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THE EFFECT OF COLLECTIVE RATING ON THE PERCEPTION OF ONLINE REVIEWS

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Abstract

In online markets, collective ratings by prior buyers are often displayed in a marked place and influential for later consumers. While the aggregated ratings transfer overall evaluation towards products, they might also bring biases to potential consumers. In this study, we hypothesize the collective rating presence induces a confirmation bias in product review perception. We also propose that the level of expectation moderates the effect of confirmation bias. Using online reviews of multiple product categories from Amazon.com, our results support the hypotheses and help understand the direct and indirect roles of collective rating presence in affecting people's perception of review information: not only people are more likely to perceive reviews that confirm their expectation as more helpful, but they are more prone to the confirmation bias as their prior expectations towards the products are higher. Our research contributes to the current understanding of collective rating presence, reconciles the inconsistent findings in prior research on online review helpfulness and provides insights to consumer behaviours on information seeking and interpretation.

Keywords: Collective rating, online product reviews, prior expectation, confirmation bias, risk-averse, review helpfulness

1 INTRODUCTION

Online markets facilitate our life by providing convenient and fast shopping experiences. To mitigate the information asymmetry due to the Internet nature, many platforms began to use review systems, which encourage buyers to post their experiences and evaluations of products. By reading prior buyers' rating and text content, potential consumers learn from the past experience and optimize their purchase decisions (Dellarocas, 2003).

However, as the amount of information increases, potential consumers are overwhelmed by a large amount of information with uncertain quality and credibility. Many shopping websites therefore adopt two approaches to help consumers identify the product quality. The first approach is the collective rating information. Figure 1 is an example on the shopping website Amazon.com. It displays an aggregate evaluation from buyers who post reviews of the product. Shown by either a number or a distribution diagram, the evaluation helps identify good products. Sellers and marketers benefit from the aggregated average rating, since the rating is positively associated with the product price, sales and the trustworthiness of sellers (Ba & Pavlou, 2002; Chen & Lurie, 2013; Duan et al., 2008; Park & Kim, 2009; Zhu & Zhang, 2010).

Figure 1. Collective rating information of customer reviews on Amazon.com

The second approach is a voting mechanism which allows customers to vote for reviews that they feel helpful or unhelpful regarding their purchase decision (Figure 2). With higher helpfulness, reviews are more likely to be read and considered. Therefore, the helpfulness votes are important in identifying good reviews and hence good products.

Figure 2. Voting mechanism of online reviews

A number of studies focus on how people perceive review information. Early research explored that review helpfulness could be determined by reviews' observable features and reviewers' characteristics, such as review age, review length, and reviewer's expertise (Connors et al., 2011; Mudambi & Schuff, 2010; Schindler & Bickart, 2012). Also, content analyses have been applied by scholars to investigate review helpfulness (Cao et al., 2011; Kuan et al., 2015; Wu et al., 2011; Yin et al., 2014).

Although the two approaches have been studied intensively, there is limited research on their connections in helping identify good products. When a customer considers a particular product, he or she might first refer to the product average rating for an impression of the product before reading the reviews. An intuitive question would be: How does the presence of collective ratings influence or change the way people perceive review information?

To answer the questions, we draw on *confirmation bias* to propose a framework of examining the effects of collective ratings. Our work adds to an increasing number of studies exploring helpfulness perceptions of online reviews, reconciling the inconsistent findings of helpfulness perception biases. We also contribute to a better understanding of collective rating in online markets.

2 THEORY BACKGROUND & HYPOTHESES

Online review is defined as peer-generated product evaluation posted on company or third party websites (Mudambi & Schuff, 2010). As an outcome of product information, diagnosticity perception displays a diverse and integrated consumer perception. Among past studies, researchers consistently use helpfulness perception as a reflection of diagnosticity value of a review (Huang et al., 2013; Mudambi & Schuff, 2010). Following them, we use review helpfulness as our focal outcome of review perception.

One common finding of helpfulness perception is negativity bias, that reviews with negative ratings are more likely to be helpful (Cao et al., 2011; Kuan et al., 2015). Since bad things are rare and revealing, they are receiving more thorough processing than good things (Baumeister et al., 2001). Meanwhile, Pan and Zhang (2011) propose an opposite view. They propose that positive reviews are more helpful than negative ones, because positively-rated reviews are more congruent with consumers' predispositions and more likely to be perceived helpful. However, the two biases both neglect the collective information that buyers can refer to while making purchase decision. In the following section, our research re-examines the perception preference from a new perspective.

2.1 Confirmation bias in online markets

To reduce risk perception, information acquisition is widely used by consumers when they make purchase decisions. Bauer (1960) and Lantos (1983) suggested that a buyer will attempt to reduce the amount of information when confronting with mass data. In examining consumer preference for information, we use studies on confirmation bias as the foundation of our answer.

Confirmation bias is frequently used in psychology literature. It posits that people tend to seek or interpret evidence in ways that are partial to existing beliefs, expectations or a hypothesis in hand (Nickerson, 1998). When processing information, people tend to believe in what they expected and the process is usually with less consciousness.

There are two important elements in the confirmation bias. The first one is prior beliefs or expectations as sources of bias. The other is the subsequent information seeking or interpretation. The process is different from the averaging strategy in information integration theory or Bayesian decision theory, both of which weigh each piece of information equally (Akerlof & Dