uninformative reviews (e.g., "*Overall good stay*," and "*Good travel*"). We also included informative reviews in both conditions to avoid redundancy in the review set. Informative reviews were reviews mentioning specific product attributes instead of expressing general assessments (e.g., "*The room was super clean,*" and "*Excellent host*"). See Appendix E for the detailed stimuli. After reading the reviews, participants were asked to answer a set of questions regarding the information presented.

Measures

[16] A priori power test for one-way ANOVA analysis using G*Power indicated that the sample size should be no less than 128 in order to achieve 80% power.

Participants first indicated their *purchase intentions* (PI) on a three-item scale with origins in Zeithaml, Berry, and Parasuraman (1996) "*I would consider booking this room*", "*It is possible that I would book this room*", "*I would give this room a try*" (1 = "*Not at all*", 7 = "*Very much*"; $\alpha = 0.968$). And they also rated their evaluation of the room using two questions "Overall, I think the listing on Airbnb is:" (1 = "*very bad*", 7 = "*very good*", and 1 = "*very unfavorable*", 7 = "*very favorable*"; $\alpha = 0.975$). We also measured participants' *perceived repetitiveness*, *perceived information completeness,* and *perceived truthfulness* of the set of reviews. Factor analysis showed that all five items for both product evaluation and purchase intention were loaded on the same factor, indicating all the items measure the impact on persuasion. And items for other constructs were loaded on single factors, respectively. In this paper, we reported the repetition effect on product evaluation and purchase intention separately, noting that combining the two measures revealed similar results.

Perceived repetitiveness is measured by asking about *redundancy* using two items "The content of these reviews looks like the same thing over and over" and "reading these reviews was very boring," and *similarity* of the review set using two items "These reviews were very similar to each other" and "Each review describes different aspects about the product," (1 = "*Not agree at all*", 7 = "*Totally agree*"), modified from Redden (2008). Although the author specified two different constructs under the perceived repetitiveness, we found that the four items were loaded on the same factor, indicating a high internal consistency among all four items ($\alpha = 0.799$). Therefore, they were averaged to a single repetitive index.

Perceived truthfulness is measured by asking participants to respond to the following items: "I believe these reviews are telling the truth," "I believe these reviews are nondeceptive," and "I believe these reviewers are honest" (1 = "*Not agree at all*," 7 = "*Totally agree*"), with three items loaded on one factor ($\alpha = 0.962$). Participants also reported their *perceived information completeness* when they made the decision, measured using the items "I feel confident that I have a complete picture regarding the room" (Shoham, Moldovan and Steinhart 2017) and "I think I have enough information about this room" (Rucker et al. 2014) (1 = "*Not agree at all*," 7 = "*Totally agree*"; $\alpha = 0.927$).

Finally, we asked participants about their prior experience using Airbnb.com with the question, "How much experience do you have with Airbnb stays?" (1 = "*None or very little*," 7 = "*A lot*") to control for their familiarity with the platform. We finished by asking demographic questions.

Results

Manipulation on Perceived Repetitiveness. A 2-cell (repetition: high vs. low) between-subjects ANOVA on perceived repetitiveness yielded a significant main effect of repetition (F(1, 163) = 26.28, p < .000, $\eta_p{}^2$ = .139). As intended, participants perceived the review set as more repetitive when all the more reviews are repeated (M_{high} = 6.067, SD = .87 vs. M_{low} = 5.268, SD = 1.12).

Perceived truthfulness. A 2 (the share of repetition: high vs. low) between-subjects ANOVA on perceived truthfulness yielded a significant main effect of the share of repetition (F(1, 163) = 28.675, p < .000, $\eta_p{}^2$ = 0.899). As predicted, participants believed the reviews are more truthful under the low (vs. high) repetition condition ($\mathrm{M_{high}}$ = 3.87, SD = 1.65 vs. $\mathrm{M_{low}}$ = 5.14, SD = 1.37).

Perceived information completeness. A 2 (repetition: high vs. low) between-subjects ANOVA on perceived information completeness yielded a significant main effect of repetition

($F(1, 163) = 15.30$, $p < .000$, $\eta_p{}^2 = .086$). As predicted, participants believed that they had a more complete picture about the product under the low (vs. high) share of repetition condition ($M_{high} = 3.79$, SD = 1.84 vs. $M_{low} = 4.85$, SD = 1.64).

Product evaluations and purchase intentions. A similar on product evaluation yielded a significant main effect of repetition ($F(1, 163) = 6.334$, $p = .013$, $\eta_p{}^2 = .037$; Figure 14A). Participants reported a higher product evaluation under the low (vs. high) share of repetition condition ($M_{high} = 4.84$, SD = 1.53 vs. $M_{low} = 5.42$, SD = 1.43). Similarly, the impact of repetition in e-WOM on purchase intention is also significant ($F(1, 163) = 6.528$, $p = .012$, $\eta_p{}^2 = .039$; Figure 14B). Participants reported a higher purchase intention under the low (vs. high) repetition condition ($M_{high} = 4.55$, SD = 1.92 vs. $M_{low} = 5.26$, SD = 1.65).

Insert Figure 14 about here

Mediation. To test our hypothesis, we conducted a mediation analysis with the level of repetition as the independent variable, perceived truthfulness as the mediator, and product evaluation as the dependent variable (Process Model 4; Hayes 2018). Factor analysis reported that perceived repetitiveness, perceived truthfulness and product evaluation were loaded at different factor[17], indicating they were measured different constructs. The results showed the indirect effect of the share of repetition on product evaluation through perceived truthfulness was significant ($b = 0.80$, 95% CI = [0.48, 1.15]), confirming the proposed process (see Figure 15 for the tested model and mediation results).

Insert Figure 15 about here

[17] Purchase intention (three items) and product evaluation (two items) were loaded on the same factor, representing the persuasiveness of e-WOM. In the current study, we chose to report the results separately, but combing them into one index would lead in similar results.

A similar analysis with the share of repetition as the independent variable, perceived information truthfulness as the mediator, and product evaluation as the dependent variable also yielded a significant indirect effect of the share of repetition on product evaluation through the perceived information completeness (b = 0.59, 95% CI = [0.28, 0.94]), confirming the proposed process (see Figure 16. for the tested model and mediation results). Figure 15 and Figure 16 also presented the results for mediation analysis on purchase intention.

Insert Figure 16 about here

Discussion

Study 2 replicated the repetition effect of e-WOM by directly measuring participants' product evaluation and purchase intentions. Containing a high (vs. low) level of repetition in the review set decreased the persuasiveness, the perceived truthfulness, and the perceived information completeness of the e-WOM regarding the product.

Study 2 highlighted the negative impact of repetition in e-WOM and investigated the underlying mechanisms. We found that the persuasiveness of e-WOM is a function of not only the objective information embedded but also the subjective perception customers developed while reading the reviews. In the study, we controlled for the amount of information across two conditions by including the same set of informative reviews (i.e., reviews mentioning certain product attributes) and keeping the valance and volume of e-WOM constant. However, participants still formed different perceptions toward the product depending on how reviewers expressed themselves and, more importantly, the composition of multiple reviews as a whole. We know that people are naturally influenced by others when giving public opinions. For example, they may fixate on certain expressions or opinions in prior examples. This phenomenon is called cognitive fixation (Smith et al. 1993; Marsh et al. 1996) and has been found in the field of creative cognition and empirically in the context of crowdsourcing platforms. In the context of e-WOM, cognitive fixation causes repetition in e-WOM without firm interventions. Our results suggest that the negative impact of repetition effect in e-WOM can be profound and thus cannot be neglected by firms and platforms. Therefore, in the following study, we aimed to explore the means to eliminate this negative impact by changing people's perceptions of repeated e-WOM.

Study 3: Repetition, Persuasion, and Review Reading Behavior

The objective of Study 3 was to replicate the main findings from Study 2 (H_1) using: 1) different levels of repetition; 2) a higher number of customer reviews; and 3) a natural setting in which reviews were presented in multiple pages. Second, we tested the effect of the type of repetition (H_4) by comparing verbatim and gist repeated reviews. Study 3 also investigated the repetition effect on consumer's information-searching processes by endogenizing participants' review-reading behavior (H_5). To do so, we employed a 2 (type of repetition: verbatim vs. gist) by 2 (level of repetition: low vs. high) between-subject design.

Design, Stimuli, and Procedures

Three hundred and twenty participants (42.7% female; Mean age = 40.6) were recruited from MTurk ($.75)[18]. Participants were randomly assigned to one of the four conditions. The procedure resembled the previous study in which participants examined one Airbnb room

[18] A priori power test for two-way ANOVA analysis using G*Power indicated that the sample size should be no less than 179 in order to achieve 80% power.

(different from the stimuli in Study 2). Participants were presented with product information, followed by a set of customer reviews (Figure 17). After reading the first page of reviews, participants could choose to read more reviews by clicking on "*Keep reading*" to see the next page. If participants believed there was no need to read more, they could click "*I'm finished reading the reviews*" to skip additional reviews and answer the questions. Participants were able to read four pages at maximum, with ten reviews per page. The number of pages read by participants for each page was collected to measure participants' review-reading behavior. On each page, the share of repetition was manipulated in a similar fashion as in Study 2, where six (vs. two) out of ten reviews were either verbatim- or gist-repeated under the high (vs. low) repetition condition. The type of repetition was manipulated using synonyms or meaning-preserving expressions to describe the repeated reviews (see Table 15). See Appendix E for the stimuli of the Airbnb room.

Insert Figure 17 and Table 15 about here

After examining the information, participants followed the same procedures as in Study 2 and reported their purchase intentions and product evaluation, as well as their perceptions of the review set. We start by reporting participants' review-reading behavior because participants' decisions about information-searching behavior would have impacted their perceptions of the reviews and the product.

Results for Review-reading Behavior

Number of pages read. Figure 18 plots the frequency of participants' reading behavior, and Figure 19 plots the average number of pages read across conditions. A 2 (the share of repetition: high, low) x 2 (the type of repetition: verbatim, gist) ANOVA on the number of pages read only yielded a significant main effect of the share of repetition in e-WOM ($F(1, 316) = 3.73$; $p = 0.05$). Both the type of repetition and the interaction are insignificant (ps > 0.25). Participants read more pages when the share of repetition is high (vs. low) (Ms = 2.08 vs. 1.84, $p = .05$). Drawing on the results in Study 2, high (vs. low) repetition in the e-WOM implies less information per page, causing people to continue the information searching process when they get insufficient information.

Insert Figure 18 and Figure 19 about here

Whether participants read more to fulfill their need for information? A 2 (the share of repetition: high, low) x 2 (the type of repetition: verbatim, gist) ANOVA on perceived information completeness yielded a significant main effect of the repetition in e-WOM ($F(1,316) = 4784$, $p = .029$; $\eta_p{}^2 = .015$), qualified with a marginal significant interaction effect ($F(1,316) = 3.154$, $p = .077$; $\eta_p{}^2 = .010$; see Figure 20). Consistent with Study 2, participants reported a lower level of information completeness under the high (vs. low) repetition ($Ms = 5.084$ vs. 5.416). Again, only under the high share of repetition, participants reported a lower level of information completeness when facing with the verbatim (vs. gist) reviews ($Ms = 4.867$ vs. 5.300; $F(1, 316) = 4.036$, $p = .045$; $\eta_p{}^2 = .013$). There is no significant difference across the two low repetition conditions. Such results indicated that even though we endogenized the information-seeking behavior and allowed participants to choose when they wanted to stop, their perceived information completeness was not able to be fulfilled. In other word, the lack of information does not always lead to further reading. If people believe the expected utility (i.e., information) they could derive from reading additional reviews is less than the effort they must invest, they could terminate the process even with low perceived information completeness. In our case, the share of repetition was kept constant for each page within conditions, so participants, after reading the first or second page, could infer the additional information embedded in the following pages, and therefore, they may stop reading to avoid useless works.

Insert Figure 20 about here

Results for Persuasion

Manipulation checks on perceived repetitiveness. A 2 (share of repetition: high vs. low) x 2 (type of repetition: gist vs. verbatim) ANOVA on perceived repetitiveness yielded a significant main effect of the share of repetition ($F(1,315) = 16.64$; $p < .000$; $\eta_p^2 = .04$; Figure 21), controlling for the number of pages read. As intended, participants reported a higher level of perceived repetitiveness under the high (vs. low) share of repetition condition ($M_{\text{high}} = 5.56$, SD = 1.08 vs. $M_{\text{low}} = 5.07$, SD = 1.14). And not surprisingly, participants who read more pages of reviews also reported a higher level of perceived repetitiveness ($F(1,315) = 7.74$, $p = .01$; $\eta_p^2 = .02$). Both the main effect of the type of repetition and the interaction effect were insignificant ($p > .12$)

The results seemed to be inconsistent with our hypothesis as the impact of the type of repetition is insignificant. We argued that it was due to the easily overlooked differences between the two low repetition conditions. As shown in Figure 18, nearly half of the participants only read one page of reviews before answering the set of questions. And they were highly likely to form similar perceived repetitiveness toward the review set, since the stimuli under the low gist and low verbatim repetition conditions only have one-word difference per page (i.e., the synonym word used to replace the verbatim adjective word in the repeated review, see Appendix E). While under the high repetition condition, we observed participants perceived the e-WOM under the high verbatim (vs. high gist) condition as more repetitive (M_{gist} = 5.363 vs. M_{verbatim} = 5.719), which was consistent with our hypothesis.

Insert Figure 21 about here

Product evaluations and purchase intentions. We found similar effects for repetition on both product evaluations and purchase intentions. The number of pages read by participants showed no direct impact on participants' perceptions and behavioral intentions, thus was excluded from the ANOVA analysis.

A two-way ANOVA yielded a significant main effect of the share of repetition on product evaluations ($F(1,316) = 5.05$, $p = .035$; $\eta_p{}^2 = .014$) as well as a significant interaction effect between the share and the type of repetition ($F(1,316) = 11.70$, $p = .001$; $\eta_p{}^2 = .032$). The main effect of the type of repetition was insignificant ($p = .301$). Consistent with prior studies, participants formed a more negative evaluation toward the product under the high (vs. low) share of repetition condition (M_{high} = 5.83, SD = 1.19; M_{low} = 6.09, SD = .95; see Figure 22). In the high repetition conditions, participants evaluated the product more negatively when facing with verbatim (vs. gist) repeated reviews (*Ms* = 5.58 vs. 6.09; $F(1, 316) = 9.04$, $p = .003$; $\eta_p{}^2 = .028$). While in the low repetition conditions, the difference between the two types of repetition was insignificant (*Ms* = 5.96 vs. 6.22; $F(1, 316) = 2.42$, $p = .121$). The results suggested that gist (vs. verbatim) repetition exerts a different impact on participants' perception. Even with a high level of perceived repetitiveness, the negative effect of high repetition on product evaluation was eliminated for gist repetition. This is important since we could design strategies for sellers and platform designers to eliminate the negative effect of repetition by guiding consumers' online contributions.

Insert Figure 22 about here

Similar analysis revealed a significant interaction effect on the purchase intention (F(1,316) = 4.367, p = .037; $\eta_p{}^2$ = .014), and a marginal significant main effect of the share of repetition (F(1,316) = 3.663, p = .057; $\eta_p{}^2$ = .011; see Figure 23). The effect of repetition type was insignificant (p = .773). Consistent with prior studies, participants indicated a lower level of behavior intention under high (vs. low) repetition condition (M_{low} = 5.904, SD = 1.155; M_{high} = 5.631, SD = 1.388). In terms of the repetition type, we found that participants facing with verbatim reviews reported a significant lower purchase intention under high (vs. low) repetition condition (Ms = 5.462 vs. 6.031; F(1, 316) = 8.014, p = .005; $\eta_p{}^2$ = .025). While under gist conditions, there was no significance between the high and low share of repetition conditions (p = .901).

Insert Figure 23 about here

Perceived truthfulness. A 2 (the share of repetition: high, low) x 2 (the type of repetition: verbatim, gist) ANOVA on perceived truthfulness yielded a significant main effect of the repetition in e-WOM (F(1,316) = 3.981, p = .047; $\eta_p{}^2$ = .012), a significant main effect of the type of repetition (F(1,316) = 5.905, p = .016; $\eta_p{}^2$ = .018), qualified with a marginal significant interaction effect (F(1,316) = 2.902, p = .089; $\eta_p{}^2$ = .009; see Figure 24). Consistent with the results in Study 2, participants considered high (vs. low) repetition as less truthful (Ms = 5.401 vs. 5.686). And the type of repetition also affected the perceived truthfulness. As predicted, verbatim is considered less truthful than gist (Ms = 5.72 vs. 5.37). Recall that, across the two low repetition conditions, there is no significant difference in terms of perceived repetitiveness; here, we also did not find a significant difference in terms of perceived truthfulness (p = .607). Only under the high share of repetition, participants reported a higher level of truthfulness when facing with the gist (vs. verbatim) reviews (Ms = 5.696 vs. 5.105; $F(1, 316) = 8.491$, $p = .004$; $\eta_p^2 = .026$).

Insert Figure 24 about here

Mediation through perceived truthfulness. To replicate the results in Study 2, we tested whether the perceived truthfulness mediated the effect of repetition in e-WOM on persuasion (see Figure 25 for the tested model and the mediation analysis results). As we showed earlier, there was no significant difference between low-gist and low-verbatim repetition conditions in terms of participants' perceptions, product evaluations, and purchase intentions, so we focused on the two high-repetition conditions and answered the question whether the verbatim repetition resolve the negative impact on persuasion through perceived truthfulness. Using the high-verbatim repetition condition as the reference group, we found that the relative indirect effect of high-gist repetition on product evaluation through perceived truthfulness was significant (b = 0.31, 95% CI = [0.08, 0.54]), so was the relative indirect effect of low repetition (b = 0.30, 95% CI = [0.09, 0.49]). Similar results were found using purchase intention as the dependent variable: the relative indirect effect of high-gist repetition on purchase intention through perceived truthfulness was significant (b = 0.36, 95% CI = [0.08, 0.67]), so was the relative indirect effect of low repetition (b = 0.36, 95% CI = [0.11, 0.62]).

Insert Figure 25 about here

Discussion

In this study, we replicated the results from Study 1 and Study 2 by identifying the negative effect of the high repetition in e-WOM and product evaluation (and purchase intention). We provided evidence to support H_1 in a more natural setting in which participants' information seeking was endogenized. Second, gist repetition seems to resolve the negative effect of high repetition because it not only implies a different level of repetitiveness but also affects persuasion. Besides replicating the main finding of the repetition effect, Study 3 provided preliminary evidence of the repetition effect on review-reading behavior. We found that participants tended to continue information searching under the high repetition conditions even though the low information completeness could not be offset. Moreover, the type of repetition also affected participants' information-searching behavior. Participants considered the reviews they read in the high verbatim- (vs. gist-) repetition condition to be more repetitive and less informative, and they were therefore more likely to continue reading after the first page.

Perhaps more importantly, we found that allowing people to read more reviews did not help solve the negative perceptions elicited by high repetition. Further study could explore possible ways to increase the perceived information completeness of high repetition e-WOM (e.g., providing a summary of repeated information at the top). In the next study, we will test another technique—moderating the cause of repetition—which aims to resolve the negative repetition effect in e-WOM through another route (i.e., perceived truthfulness).

Study 4: The Moderating Role of the Cause of Repetition

The aim of Study 4 was to test whether an inference about the cause of repetition could moderate the relationship between repetition and persuasion (H_6). We aimed to provide a potential way to eliminate the adverse impact of high repetition by changing the perception of the cause of repetition to be exogeneous and computer generated. In addition, we ruled out the potential mechanism for the negative repetition effect by measuring the perceived effort of posting e-WOM.

We manipulated participants' inferences about the cause of repetition using different reviewing experiences. For the computer-generated condition, participants were presented with an interface to write a review where pre-defined review contents were provided. The layout of the website was designed to mimic some e-commerce websites on which suggestions and pre-defined review content are provided, such as Uber.com and Instacart (See Figure 26), to reduce the cost of posting reviews. Buttons usually display phrases frequently used by other reviewers so that customers can select the ones they agree with instead of typing the content in the text box. To make the two conditions comparable, we included the text box function in both, although it is optional for some websites. For the customer-generated condition, the interface is similar to most e-commerce websites on which customers can select the star rating and write comments in the text box.

Insert Figure 26 about here

We argue that participants perceive repeated e-WOM differently under the two repetition cause conditions. It is abnormal to have too many identical reviews in the review set if each customer composes his/her own evaluation independently. When participants faced reviews with a high level of verbatim repetition, they doubted the truthfulness and potentially the motivation of such reviews, as shown in previous studies. In contrast, if participants had experienced the computer-facilitated review writing process, they were more likely to attribute the repetition to the design of the website rather than reviewers. Therefore, we expect products with a high share of repeated reviews to be seen as less truthful and thus have a lower evaluation than with a low share of repeated reviews only under the customer-generated condition and not the computer-generated condition.

Design, Stimuli, and Procedures

The study used a 2 (the cause of repetition: customer-generated reviews vs. computer-generated reviews) by 2 (repetition: high vs. low) between-subject design. Five hundred and forty-seven participants were recruited from MTurk and were randomly assigned to one of the four conditions. Five participants who did not correctly answer the attention check question were removed from the dataset. Therefore, we ended up with five hundred and forty-two participants (Mean age = 43.13; 49.71% female)[19].

The cover story explained that the study was about designing a user-friendly e-commerce platform. Participants were informed that they were invited as testers to try the website and provide feedback to the designer. The participants were asked to complete two tasks. First, participants were asked to try a website interface designed for consumers to write product reviews. In the customer-generated reviews condition, participants were asked to provide a star rating and write review text in the textbox. In the computer-generated reviews condition, a function in addition to the star rating and textbox was included: four pre-existing buttons were presented on the website (shown in Figure 27), including "*A+ seller*," "*Great purchase*," "*Item as described*," and "*Okay*."

[19] In addition to the prior test (similar to Study 3), a post-hoc power test for two-way ANOVA was conducted using G*Power and revealed almost 1.0 power which is greater than 80%, confirming the validity of the sample size.

Participants could click the buttons, and the content would appear in the review text. We arbitrarily chose these frequently used phrases from real customer reviews on eBay.com. To provide a natural testing experience, we decided not to force participants to use all the functions on the website and also informed them that their input would not be recorded for analysis.

Insert Figure 27 about here

After writing the review, participants were asked to act as normal customers and do online shopping, so the second task was to make a hypothetical purchase decision on the platform. Participants read product information and ten customer reviews. Each condition contained identical product information (name, price, image, etc., see Appendix for the stimuli). The level of repetition was manipulated by including different shares of repeated reviews in the review set (80% vs. 30%) (see Figure 28). Under the high repetition condition, eight out of ten reviews were identical, and the review content was included in pre-defined buttons, which were presented under the computer-generated condition in the first task (e.g., "*Great purchase.*"). Under the low repetition condition, three out of ten reviews were verbatim. Participants then answered a set of questions based on the information presented.

Insert Figure 28 about here

Measures

Participants first reported their intentions to purchase and their evaluations of the product[20]. Next, we asked participants about their perceptions of the set of reviews in terms of perceived

[20] Again, factor analysis showed that all five items were loaded on the same factor, indicating they are all measuring the persuasiveness of e-WOM.

repetitiveness (four items) and perceived truthfulness (three items) using the same set of questions as in previous studies. Next, participants rated their perceived review-writing effort ("*I think reviewers put a lot of effort into writing those reviews*," "*Reviewers took time to craft those reviews*," and "*Reviewers put a lot of thoughts into those reviews*"; 1 = *Totally disagree*, 7 = *Totally agree*) adopted from Grewal and Stephen (2019). The three items were loaded on the same factor and were averaged to form the index[21]. Finally, all participants answered the attention check question and demographic questions.

Results

Manipulation checks on perceived repetitiveness. As intended, the ANOVA analysis yielded a significant main effect of the share of repetition on perceived repetitiveness towards the review set ($F(1, 538) = 9.27$, $p = .002$, $\eta_p{}^2 = .017$), coupled with a significant main effect of the cause of repetition ($F(1, 538) = 4.00$, $p = .046$, $\eta_p{}^2 = .007$; see Figure 29). The interaction effect was insignificant ($p = .957$). Participants reported a higher level of perceived repetitiveness under the high (vs. low) share of repetition condition ($M_{high} = 5.83$, SD = 1.14 vs. $M_{low} = 5.55$, SD = 1.14), confirming the effectiveness of our manipulation. Out of our expectations, participants also reported a higher level of perceived repetitiveness under the computer-generated (vs. customer-generated) condition ($M_{computer} = 5.60$, SD = 1.16 vs. $M_{consumer} = 5.78$, SD = 1.13), indicating that perceived repetitiveness is a subjective measure and could be affected by how consumers inference the cause of repetition.

Insert Figure 29 about here
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[21] We found item 4 for perceived repetitiveness was (negatively) loaded on this perceived effort factor, therefore, we removed item 4 and took average for the other three items to form the perceived repetitiveness index in this study.

Product evaluation. H_1 posits that consumers form a lower product evaluation facing with a high level of repetition in the review set compared to a lower level of repetition. And H_6 further predicts that priming customers with an exogeneous cause of repetition (i.e., to be computer-generated) could eliminate the negative effect. To test those hypothesis, a 2 (cause of repetition: computer vs. customer) x 2 (share of repetition: high vs. low) ANOVA on product evaluation was conducted, yielding a significant main effect of the share of repetition ($F(1,538) = 4.128$; $p = .046$, $\eta_p^2 = .008$), as well as a significant main effect of the cause of repetition ($F(1,538) = 4.01$; $p = .043$, $\eta_p^2 = .007$) (Figure 30). The interaction effect is not significant ($p = .484$).

Insert Figure 30 about here

Consistent with H_1, product evaluations were lower under the high share of repetition condition than the low share of repetition condition ($M_{high} = 5.81$ vs. $M_{low} = 5.98$). In terms of the cause of repetition, participants also reported higher product evaluations under the computer-generated (vs. customer-generated) condition (*Ms* = 5.98 vs. 5.81). The result was not surprising. Recall in the manipulation checks, we found significant main effects for both the share of repetition and the cause of repetition. Both findings are consistent with our hypothesis and could be explained by the fact that customers favored the product with a lower level of repetitiveness than a high level of repetitiveness in the e-WOM. More importantly, the negative effect of high repetition vanishes under the computer-generated condition. The results support our hypothesis H_6, as we found that for the computer-generated condition, high (vs. low) repetition in e-WOM no longer leaded to more negative product evaluation.

Purchase intention. The two-way ANOVA yielded no significant main effect for the share of repetition or the cause of repetition. However, the interaction is marginally significant (F (1, 538) = 3.15, p = .07). Participants reported significant lower purchase intention under the customer-generated, high share repetition condition compared to the computer-generated, high share repetition condition (Ms = 5.20 vs. 5.57, F(1,538) = 5.27, p = .022; see Figure 31), and compared to the customer-generated, low share repetition condition (Ms = 5.20 vs. 5.47, F(1,538) = 2.93, p = .08). The results were consistent with our hypothesis (H_6), which posits that the negative repetition effect only occurs under the customer-generated condition, and the negative impact of repetition on persuasion vanishes by changing the cause of repetition from endogenously determined to exogenously determined.

Insert Figure 31 about here

Perceived truthfulness. H_6 posits that when participants infer the cause of repetition to be exogenous (i.e., computer-generated) rather than endogenous (i.e., customer-generated), they would not doubt the credibility issue for the high repeated e-WOM. A two-way ANOVA on perceived truthfulness yielded a significant main effect of the cause of repetition (F(1, 538) = 23.852, p < .000; Figure 32) and a marginal significant main effect of the share of repetition (F(1, 538) = 3.350, p = .068). When participants believed the cause of repetition was exogenous (vs. endogenous), they reported a higher level of perceived truthfulness ($M_{computer}$ = 4.97 vs. $M_{customer}$ = 4.47). And consistent to H_2, high repetition was considered as less truthful than low repetition (M_{high} = 4.62 vs. M_{low} = 4.81). Replicating findings in previous studies, we found that under the customer-generated condition, participants had a lower level of truthfulness regarding the e-WOM with a high (vs. low) share of repetition (Ms = 4.30 vs. 4.63). As predicted under H_6, for the computer-generated condition, a high (vs. low) level of repetition in e-WOM were no longer perceived to be less truthful (*Ms* = 4.944 vs. 4.990).

Insert Figure 32 about here

To test our conceptual model, we conducted the mediation analyses to test our hypothesis 6. That is, under the high share of repetition condition, whether the perceived truthfulness mediated the relationship between the cause of repetition and persuasion[22]. We performed a mediation analysis (Process Model 4, see Figure 33 for the tested model and mediation results). As predicted, there was a significant indirect effect from the cause of repetition on purchase intention (b = - 0.37, 95% CI = [-0.55, -0.20]). Inference to the computer-generated (vs. customer-generated) repetition in e-WOM generated higher perceived truthfulness, positively impacting purchase intention toward the product. Similar results were found for product evaluation (b = - 0.29, 95% CI = [-0.43, -0.16]).

Insert Figure 33 about here

Perceived review writing effort. The effort heuristic (Kruger et al. 2004) suggests that consumers perceive the review as more credible if they believe the reviewer put considerable effort into writing the review. Compared to customer-generated condition, reviews generated under the computer-generated conditions could associate with a lower level of effort, as clicking buttons requires less effort compared to typing reviews. If that is the case, differences in persuasion between computer and customer-generated conditions are due to the perceived effort

[22] For completeness, we replicated the findings in Study 2 by conducting another mediation analysis under customer-generated condition only. See Appendix for the tested model and mediation results.

in writing reviews rather than the cause of repetition. However, there were no significant differences in perceived effort between the two repetition cause conditions ($M_{computer} = 2.36$, SD = 1.61 vs. $M_{customer} = 2.21$, SD = 1.52, $p = .214$; See Figure 34). Thus, the results ruled out the possible alternative explanation for the repetition effect.

Insert Figure 34 about here

Discussion

Study 4 demonstrates that unfavorable perceptions of repetition in e-WOM are due to perceived low truthfulness and can be eliminated by manipulating the cause of repetition. First, using the customer-generated condition, we replicated the repetition effect on persuasion using a different set of stimuli and confirmed the mediation role of perceived truthfulness. More importantly, we found that the cause of repetition could play a major role in affecting consumers' evaluations and behavioral intentions. Products with a high (vs. low) share of repeated reviews were viewed as less favorable if the reviews were considered to be generated endogenously. However, if the exogenous cause exists, the effect of repetition in e-WOM becomes trivial. Our results showed that under the computer-generated condition, participants formed similar perceptions toward the e-WOM and the product regardless of the level of repetition. In fact, we found that participants had similar product evaluations and behavioral intentions for the computer-generated conditions (both high and low repetition) compared to the customer-generated, low-repetition condition. The results offer possible prescriptions to address the prevalence of repetition in e-WOM by including computer-facilitated functions in the review-writing process, as the results suggest the negative effect of repetition would vanish if people believe the repetition is caused by a computer-suggesting function.

Although we found that changing participants' belief in the cause of repetition can effectively resolve the high repetition effect on persuasion, the results indicate that the cause of repetition has a significant main effect on perceived repetitiveness. Therefore, we solve the adverse impact by manipulating the same construct, i.e., repetition in e-WOM. Future analysis could consider different manipulations to maintain the perceived repetitiveness for the review set with the same share of repeated online reviews but still increase the perceived truthfulness of the repeated e-WOM.

GENERAL DISCUSSION

Prior investigation of the impact of e-WOM has been largely restricted to a single e-WOM and characteristics for a single review. However, consumers often read a set of reviews associated with the product, integrate opinions from multiple prior consumers, and make the purchase decision. Our paper looks at the impact of repetition in e-WOM on consumer behavior, which is a prominent characteristic of review content for multiple reviews. We find that a high level of repetition in e-WOM negatively impacts consumers' stated purchase intentions and product evaluations by decreasing perceived truthfulness and information completeness. Using four studies, we demonstrate the negative repetition effect in e-WOM by manipulating different shares of repetition and the total number of reviews in the review set (see Table 16 for the summary of the manipulation). Study 1 confirmed the effect of negative repetition on persuasion by measuring participants' choice of product pairs. Study 2 and 3 investigated the repetition effect in e-WOM by asking participants to evaluate the product and review sets. Moreover, Study 3 studied the effect of repetition on review-reading behavior. Study 4 further investigated how firms can resolve the negative impacts by manipulating people's thoughts about the cause of repetition.

Insert Table 16 about here

Theoretical Implications

This research contributes to the general literature on e-WOM by extending the scope of prior research on the impact of e-WOM. The effect of e-WOM has received a lot of attention in marketing literature, with most concentrating on numeric attributes (valence, variance, and volume). Although an increasing amount of attention has been devoted to studying the impact of review content, the research scope is often limited to a single review, focusing on certain expressions or linguistic features of review text (see Table 10 for a comprehensive literature review). Thus, little is known about the impact of review content on the aggregate product level. This is important because customers usually read more than one review per purchase occasion, and they form their overall impression based on the influence of multiple reviews. The overall impact of reading multiple reviews is surely different from the simple summation of them. Instead, multiple reviews jointly affect consumers' product evaluation, and the effect depends on how consumers integrate multiple opinions. Moreover, some attributes of e-WOM, such as repetition, cannot be investigated using single reviews as stimuli. To the best of our knowledge, there is no existing paper investigating repetition as an integral feature of e-WOM content and studying the impact of repetition in e-WOM on consumers' affection, cognition, and choice behavior. Our work focused on repetition in e-WOM and considered the impression of reviews for a particular product. We show that the level of repetition in review content can change consumers' perceptions and thus affect their product evaluations and purchase intentions. In doing so, our work sheds light on a novel mechanism underlying consumers' information processing and product judgment. By delineating the repetition effect in e-WOM, this research contributes to a better understanding of cognitive information processing of multiple sources.

Our paper is one of very few to study the effect of online reviews on consumers' review-reading behavior. Study 3 provided initial evidence for consumers' information searches by studying the causal impact of repetition in e-WOM on consumers' information-seeking processes through perceived information completeness. We found that even when the searching behavior was endogenized, participants chose to stop reading the repeated reviews, and their perceived information completeness was still lower than for low repetition conditions. The results raise attention to considering review-reading behavior when studying the impact of e-WOM, as most prior research uses a fixed number of reviews as stimuli and assumes participants pay full attention to them.

Managerial Implications

The current research provides managerial implications for marketing practitioners and platform designers in terms of review management, review displaying, and customer relationship management strategies. Admittedly, the management of repetition in e-WOM should not affect (decrease) consumers' review contributions because the numerical aspect of e-WOM has an irreplaceable role in sales performance, determining the product's ranking in the recommendation system or serving as a critical variable for the pre-choice screening of options. While too much repeated content in the reviews may have undesirable effects on persuasion, it can be eliminated by changing how the reviews are posted by reviewers and displayed on the product review page. The current research provides guidance on how firms and platforms can benefit from repeated reviews even when more reviews do not generate additional information value to potential consumers.

Our results suggest that firms could provide guidelines when gathering customer reviews. Firms could 1) highlight the potential product attributes that reviewers could mention in the review (e.g., please review our product based on each aspect); 2) ask reviewers to emphasize their unique experience with the product; and 3) encourage reviewers to upload pictures or videos. Second, companies may enhance their products and brand perceptions via a positive spillover of the platform. Our research shows that customers develop a more positive evaluation of the product if they experience the computer-facilitated interface in the review process. Thus, firms are likely to see benefits for their products and brands with a user-friendly online interface.

In addition, firms and platform designers could adopt display strategies to avoid displaying verbatim content but maintain consensus among reviewers. For example, some platforms analyze consumer reviews and present summaries of repeated content: Google Maps lists frequently used keywords and their corresponding frequencies right below the average star rating; TripAdvisor also provides a list of "*Popular mentions*" above actual customer reviews. Such summary tactics could save customers' effort in reading multiple reviews, solve the negative impact of repetition in e-WOM, and still convey the high level of agreement reached by reviewers; thus, with positive valence, they exert a positive impact on persuasion.

Future Research and Limitation

Consumer preferences, involvement, and goals

One factor we did not include in our investigation is consumers' heterogeneous preferences. This is important because consumers' product preferences are inherently idiosyncratic. E-WOM can be considered more helpful if the consumer believes that the reviewer is similar to herself or has similar preferences. (He Bond, 2013; Reichelt, Sievert, and Jacob 2014) Consequently, the prospective consumer may place different weight in different WOMs based on the similarity between herself and the reviewers. Heterogeneity can also take place across purchase occasions in terms of personal involvement (Petty and Cacioppo 1984), and thus consumers' response to repetition in e-WOM would be moderated by their motivations and abilities to process the information. For example, consumers may go with the "wisdom of crowd" heuristic for frequently purchased products, and so the repetition in e-WOM could serve as a good peripheral cue and increase purchase likelihood and sales. In contrast, the reactance to high repetition would more likely occur under occasions for choosing experiential consumptions. Moreover, consumers may have different goals (e.g., value certain product attributes more than other attributes) before reading online reviews; in this case, they will intentionally search for relevant information from reviews and evaluate the product based on the information they are interested in, thus neglecting the rest of the contents. Our research accounts for situations in which consumers have only general preferences toward the product and do not have specific goals before making purchase decisions. Thus, future research could study the potential impact of consumers' different goals and how these factors influence consumers' attention allocation and aggregation approach to making their own evaluations and choices. Additional experiments may consider collecting data from real customers so as to increase external validity.

Valence of e-WOM

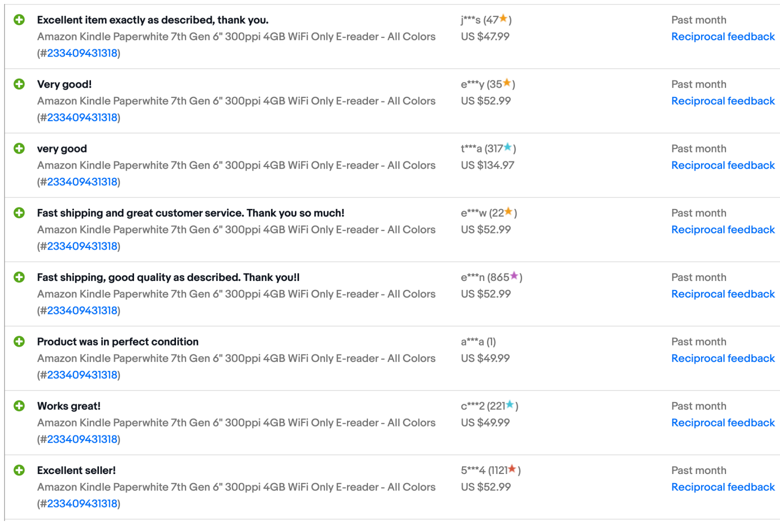
In the paper, we did not find that other types of inferences regarding repetition influenced the persuasiveness of e-WOM (e.g., review-writing effort). Nonetheless, further research could address how other e-WOM attributes, such as the valence of e-WOM, could interfere consumers' inferences about repetition in e-WOM.

For example, our research restricted repeated information and general product evaluations to being positive. Further research could also look at negative repeated information in e-WOM and how it acts differently from positive repeated information in terms of perceived truthfulness and persuasiveness. Several studies demonstrate that consumers value negative WOM more than positive ones and consider them to be more diagnostic (Chevalier and Mayzlin, 2006; Herr, Kardes, and Kim, 1991; Chen and Lurie 2013; Rozin and Royzman, 2001). We predict that the impact of repeated negative information will always increase as the level of repetition increases, regardless of what phrases are used in reviews. This is because when multiple reviewers mention one product attribute that is disappointing (e.g., the battery life is very short), consumers may believe that the battery in that product is of poor quality, which will increase the likelihood that attributions of blame for dissatisfaction are placed on the product or the firm rather than on the product user.

More importantly, we argue that the negative repetition effect in e-WOM has a higher level of persuasiveness than positive repetition in e-WOM if we control for the same level of repetitiveness. This is because consumers are more likely to be influenced by negative WOM, and to produce the same level of influence, such as on purchase decisions, less repetition is required when the valence is negative (vs. positive).

FIGURE 12

EXAMPLE OF REPETITION IN E-WOM: EBAY (ESSAY II)



Excellent item exactly as described, thank you. Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	j***s (47★) US $47.99	Past month Reciprocal feedback
Very good! Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	e***y (35★) US $52.99	Past month Reciprocal feedback
very good Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	t***a (317★) US $134.97	Past month Reciprocal feedback
Fast shipping and great customer service. Thank you so much! Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	e***w (22★) US $52.99	Past month Reciprocal feedback
Fast shipping, good quality as described. Thank you!! Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	e***n (865★) US $52.99	Past month Reciprocal feedback
Product was in perfect condition Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	a***a (1) US $49.99	Past month Reciprocal feedback
Works great! Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	c***2 (221★) US $49.99	Past month Reciprocal feedback
Excellent seller! Amazon Kindle Paperwhite 7th Gen 6" 300ppi 4GB WiFi Only E-reader - All Colors (#233409431318)	5***4 (1121★) US $52.99	Past month Reciprocal feedback

FIGURE 13

STIMULUS CHOICE PAIR EXAMPLE (STUDY 1)

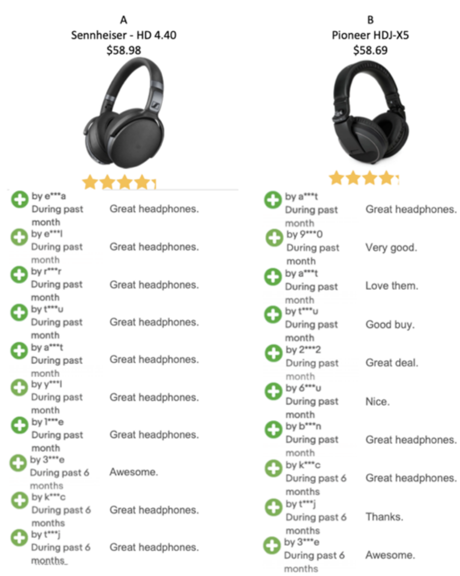
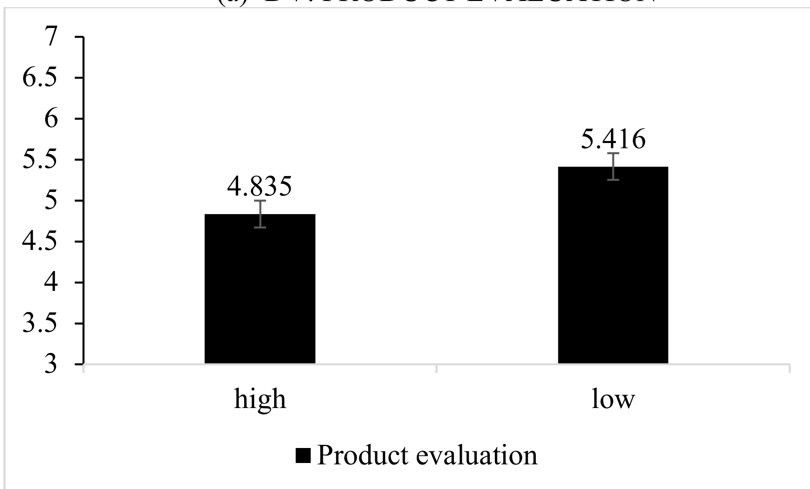


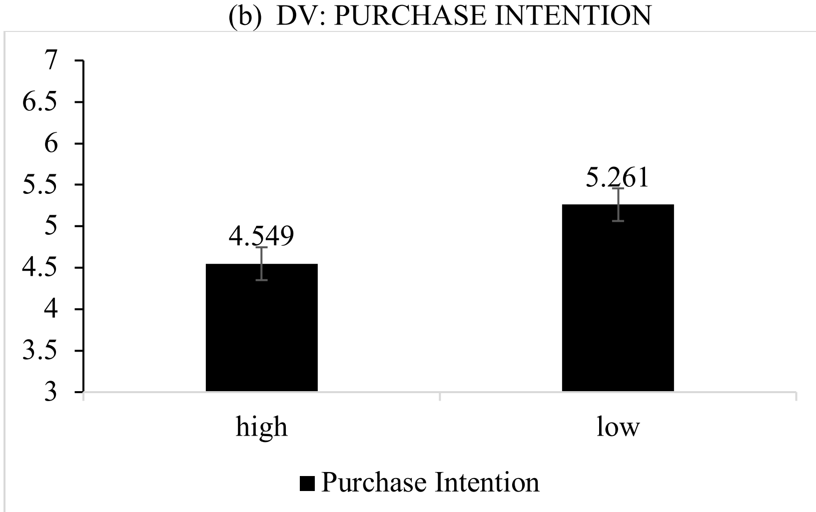
FIGURE 14

IMPACT OF REPETITION ON PERSUASION (STUDY 2)

(a) DV: PRODUCT EVALUATION



(b) DV: PURCHASE INTENTION

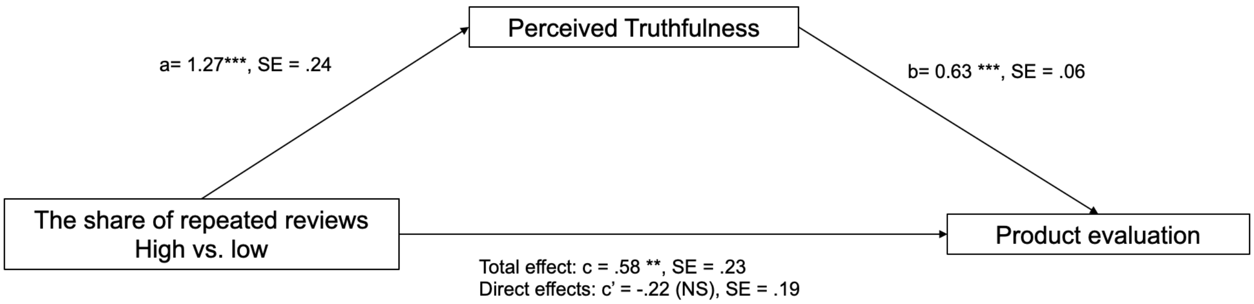


Notes. Error bars represent standard errors of the mean.

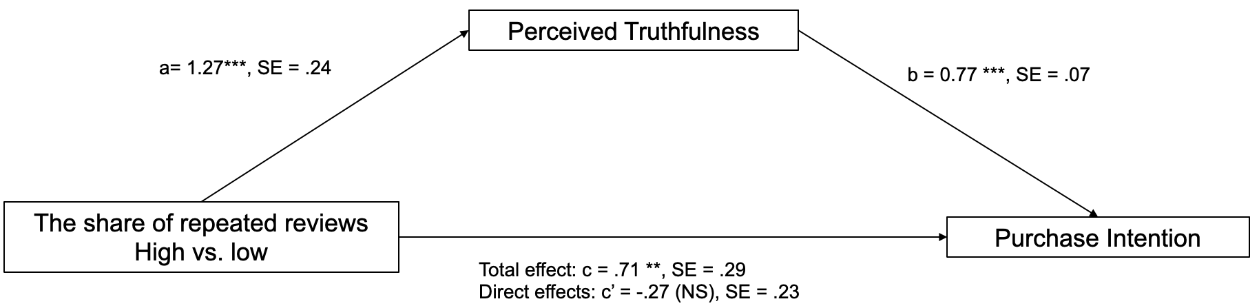
FIGURE 15

MEDIATION BY PERCEIVED TRUTHFULNESS (STUDY 2)

(a) DV: PRODUCT EVALUATION



(b) DV: PURCHASE INTENTION

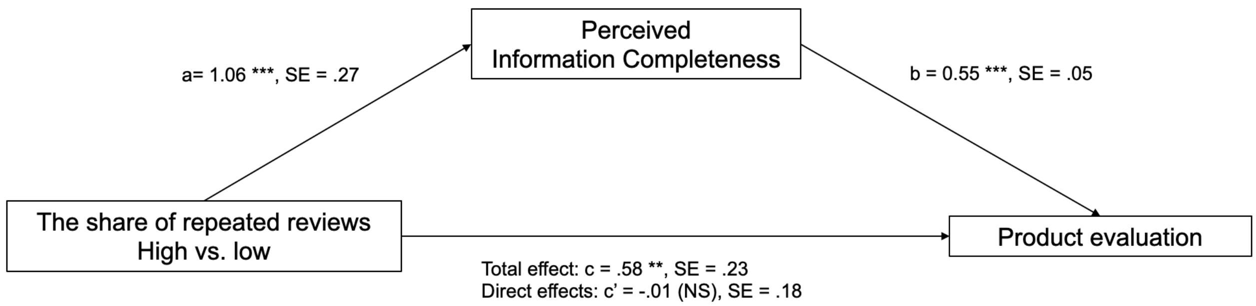


Notes. *** indicates significant at .001 level; ** indicates significance at .05 level; * indicates significance at .1 level.

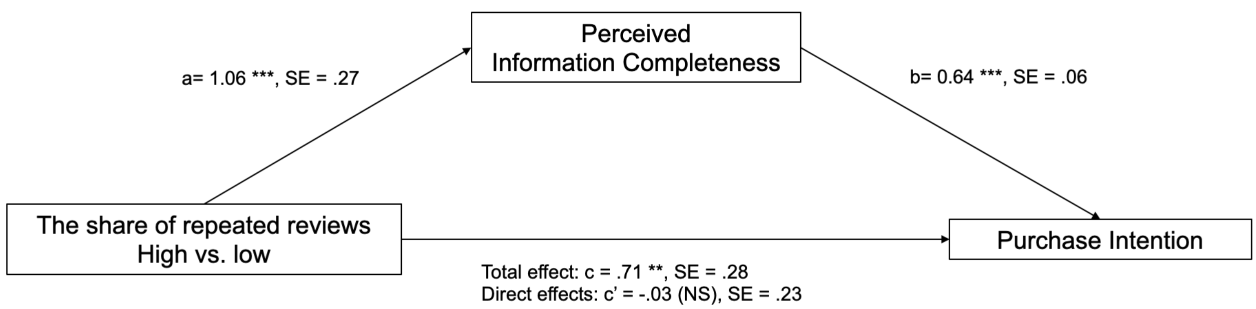
FIGURE 16

MEDIATION BY PERCEIVED INFORMATION COMPLETENESS (STUDY 2)

(a) DV: PRODUCT EVALUATION



(b) DV: PURCHASE INTENTION



Notes. *** indicates significant at .001 level; ** indicates significance at .05 level; * indicates significance at .1 level.

FIGURE 17

STIMULI FOR REVIEW SET PAGE ONE (STUDY 3)

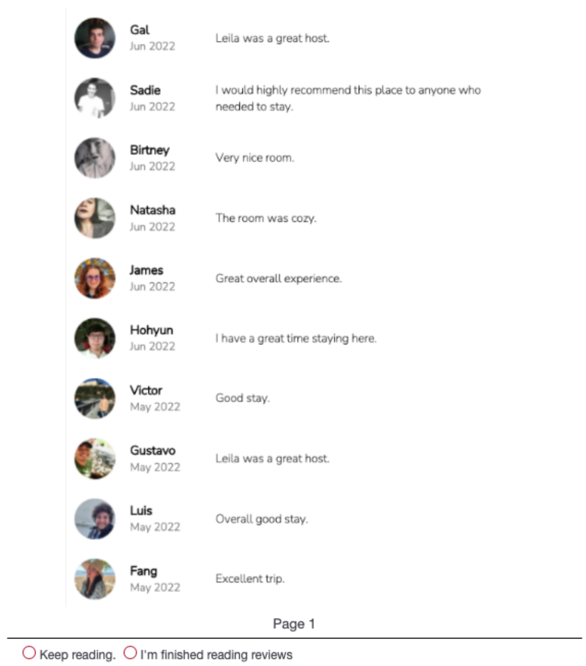
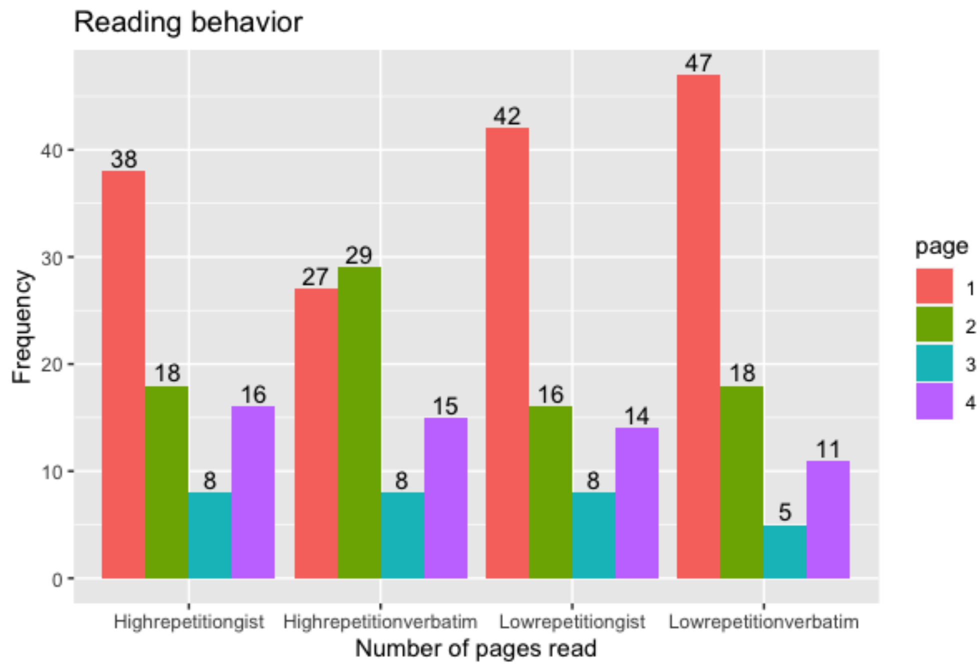


FIGURE 18

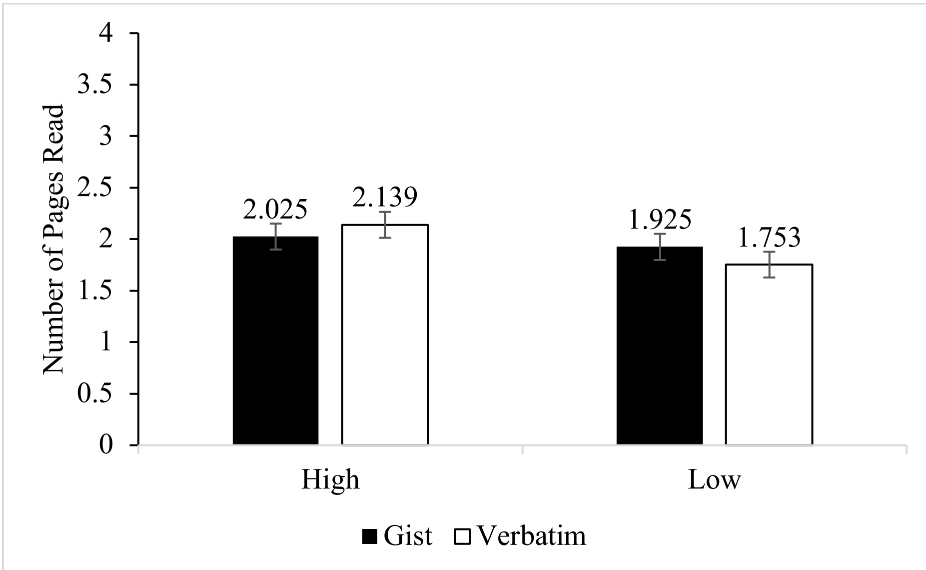
NUMBER OF PAGES READ ACROSS CONDITIONS – FREQUENCY (STUDY 3)



Notes. Frequency represents the number of participants chose "*I'm finished reading the reviews.*" after reading certain number of pages.

FIGURE 19

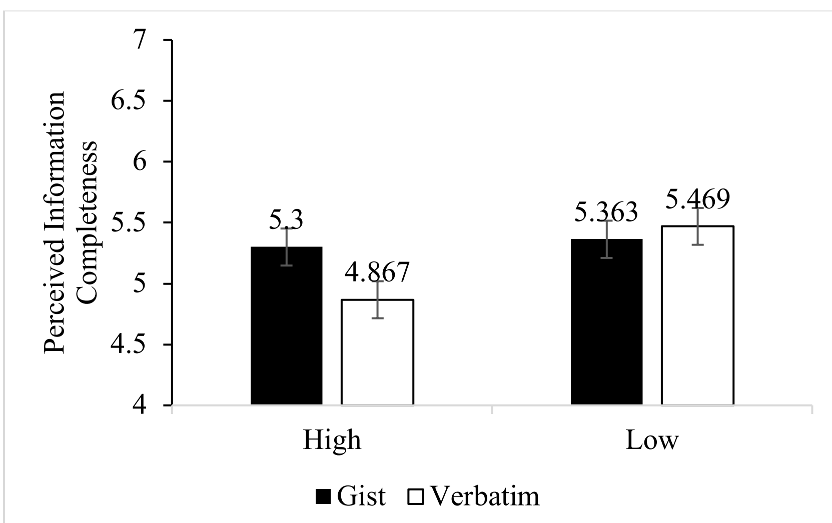
REVIEW READING BEHAVIOR: NUMBER OF PAGES READ (STUDY 3)



Notes. Error bars represent standard errors of the mean.

FIGURE 20

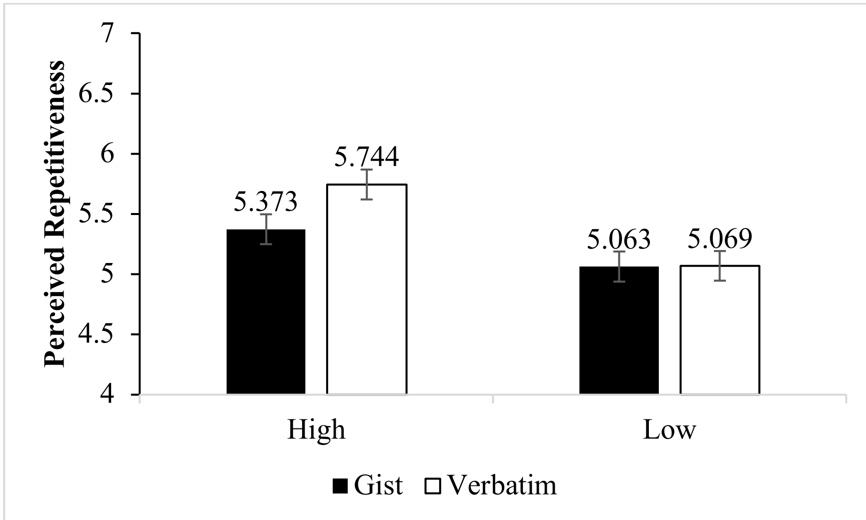
PERCEIVED INFORMATION COMPLETENESS (STUDY 3)



Notes. Error bars represent standard errors of the mean.

FIGURE 21

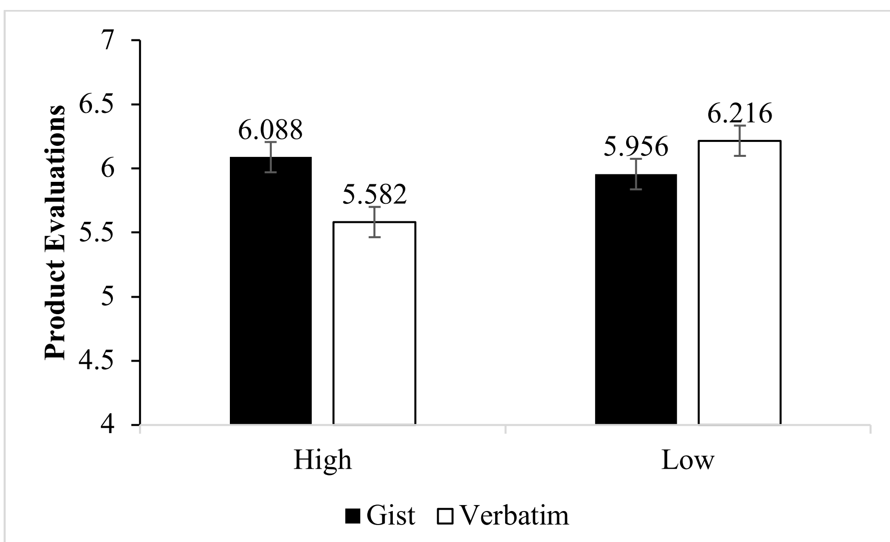
PERCEIVED REPETITIVENESS (STUDY 3)



Notes. Error bars represent standard errors of the mean.

FIGURE 22

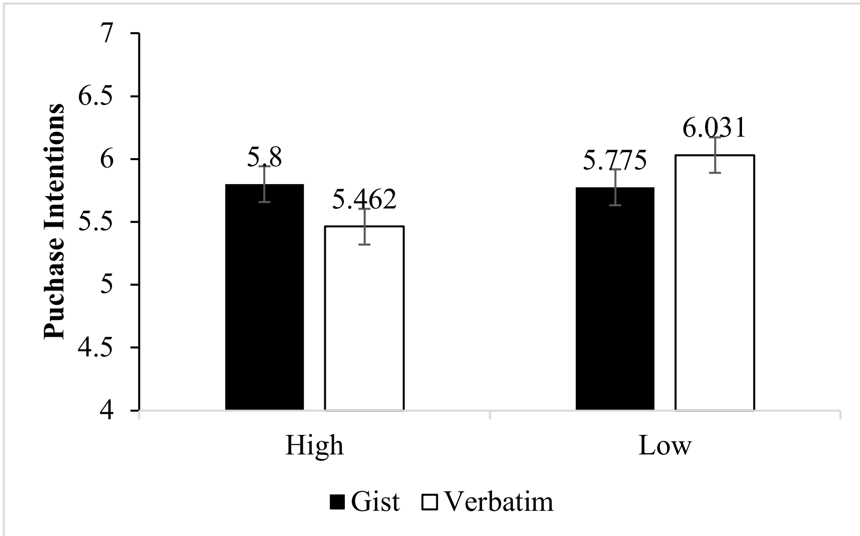
PRODUCT EVALUATIONS (STUDY 3)



Notes. Error bars represent standard errors of the mean.

FIGURE 23

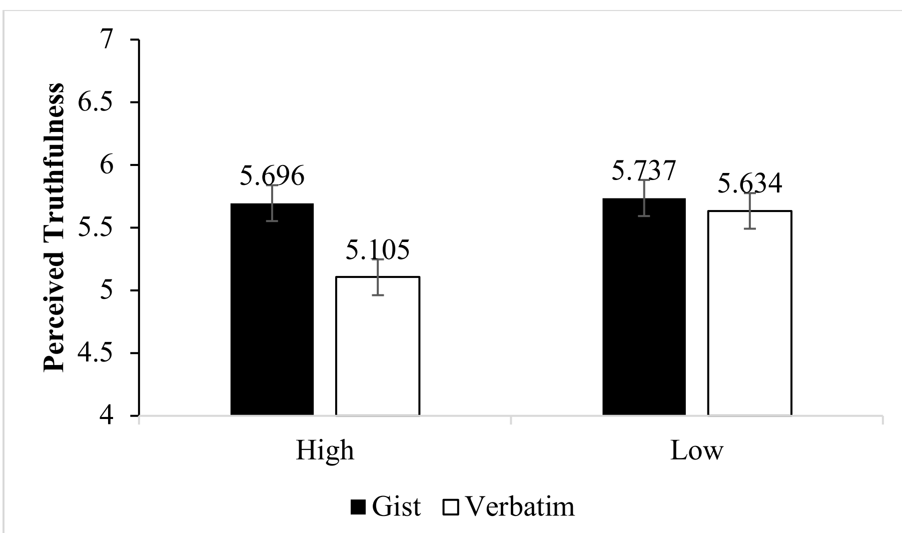
PURCHASE INTENTIONS (STUDY 3)



Notes. Error bars represent standard errors of the mean.

FIGURE 24

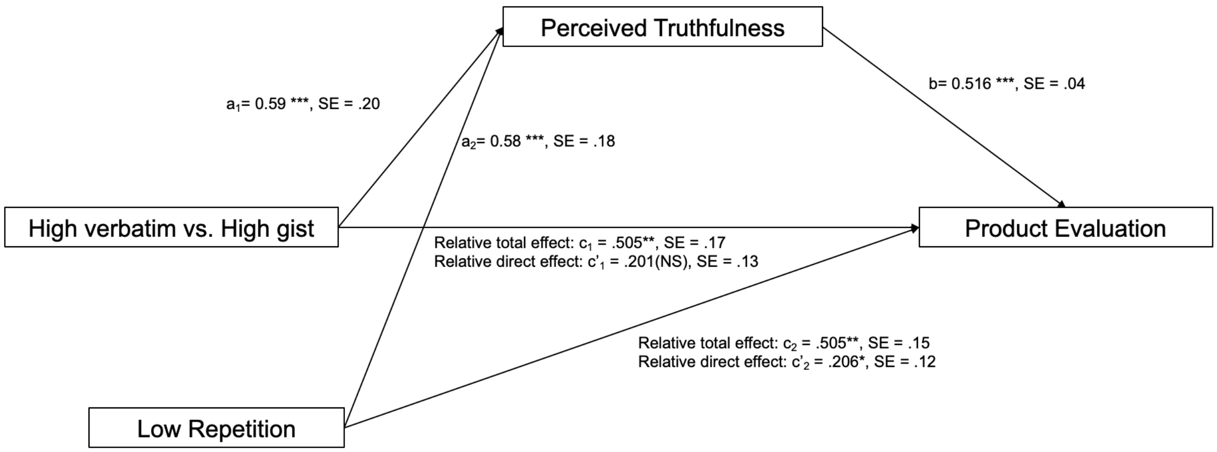
PERCEIVED TRUTHFULNESS (STUDY 3)



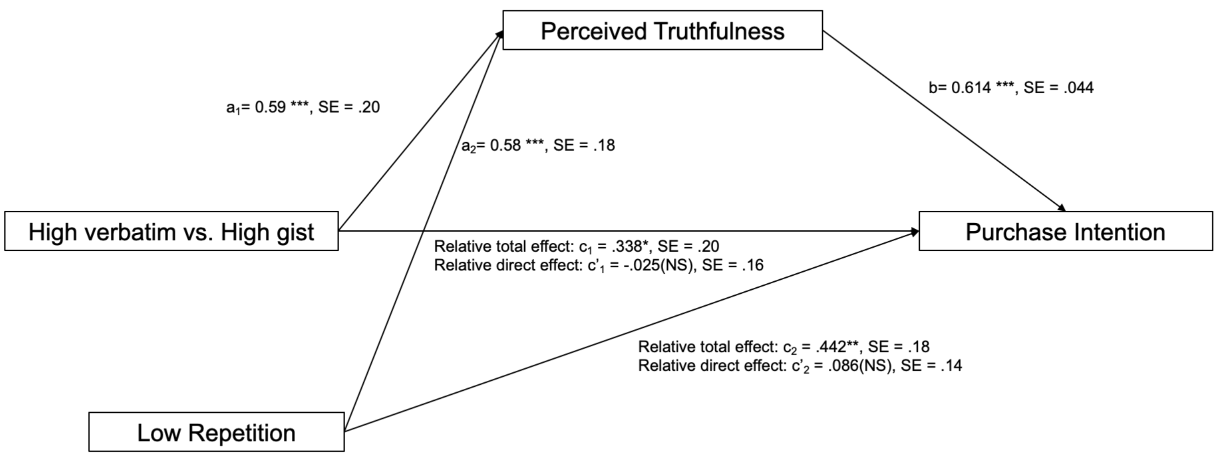
Notes. Error bars represent standard errors of the mean.

FIGURE 25

MEDIATION BY PERCEIVED TRUTHFULNESS (STUDY 3)



(a) Product Evaluation as Dependent Variable

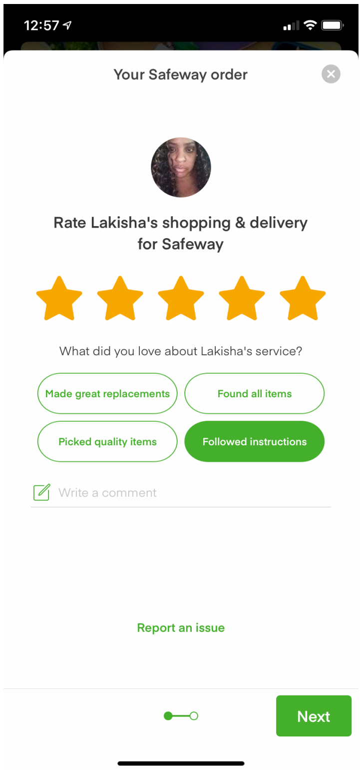


(b) Purchase Intention as Dependent Variable

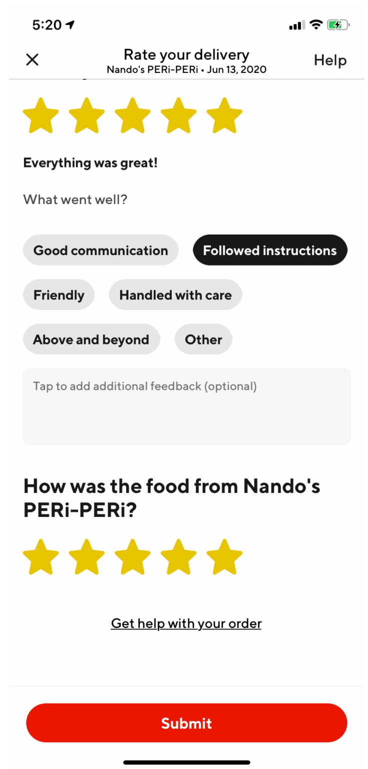
Notes. *** indicates significance at .001 level; ** indicates significance at .05 level; * indicates significance at .1 level.

FIGURE 26

EXAMPLES FOR PRE-DEFINED CONTENT IN THE CONTEXT OF E-WOM (STUDY 4)



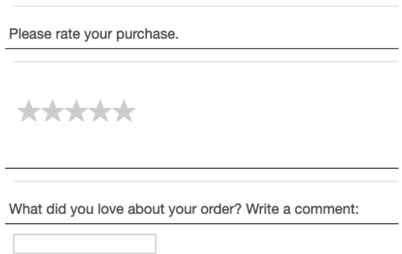
(A) Instacart

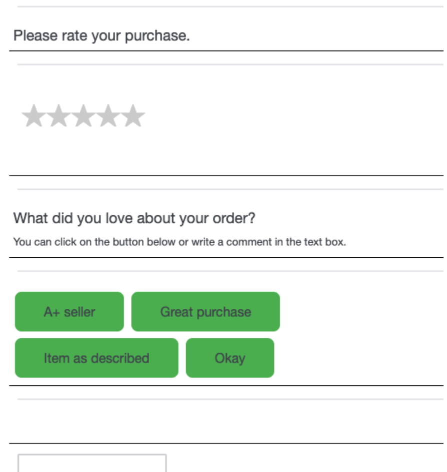


(B) DoorDash

FIGURE 27

MANIPULATION FOR THE CAUSE OF REPETITION (STUDY 4)



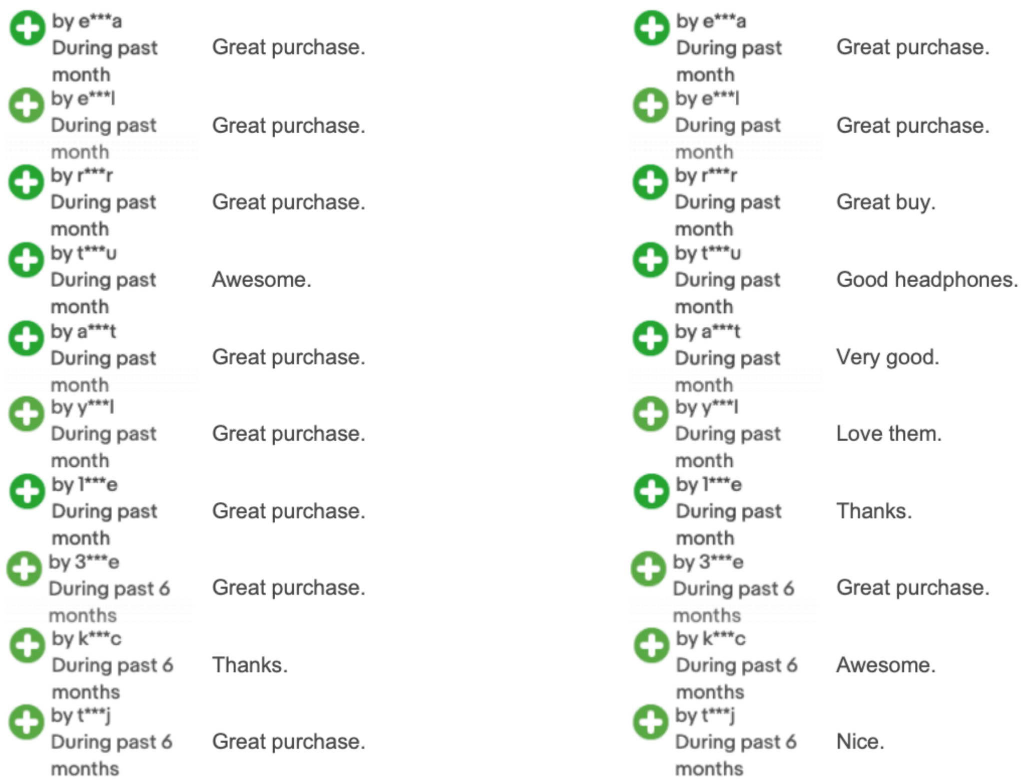


(A) Customer-generated repetition (B) Computer-generated repetition

FIGURE 28

STIMULI FOR THE REVIEW SET WITH DIFFERENT LEVEL OF REPETITION

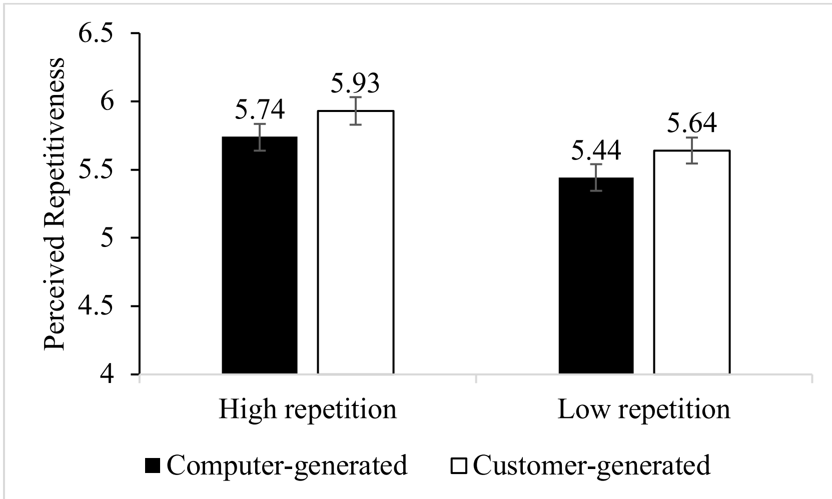
(STUDY 4)



(A) High repetition (B) Low repetition

FIGURE 29

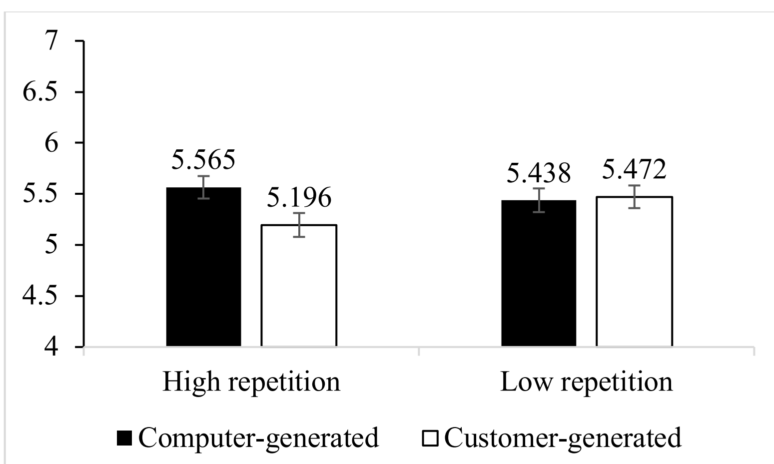
MANIPULATION ON PERCEIVED REPETITIVENESS (STUDY 4)



Notes. Error bars represent standard errors of the mean.

FIGURE 30

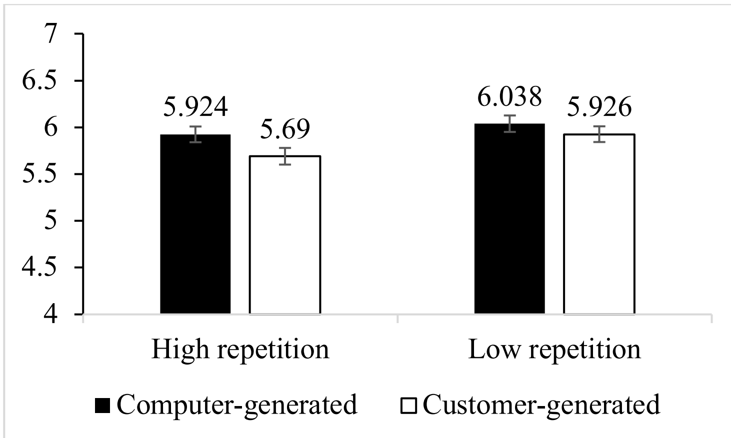
LEVEL OF REPETITION AND THE CAUSE OF REPETITION ON PURCHASE INTENTIONS (STUDY 4)



Notes. Error bars represent standard errors of the mean.

FIGURE 31

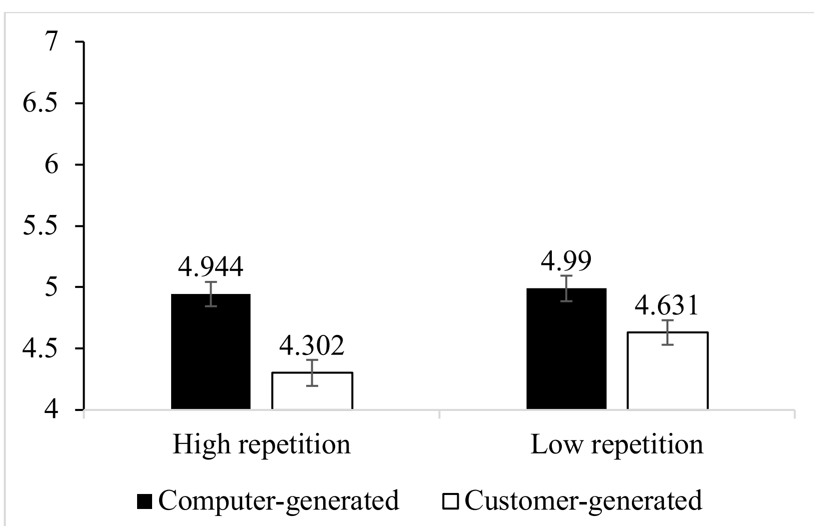
LEVEL OF REPETITION AND THE CAUSE OF REPETITION ON PRODUCT EVALUATIONS (STUDY 4)



Notes. Error bars represent standard errors of the mean.

FIGURE 32

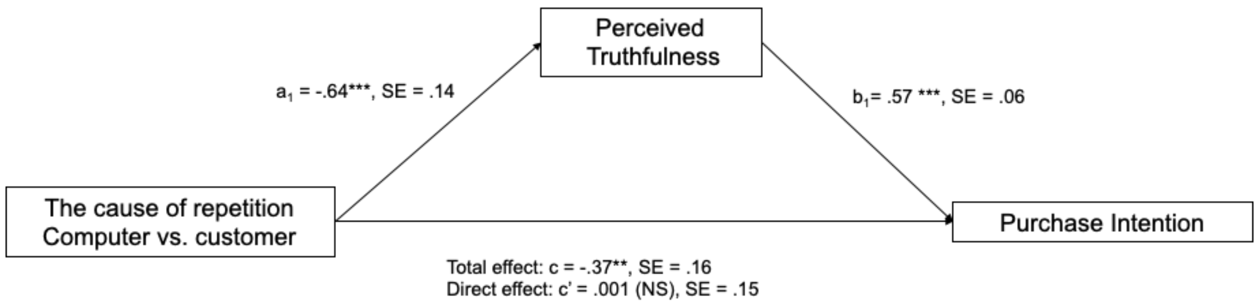
LEVEL OF REPETITION AND THE CAUSE OF REPETITION ON PERCEIVED TRUTHFULNESS (STUDY 4)



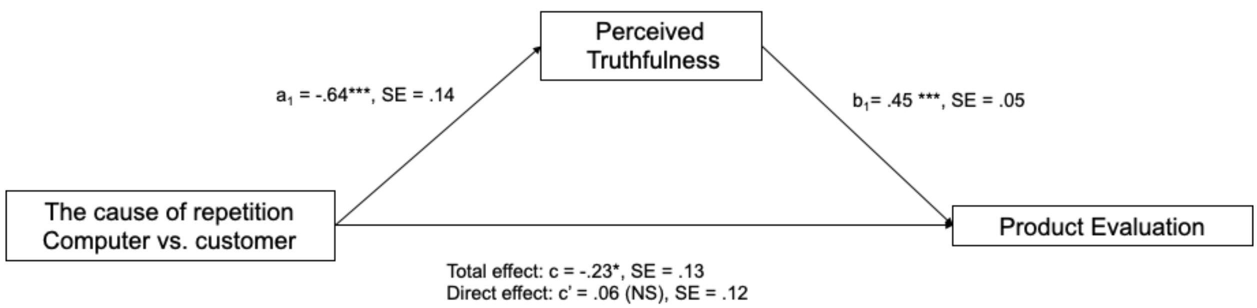
Notes. Error bars represent standard errors of the mean.

FIGURE 33

MEDIATION UNDER THE HIGH REPETITION CONDITION (STUDY 4)



(A) Purchase Intention as Dependent Variable



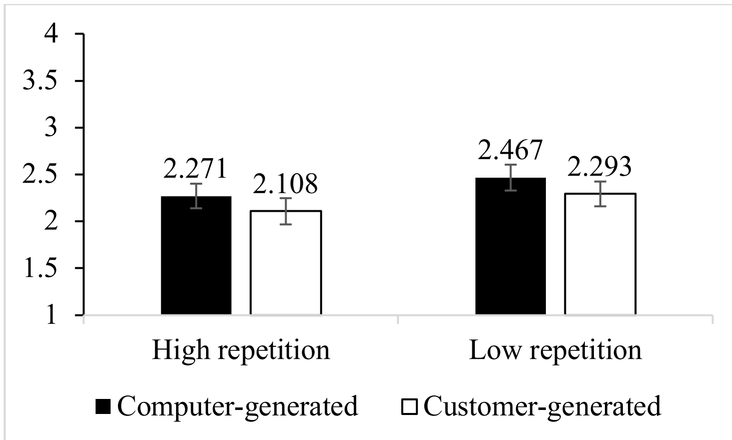
(B) Product Evaluation as Dependent Variable

Notes. *** indicates significant at .001 level; ** indicates significance at .05 level; * indicates significance at .1 level

FIGURE 34

LEVEL OF REPETITION AND THE CAUSE OF REPETITION ON PERCEIVED EFFORT

(STUDY 4)



Notes. Error bars represent standard errors of the mean.

TABLE 10

LITERATURE ON THE IMPACT OF E-WOM CONTENT (ESSAY II)

Research	Key IVs	Key DVs	Main Result	Product vs. Review Level	Mediators
Schellekens, Verlegh, & Smidts (2010)	Language abstraction (vs. concrete language)	Product attitude	Positive abstract WOM makes the receiver believe the sender has a positive product evaluation, and thus a higher purchase intention. The reverse is found for negative WOM.	Review level	\
Schlosser (2011)	One-sided vs. two sided arguments	Review helpfulness, persuasion	Two-sided argument is not always more helpful and can be less persuasive depending on the perceived consistency between a reviewer's arguments and rating	Review level	The beliefs that the reviewer is able (vs. willing) to tell the truth, credibility
Schindler & Bickart (2012)	Content and style	Review helpfulness	Positive product-descriptive statement, reviewer information statement, and entertaining elements increase the review helpfulness; while negative stylistic elements decrease helpfulness.	Review-level (statement-level)	\
Ludwig et al. (2013)	Affective linguistic elements; Linguistic style match (LSM)-irrespective of content	Conversion rate	The influence of positive affective content on conversion rate is asymmetrical; positive changes in affective cues and increasing congruence with the product interest group's typical linguistic style directly and conjointly increase conversion rate.	Product level	\
Chen & Lurie (2013)	Temporal Contiguity	Review value (usefulness), product choice	The presence of temporal contiguity cues reduces the relative extent to which positive reviews are attribute to the reviewer and mitigates the negativity bias.	Review level	Causal attribution
Kronrod & Danziger (2013)	Figurative language	Product attitude; choice on product type	Figurative (vs. literal) language predicted greater favorability toward hedonic, but not utilitarian, products.	Review level	Conversational norms (typicality)
Yin, Bond, & Zhang (2014)	Anxiety vs. Anger	Review helpfulness	Anxiety expressed toward merchant about purchase process was considered more helpful than expressed anger.	Review level	Perceived reviewer effort
Hamilton et al. (2014)	Dispreferred markers	Product evaluation, WTP	Consumers evaluate communicators who use dispreferred markers as more credible and likable than communicators who assert the same information without dispreferred markers	Review level	\
Tang, Fang, & Wang (2014)	Neutral text and numerical UGC	Sales, purchase intention	Reviewers may give the same ratings for totally different reasons. Mixed-neutral UGC amplifies and indifferent-neutral attenuated the effects.	Review level	Motivation and ability to process positive and negative UGC
Moore (2015)	Explained actions vs. explained reactions	Product choice	Explained actions (reactions) were more helpful for utilitarian (hedonic) products.	Review level	Attitude predictability, review helpfulness

Packard, Gershoff, & Wooten (2016)	Source boasting	Persuasion	Although boasting is perceived negatively, such immodest self-presentations can either impede or enhance social perceptions and persuasion.	Review level	Dubious motive vs. Expert perceptions
Yin, Bond, & Zhang (2017)	Emotional arousal/emotional expression	Review helpfulness	The marginal effect of arousal on perceived helpfulness is positive at low levels of arousal but diminishes at higher levels.	Review level	Perceived reviewer effort
Lee & Kronord (2020)	Consensus language	Validity, persuasion	Weak ties are more influential than strong ties when using consensus language.	Review level	Perceived group size, group diversity
Rocklage & Fazio (2020)	Emotionality (extent to which evaluation is based on feelings/emotional reactions)	Review helpfulness, product choice	When and why positive emotion can have enhancing vs. backfiring effects.	Review level	Trust in review
Kim, Moore, & Murray (2021)	Negation Style: Contracted ("isn't") vs. full negations ("is not")	Product evaluation, WTP	Consumers evaluate products more positively when reviews contain contracted negations, as compared to full negations.	Review level	Reviewer Warmth, reviewer Competence
Current Study	Repetition in e-WOM;(the share and type of repetition in the review set)	Persuasion, product choice	High repetition in e-WOM could backfire the persuasiveness of the review set through credibility issue and lack of information.	Product level	Perceived truthfulness, perceived information completeness

Notes: IVs = independent variables; DVs = Dependent variables; WTP = willingness-to-pay

TABLE 11

SUMMARY OF HYPOTHESIS TESTED IN EACH STUDY (ESSAY II)

	Hypotheses Tested	**Main Results**
Study 1	H_1	Demonstrated the effect of repetition in e-WOM on persuasion in the choice setting.
Study 2	$H_1 – H_3$	Replicated the effect of repetition in e-WOM on persuasion by measuring participants' product evaluations and purchase intentions and demonstrated the mediation role of perceived truthfulness and information completeness.
Study 3	H_1, H_2, H_4, H_5	Demonstrated the effect of repetition in e-WOM on review-reading behavior; replicated prior findings under a more natural review display setting; demonstrated the different impact of the role of repetition in e-WOM on persuasion.
Study 4	H_1, H_2, H_6	Replicated prior findings and tested how to eliminate the negative repetition effect by moderating the cause of repetition.

TABLE 12

MANIPULATION FOR THE LEVEL OF REPETITION (STUDY 1)

Level of repetition	Low	Moderately low	Moderately high	High
Share of repeated reviews	30%	50%	70%	90%

Notes. Each option contains a review set with 10 reviews included.

TABLE 13

STIMULUS (STUDY 1)

Product category	Group 1	Group 2	Group 3
Airbnb	moderately low vs. low	moderately high vs. low	high vs. low
café	moderately high vs. low	high vs. low	moderately low vs. low
headphone	high vs. low	moderately low vs. low	moderately high vs. low

Notes. Participants were randomly assigned to one of the three groups. Stimuli were presented based on a Latin square design, in which participants will see all three types of choice set with all three product categories.

TABLE 14

RELATIVE CHOICE SHARE OF THE OPTION WITH A HIGHER LEVEL OF REPETITION

(STUDY1)

Product category	**Type of comparison**			
	High-low	Moderately-high-low	Moderately-low-low	**Combined**
Headphone	0.368 (N = 76)	0.405 (N = 74)	0.466 (N = 73)	0.413 (N = 224)
Café	0.26 (N = 73)	0.447 (N = 76)	0.432 (N = 74)	0.381 (N = 223)
Airbnb	0.608 (N = 74)	0.581 (N = 74)	0.697 (N = 76)	0.629 (N = 223)
Combined	0.413 (N = 223)	0.478 (N = 224)	0.534 (N = 223)	

Notes. Values represent percentage of participants choosing the option with a higher level of repetition in the review set.

TABLE 15

MANIPULATION OF REPETITION IN E-WOM (NUMBER OF REVIEWS PER PAGE)

(STUDY 3)

	Verbatim			Gist		
	Repeated	Informative	Uninformative	Repeated	Informative	Uninformative
High share	6	2	2	6	2	2
Low share	2	2	6	2	2	6

TABLE 16

SUMMARY OF MANIPULATION ON THE SHARE OF REPETITION (ESSAY II)

	Share of repetition	**Total number of reviews in the review set**
Study 1	30%, 50%, 70%, 90%	10
Study 2	70%, 15%	20
Study 3	60%, 20%	40
Study 4	80%, 30%	10

Appendices

APPENDIX A

INCENTIVIZED VERSUS ORGANIC REVIEWS: CONTENT ANALYSIS (CHAPTER 2)

The analysis presented in the main paper indicates that incentivized reviews are generally more positive and longer than organic reviews. In Appendix A, we explore if the topical content of incentivized reviews systematically differs from that of organic reviews.

Our analysis starts with identifying the review topic/aspect by classifying the review text into four categories: price, feature, experience, and recommendation. We follow Büschken and Allenbys' (2016) method and also adopt sentence-based analysis to identify topics and perform sentiment analysis. Keywords for each topic are generated in the following steps using Python and Natural Language Toolkit (NLTK) package:

1. Tokenize the reviews, removing all punctuation marks.
2. Remove stop words from the data.
3. Stem the tokens, removing morphological affixes from words.
4. Remove less frequent words and identify bag-of-words for each topic.

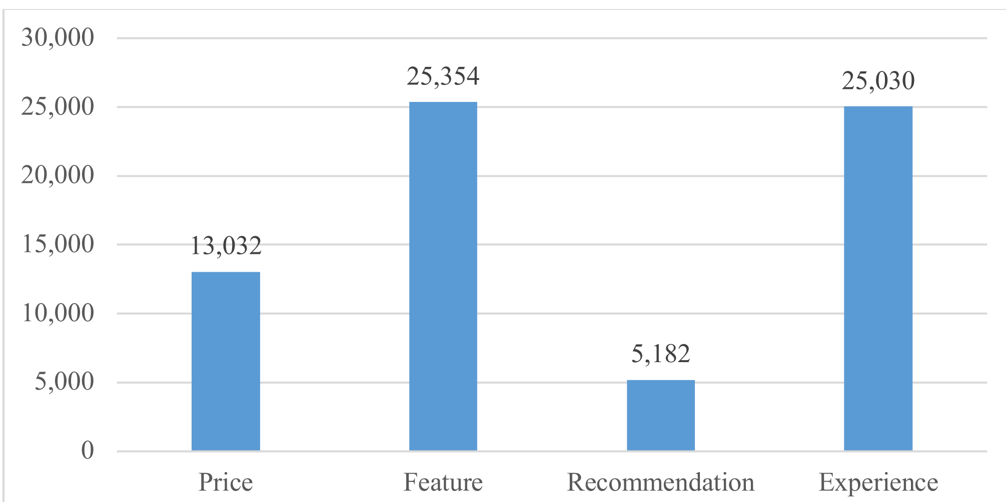
After generating the keyword list for each topic, we split all reviews into sentences and match them with the keywords for each topic. Note that synonyms are also included based on WordNet, which is a lexical database of semantic relations between words. In addition, keyword lists are determined at the product category level. Table A1 provides some examples of this topic/aspect identification task.

Table A1: Examples for Each Topic.

Topic/Aspect	Example
Price	"It is worth the money." "The price is about the best I have found on the internet."
Feature	"Compared to first generation XM2GO radios, the Inno is much more portable. It is smaller and fits easier in the pocket or a purse."
Experience	"It works fine. They do a good job of staying put while she's sleeping, too."
Recommendation	"I would highly recommend this product."

Figure A1 shows that almost all the reviewers mention product information and consumption experience. In contrast, fewer reviews also mention the price and experience, and it only happens when these aspects are worth mentioning, either very good or extremely bad consumption experience.

Figure A1. Number of reviews containing each topic (health care product).



Next, we compare review content of organic versus incentivized posts in terms of topic distribution. As Table A2 shows, the probabilities of mentioning each topic in incentivized reviews are all significantly higher than organic reviews, which means that incentivized reviews are more likely to contain all the topics. It is consistent with the findings that incentivized reviewers put more effort into writing a review.

Table A2. Comparison of Organic Reviews and Incentivized Reviews (Topic Analysis).

	Topic Probability		t-Test
	Organic Reviews	**Incentivized Reviews**	
Price	.492	1	–164.74***
Feature	.961	1	–32.741***
Recommendation	.195	.567	–7.6181***
Experience	.948	1	–37.782***

***$p < .001$.

We conduct sentiment analysis on each topic using a public NLTK-powered text classification process. This provides sentiment scores for positive, negative, and neutral in the form of probability. As Table A3 shows, our analysis is based on these numerical results. Although incentivized reviews are more likely to cover most (if not all) of the topics (compared with organic reviews, which cover fewer topics), the review content is not conveyed in a more positive way. We find that three out of four topics for incentivized reviews have significantly lower topic sentiment than organic reviews. In other words, incentivized reviewers tend to express a more neutral tone even though they give higher star ratings for the product.

Table A3. Comparison of Organic Reviews and Incentivized Reviews (Sentiment Analysis).

	Topic Sentiment (Positive Probability)		t-Test
	Organic Reviews	**Incentivized Reviews**	
Price	.475	.493	$–1.493^{\dagger}$
Feature	.476	.445	2.005*
Recommendation	.528	.488	2.835***
Experience	.535	.509	1.662**

'†'$p < .1$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

APPENDIX B

ADDRESSING ENDOGENEITY BY MODELING INCENTIVES DECISION (CHAPTER 2)

As an additional robustness check, we address potential endogeneity by modeling firms' decisions whether to offer incentives after the product enters the market. It is possible that if the product received very few reviews or had a poor average star rating, the firm may want to provide incentives to improve online review performance. If so, the variable INC in our main model may be correlated with the error term, leading to an endogeneity problem.

A common approach to solving the endogeneity issue is to find an instrument, estimate the endogenous variable using a separate equation, and then plug in the predicted value of the endogenous variable into the main model (Wooldrige 2010, p. 97). However, our potentially endogenous variable (INC) is a dummy variable. Instead of inserting the predicted value of an endogenous binary regressor, Wooldrige (2010) proposes modeling the binary regressor with a probit model and then using residuals in the main model.

Adopting this approach, we modeled the firm's decision of whether to offer incentives using a probit model:

$$\Pr(INC_{ib} = 1|X) = \Phi(\alpha \mathrm{X}_{ib}) \tag{B.1}$$

where $\mathrm{INC_{tb}} = 1$ denotes that by the time product b is reviewed by reviewer i, the first incentivized review has already been posted. Predictor variables $\mathrm{X_{ib}}$ include the number of reviews, the star rating for the last organic review, the number of negative reviews, and the average star rating (detailed in Table B1).

Table B1. Descriptive Statistics for Predictor Variables.

Variable Name	Description
$LAST_{ib}$	Star rating of the last review posted before review i for product b
NUM_{ib}	Number of reviews posted before the review posted by consumer i for product b
AVG_{ib}	Average rating of all reviews posted for product b before the review posted by consumer i
NEG_{ib}	Number of negative (i.e., one or two stars) reviews posted for product b before the review posted by consumer i

Finally, we define the variable RESI as the difference between INC and the predicted probability ($\Pr(\mathrm{INC}_{ib} = 1|\mathrm{X})$) derived from the probit model. Note that we keep the potentially endogenous variable INC in the model (Equation B.2), but add an additional regressor, RESI. This method is similar to the control function approach developed by Petrin and Train (2010) and has been adopted in other marketing research by Danaher et al. (2015), Stephen and Toubia (2010), and Che, Chen, and Chen (2012).

$$\mathrm{U}_{ib} = \beta_1 \cdot \mathrm{TIME}_{ib} + \beta_2 \cdot \mathrm{ORDER}_{ib} + \beta_3 \cdot \mathrm{REVAVG}_{ib} + \beta_4 \cdot \mathrm{INC}_{ib} + \beta_5 \cdot \mathrm{RESI}_{ib} + \delta_b + \epsilon_{ib}. \quad \text{(B.2)}$$

The estimation results of the ordered logit regression appear in Table B2. All the coefficients are similar to the results in our main model, while the effect of variable RESI is not significant, ruling out the correlation between variable INC and the error term.

Table B2. Ordered Logit Regression Estimation Result: Addressing Endogeneity.

Variables	Model
REVAVG	.719***
	(.0155)
TIME	.0001***
	(.0000)
ORDER	–.0004***
	(.0001)
INC	–.232**
	(.126)
RESI	.148
	(.159)

*p < .1.
**p < .01.
***p < .005.

APPENDIX C

PLACEBO ANALYSIS AND FINDING PSEUDO INCENTIVIZED REVIEWS (CHAPTER 2)

In this section, we describe the procedure used to identify placebo-incentivized reviews. For each product, we aim to find an organic review that has identical or similar review characteristics as the real incentivized review. In the matching process, we considered both numeric ratings and the textual aspect of the review. First, the pseudo-review should be positive, so we only look at reviews with four or five stars.[23] Second, the pseudo-review should be as detailed as the incentivized review. We calculate the review length and number of words contained in the review text to make sure that the two reviews have a similar review length. We only keep the first candidate review posted before the time stamp of the first incentivized review to have enough observations after the placebo treatment. Last, the INC_placebo was generated by comparing the time stamp for each review and the placebo. Similar to INC, INC_placebo equals 1 when the focal organic review was posted after the placebo incentivized review; otherwise, it takes a value of 0. In Table C1, we provide summary statistics for both the pseudo-incentivized and the actual incentivized reviews.

Table C1. Descriptive Statistics for Pseudo Reviews and Incentivized Reviews.

Variable		Incentivized	Pseudo
N		2,766	2,329
Ratings	Mean	4.63	4.57
	(SD)	(.82)	(.88)
Number of sentences	Mean	7.51	7.36
	(SD)	(5.92)	(5.90)
Number of words	Mean	137.40	133.82
	(SD)	(128.40)	(127.70)

Notes: Pseudo reviews are all positive reviews (four or five stars).

[23] Due to availability, we did not use exact matching in terms of the star rating but included all positive (four- or five-star reviews) candidates.

APPENDIX D

MODERATING EFFECT OF THE VALENCE OF PRIOR REVIEWS (CHAPTER 2)

In this study, we explore the impact of both positive and negative prior reviews on subsequent evaluations. Although our empirical data contain only positive incentivized reviews, the negative impact of prior incentivized reviews should also hold when there is a negative or neutral valence. If a consumer reads a negative review stating that the reviewer received an economic incentive from the merchant, the consumer may view the incentivized review as an independent and truthful opinion rather than a biased review. Prior literature has demonstrated that prior negative reviews have a negative impact on subsequent reviews (Schlosser 2005); thus, we expect a negative impact on participants' product evaluation regardless of the type of prior reviews.

Design and Procedure

We use a 2 (consumption experience: positive vs. negative) by 2 (type of prior review: incentivized vs. organic) by 2 (valence of prior review: positive vs. negative/neutral) between-subjects design. We recruited 497 participants (female =57.38%, M_{age} = 42.49 years, $0.50 payment) from MTurk and randomly assigned them to one of the eight between-subjects conditions. The participants were primed with either a positive or a negative consumption experience scenario. After that, they read a randomly selected prior review from the website before answering a set of questions. To manipulate the valence of the prior review, we randomly selected one from two positive reviews (5 or 4 stars) for the positive prior review condition and one from two negative/neutral reviews (3 or 2 stars) for the negative/neutral prior review condition. We used the same manipulation for type of prior review (incentivized vs. organic) by including the disclosure of an incentive within the review text. Then, we asked participants about their product evaluation ($\alpha = .992$) and motivation to post their own reviews ($\alpha = .941$). Next, we asked participants to write their own review (i.e., star rating and review text) and to rate the perceived expertise for the reviewers ($\alpha = .914$) and the perceived trustworthiness ($\alpha = .960$) of the prior review. Finally, participants answered a survey about their online shopping and reviewing behavior and provided demographic information.

Result

Product evaluation. A three-way ANOVA on product evaluation reveals a significant main effect of consumption experience on product evaluation ($F(1, 489) = 496.59$, $p < .001$), a significant main effect of the type of prior reviews ($F(1, 489) = 5.711$, $p = .017$), and a significant main effect of the valence of prior reviews ($F(1, 489) = 90.65$, $p < .001$). There was also a significant interaction between consumption experience and the valence of prior reviews ($F(1, 489) = 22.536$, $p < .001$) and a significant interaction between the type and the valence of prior reviews ($F(1, 489) = 4.629$, $p = .032$). The interaction between consumption experience and the type of prior review was not significant ($p = .151$), and the three-way interaction was also not significant ($p = .435$). These results confirm that consumption experience does not moderate the impact of incentivized prior reviews on product evaluation.

In terms of the valence of the prior review, participants reported lower evaluations when faced with negative prior reviews than when faced with positive one ($M_{neg\_prior} = 3.08$, $SD = 1.65$ vs. $M_{pos\_prior} = 4.20$, $SD = 2.25$). However, the negative prior reviews had a different impact under different consumption experience conditions: participants with a positive consumption experience had much lower evaluations with negative prior reviews than with positive priors ($M_{neg\_prior} = 4.165$, $SD = 1.43$ vs. $M_{pos\_prior} = 5.90$, $SD = 1.28$) compared with the case of participants who had a negative product experience (M_{neg_prior} = 1.97, SD = 1.03 vs. M_{pos_prior} = 2.57, SD = 1.71).

Motivation to post reviews. We ran a 2 (consumption experience: positive vs. negative) by 2 (valence of prior review: positive vs. negative) by 2 (type of prior review: incentivized vs. organic) three-way ANOVA on participants' motivation to post reviews. The main effect of the type of prior review was not significant (p = .293); the same was true for all interactions related to the type of prior review (ps > .14). The effect of consumption experience and the valence of prior reviews were significant: participants had a higher level of motivation to post reviews when they were unsatisfied (vs. satisfied) with the product (M_{neg_exp} = 4.70, SD = 1.87 vs. M_{pos_exp} = 4.19, SD = 1.86) and when they read positive (vs. negative) prior reviews (M_{neg_prior} = 3.97, SD = 1.89 vs. M_{pos_prior} = 4.90, SD = 1.89). These results further reject motivation theory, which argues that incentivized disclosure affects subsequent reviewers' motivation to post reviews.

Discussion.

The results of this study provide comprehensive evidence that is consistent with our observation that incentivized reviews have a negative impact on the valence of subsequent organic reviews and that this negative impact maintains regardless of the valence of prior reviews and the valence of consumption experience with the product. Our results provide insights into the mechanism underlying a long-term negative impact of incentivized reviews. We find that in terms of motivation to post reviews, the existence of an incentivized relationship does not encourage or discourage subsequent consumers' incident decisions.

APPENDIX E

EXPERIMENT STIMULI (CHAPTER 3)

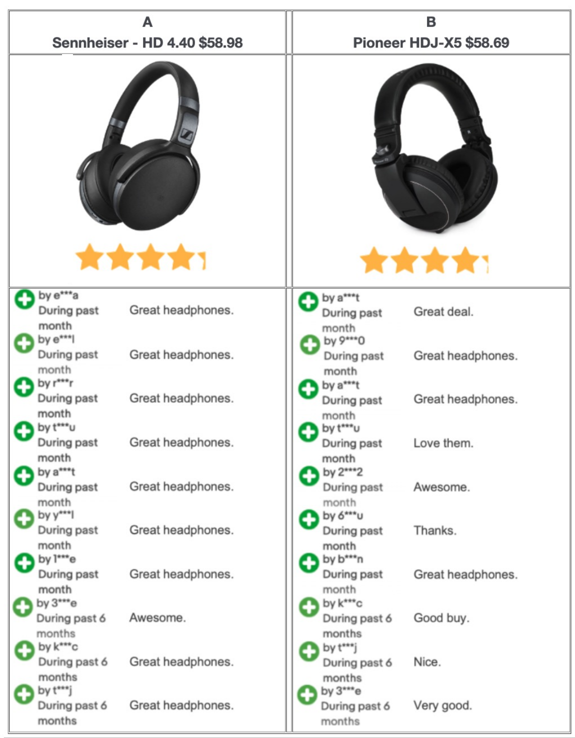
Study 1: Repetition in e-WOM and product choice

Buying headphones online

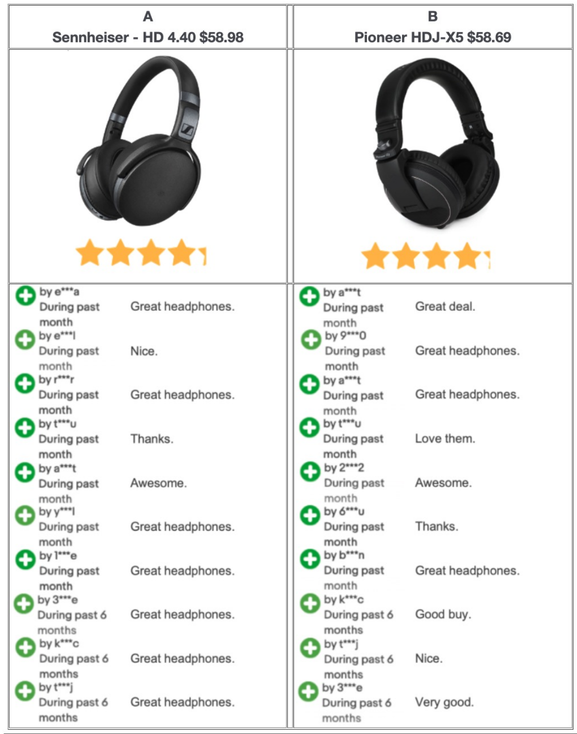
Listening to music makes you happy throughout the day. You want to purchase a new set of headphones that you can wear for an extended period of time each day. You decide to do some comparison shopping online, and so you visit www.ebay.com.

After some research, you have narrowed down your choices to two different sets of headphones that meet your needs. They each have noise-canceling functionality, over-the-ear padding, and an extended cord. You plan on buying one of these soon.

1. High vs. low repetition

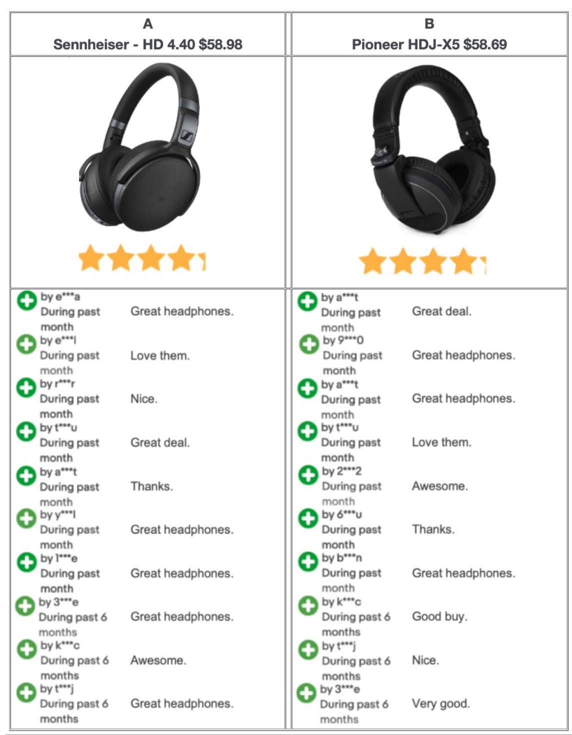


2. Low vs. moderately high repetition



A Sennheiser - HD 4.40 $58.98			B Pioneer HDJ-X5 $58.69		
by e***a	During past month	Great headphones.	by a***t	During past month	Great deal.
by e***l	During past month	Nice.	by 9***0	During past month	Great headphones.
by r***r	During past month	Great headphones.	by a***t	During past month	Great headphones.
by t***u	During past month	Thanks.	by t***u	During past month	Love them.
by a***t	During past month	Awesome.	by 2***2	During past month	Awesome.
by y***l	During past month	Great headphones.	by 6***u	During past month	Thanks.
by 1***e	During past month	Great headphones.	by b***n	During past month	Great headphones.
by 3***e	During past 6 months	Great headphones.	by k***c	During past 6 months	Good buy.
by k***c	During past 6 months	Great headphones.	by t***j	During past 6 months	Nice.
by t***j	During past 6 months	Great headphones.	by 3***e	During past 6 months	Very good.

3. Moderately low vs. low repetition



A Sennheiser - HD 4.40 $58.98			B Pioneer HDJ-X5 $58.69		
by e***a	During past month	Great headphones.	by a***t	During past month	Great deal.
by e***l	During past month	Love them.	by 9***0	During past month	Great headphones.
by r***r	During past month	Nice.	by a***t	During past month	Great headphones.
by t***u	During past month	Great deal.	by t***u	During past month	Love them.
by a***t	During past month	Thanks.	by 2***2	During past month	Awesome.
by y***l	During past month	Great headphones.	by 6***u	During past month	Thanks.
by 1***e	During past month	Great headphones.	by b***n	During past month	Great headphones.
by 3***e	During past 6 months	Great headphones.	by k***c	During past 6 months	Good buy.
by k***c	During past 6 months	Awesome.	by t***j	During past 6 months	Nice.
by t***j	During past 6 months	Great headphones.	by 3***e	During past 6 months	Very good.

Finding a good café on Yelp

While on a short trip, you decide to check Yelp for a café where you could get something to drink and a bite to eat.

While browsing the various cafes, you have narrowed down your choices to two café that meet your needs. They each have a nice environment, offering coffee and a bunch of stuff. You plan to go to one of these cafés soon.

1. High vs. low repetition

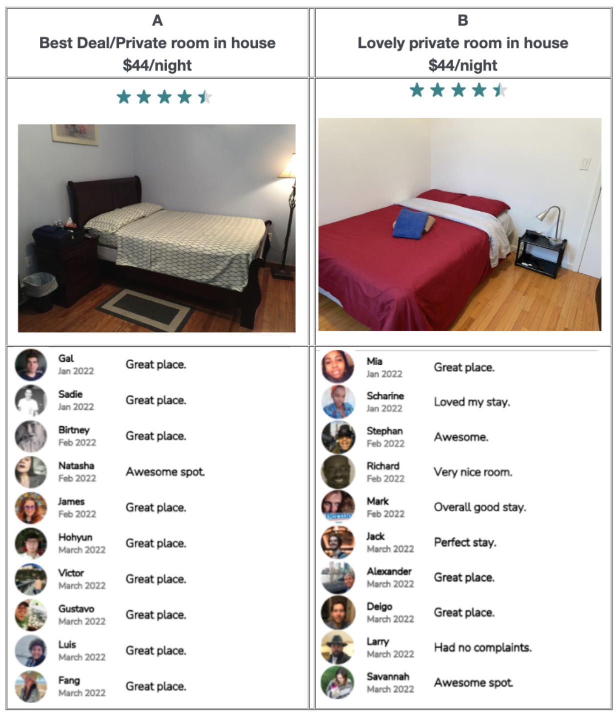
2. Moderately high vs. low repetition

3. Moderately low vs. low repetition

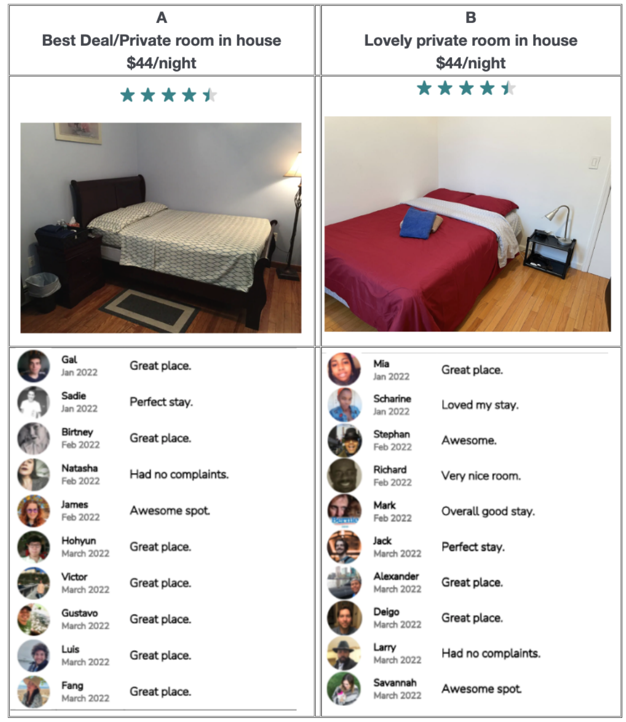
Booking an Airbnb room online
You have an upcoming weekend free and decide to take a mini vacation to New York City. You decide to check out some online reviews to find out where to stay.

While searching for rooms on Airbnb.com, you have narrowed down your choices to two different Airbnb listings that meet your needs. They each have a convenient location, a queen size bed, and bathroom. You plan to book one of these rooms soon.

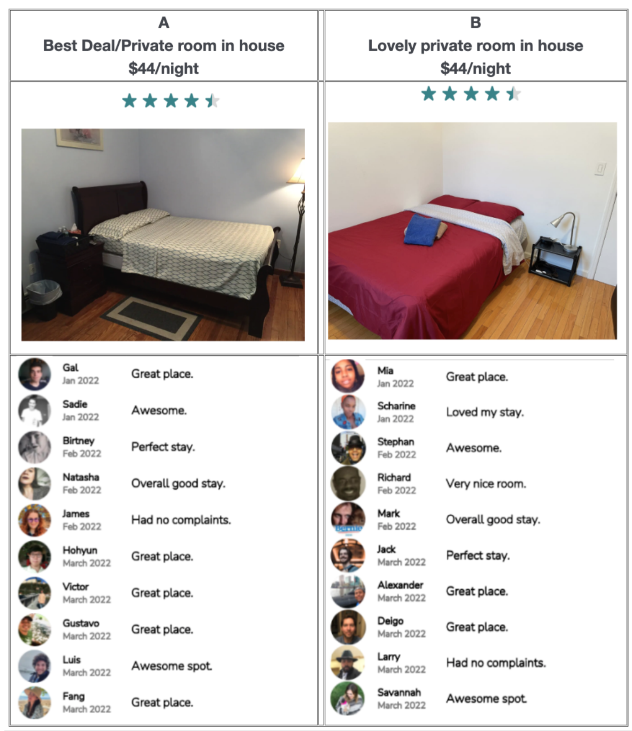
1. High vs. low repetition



2. Moderately high vs. low repetition



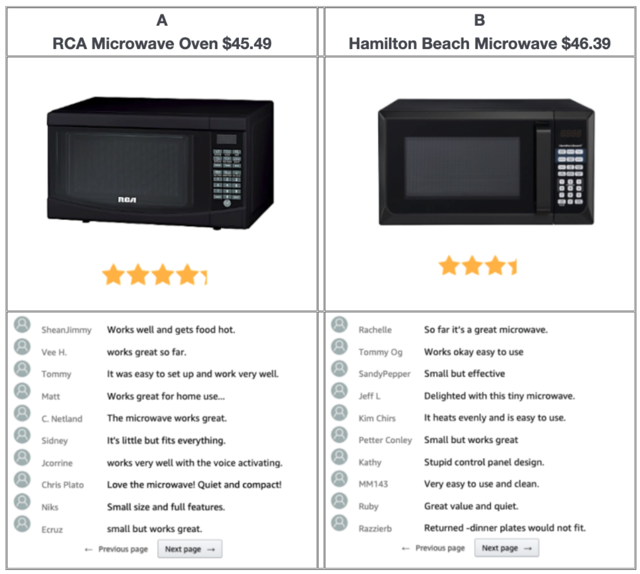
3. Moderately low vs. low repetition



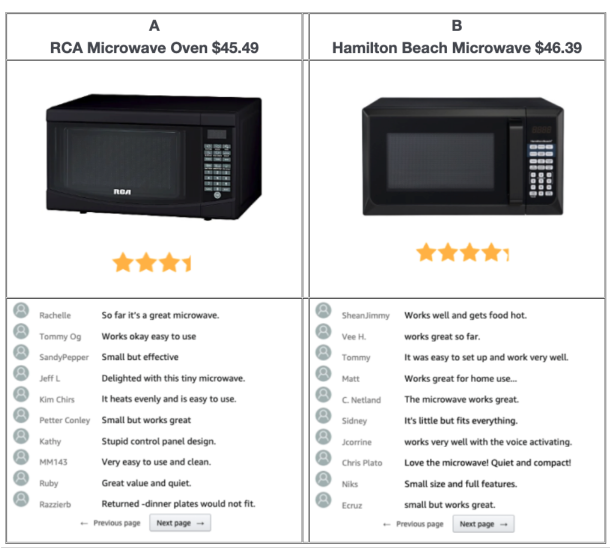
Buying a microwave online
You want to purchase a microwave so that you can quickly prepare hot meals at home. You decide to do some comparison shopping online and so you visit www.amazon.com.

After some research, you have narrowed down your choices to two different microwaves that meet your needs. They each have a defrost setting, a rotating plate, and a digital clock. You plan on buying one of these microwaves soon.

1. 4.x stars vs. 3.x stars (filler)



2. 3.x stars vs. 4.x stars (filler)



Study 2: Repetition in e-WOM and persuasion

Product information page for Study 2

Private room in house hosted by Chris
1 bedroom 1 bed

★ 4.72 (495 reviews)

Self check-in
Check yourself in with the keypad.

Free cancellation for 48 hours
After that, cancel up to 5 days before check-in and get a full refund, minus the service fee.

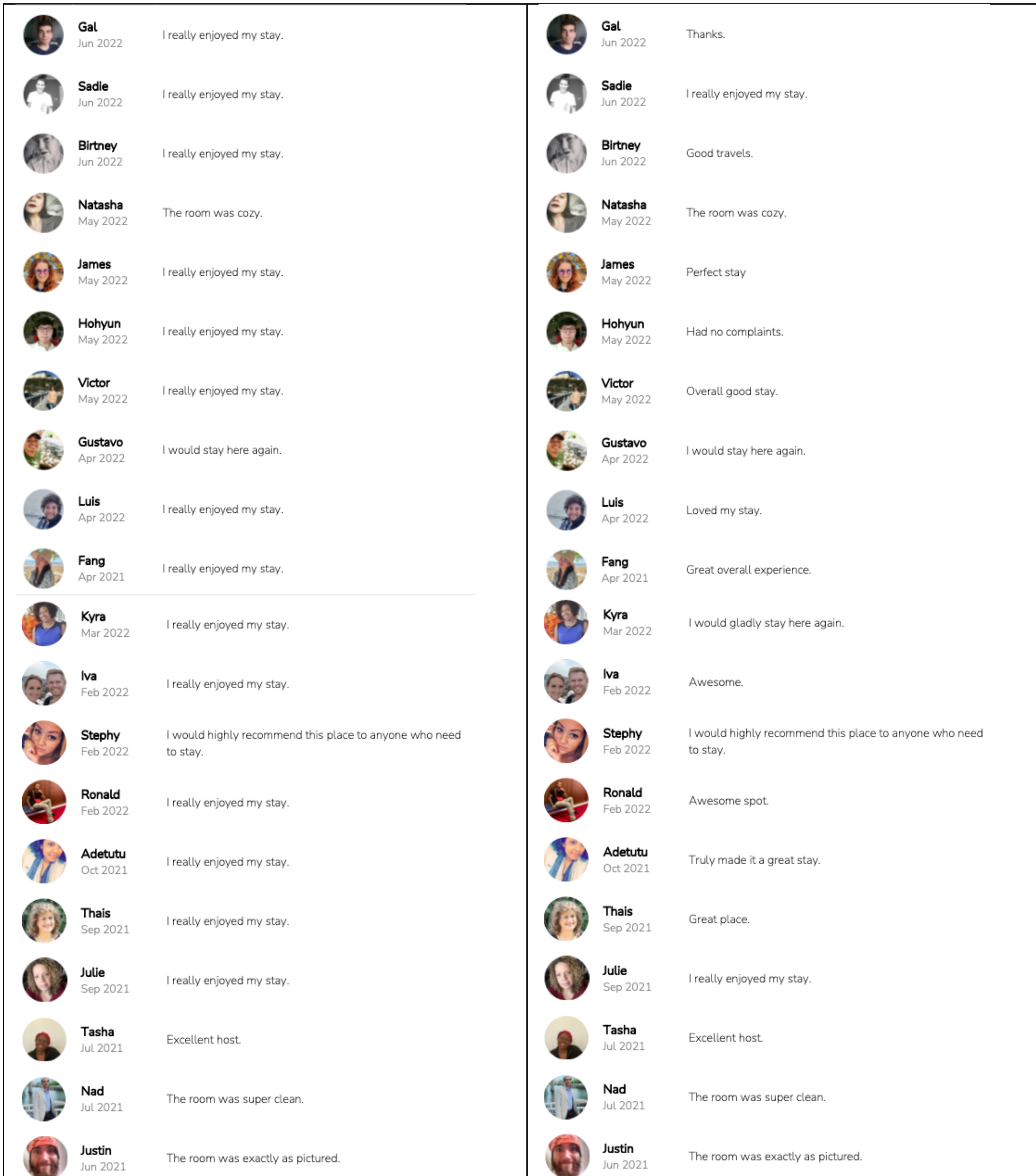
Sleeping arrangements

Bedroom 1
1 double bed

Amenities

Kitchen	Wifi
Breakfast	Cable TV
Iron	Laptop-friendly workspace
TV	Hangers
Hair dryer	Essentials

Review sets for Study 2



(A) High share of repetition (70%) (B) Low share of repetition (15%)

Study 3: Repetition, persuasion, and review reading behavior

Product information page for Study 3

Please imagine the following scenario:
You have an upcoming vacation and plan to stay a couple of days in Washington D.C., so you decide to check out some online reviews on Airbnb.com to find out where to stay. While searching for rooms on Airbnb.com, you find a room that seems to have a great location and fits your budget perfectly, so you decide to learn more about it. This is the information for this room **"Guest room and Private bath hosted by Leila"**.

Guest bedroom and private bath.

★ 4.86 · Superhost · Washington, District of Columbia, United States   Share   Save

What this place offers

- Kitchen
- Wifi
- Dedicated workspace
- Free parking on premises
- TV with standard cable
- Washer
- Dryer
- Air conditioning
- Private backyard – Fully fenced
- Indoor fireplace

Show all 34 amenities

After viewing this, you decide to inquire further and check out some reviews.

Stimuli for High Verbatim repetition conditions

	Page1	Page2	Page3	Page4
1	Leila is a great host.	Leila is a great host.	Leila is a great host.	Leila is a great host.
2	Leila was a great host.	Leila is a great host.	Leila was a great host	Leila was a great host.
3	Leila was a great host.	Leila is a great host.	Leila was a great host	Leila was a great host.
4	Leila is a great host.	Leila is a great host.	Leila was a great host	Leila was a great host.
5	Leila was a great host	Leila was a great host	Leila was a great host.	Leila was a great host.
6	Leila was a great host	Leila was a great host	Leila was a great host.	Leila was a great host
7	Thanks.	Truly made it a great stay.	Great overall experience.	Perfect stay
8	Great place.	Awesome spot.	Had no complaints	Loved my stay.
9	I would highly recommend this place to anyone who needed to stay.	The room was super clean	The room was exactly as pictured.	This was an excellent option
10	The room was cozy.	I would stay here again.	I really enjoy staying here.	The location is very convenient for both the bus and the metro.

Stimuli for High gist repetition condition

	Page1	Page2	Page3	Page4
1	Leila was a great host.	Leila was a good host.	Leila is a great host.	Leila is a great host.
2	Leila is the best host ever.	Great host.	Excellent host.	Great host.
3	Leila is a great host.	Leila is a great host.	Leila was a great host	Leila was a great host.
4	Leila is a good host.	Leila is a great host.	Leila was a great host	Leila is a great host.
5	The host was great.	Leila was a friendly host	Leila was a friendly host	Leila was friendly and hospitable.
6	Leila was an excellent host.	Leila was an excellent host.	Leila was an excellent host.	Leila was an excellent host.
7	Thanks.	Truly made it a great stay.	Great overall experience,	Perfect stay
8	Great place.	Awesome spot.	Had no complaints	Loved my stay.
9	I would highly recommend this place to anyone who needed to stay.	The room was super clean	The room was exactly as pictured.	This was an excellent option
10	The room was cozy.	I would stay here again.	I really enjoy staying here.	The location is very convenient for both the bus and the metro.

Stimuli for Low Verbatim repetition condition

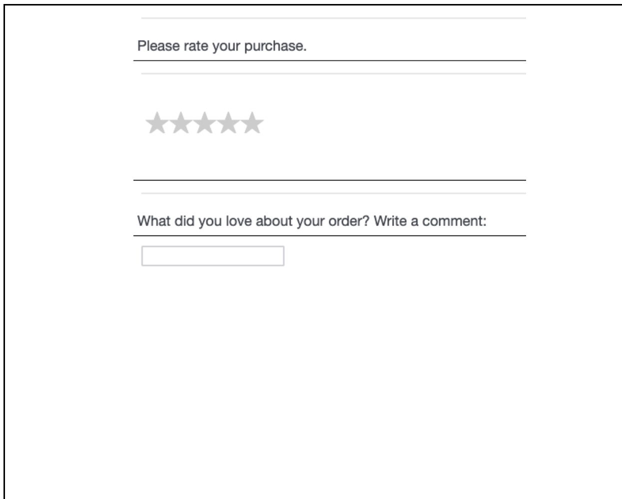
	Page1	Page2	Page3	Page4
1	Leila was a great host.	Leila was a great host.	Leila was a great host.	Leila was a great host
2	Leila was a great host.	Leila was a great host	Leila is a great host.	Leila was a great host.
3	Good stay.	We have a good stay.	Highly recommend	Awesome
4	Excellent trip.	overall, a perfect experience	Wonderful room	The place worked great.
5	I have a great time staying here.	Truly made it a great stay.	I really enjoyed my stay.	Thanks.
6	Overall good stay.	I would gladly stay here again.	Good travels.	I will definitely look up Leila and stay again!
7	Very nice room.	Great place.	Truly made it a great stay.	Perfect stay
8	Great overall experience.	Had no complaints	Awesome spot.	Loved my stay.
9	I would highly recommend this place to anyone who needed to stay.	The room was exactly as pictured.	The room was super clean	This was an excellent option
10	The room was cozy.	I really enjoy staying here.	I would stay here again.	The location is very convenient for both the bus and the metro.

Stimuli for Low gist repetition condition

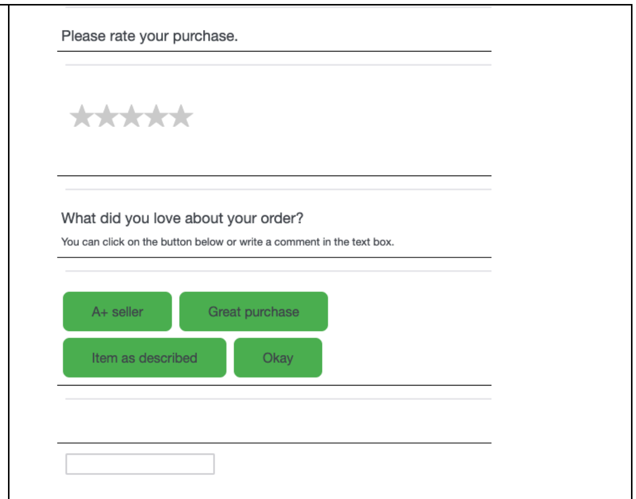
	Page1	Page2	Page3	Page4
1	Leila was a great host.	Leila was a good host.	Leila was a nice host.	Leila was a hospitable host.
2	Leila was an excellent host.	Leila was a friendly host	Leila is a terrific host.	Leila was a great host.
3	Good stay.	We have a good stay.	Highly recommend	Awesome
4	Excellent trip.	Overall, a perfect experience	Wonderful room	The place worked great.
5	I have a great time staying here.	Truly made it a great stay.	I really enjoyed my stay.	Thanks.
6	Overall good stay.	I would gladly stay here again.	Good travels.	I will definitely look up Leila and stay again!
7	Very nice room.	Great place.	Truly made it a great stay.	Perfect stay
8	Great overall experience.	Had no complaints	Awesome spot.	Loved my stay.
9	I would highly recommend this place to anyone who needed to stay.	The room was exactly as pictured.	The room was super clean	This was an excellent option
10	The room was cozy.	I really enjoy staying here.	I would stay here again.	The location is very convenient for both the bus and the metro.

Study 4: The moderating role of cause of repetition

Manipulation for the cause of repetition



(C) Computer-generated repetition



(D) Customer-generated repetition

Product information page

Stimuli for the review set with different level of repetition (Study 4)

by e***a	During past month	Great purchase.	by e***a	During past month	Great purchase.
by e***l	During past month	Great purchase.	by e***l	During past month	Great purchase.
by r***r	During past month	Great purchase.	by r***r	During past month	Great buy.
by t***u	During past month	Awesome.	by t***u	During past month	Good headphones.
by a***t	During past month	Great purchase.	by a***t	During past month	Very good.
by y***l	During past month	Great purchase.	by y***l	During past month	Love them.
by 1***e	During past month	Great purchase.	by 1***e	During past month	Thanks.
by 3***e	During past 6 months	Great purchase.	by 3***e	During past 6 months	Great purchase.
by k***c	During past 6 months	Thanks.	by k***c	During past 6 months	Awesome.
by t***j	During past 6 months	Great purchase.	by t***j	During past 6 months	Nice.
(C) High share of repetition			(D) Low share of repetition		

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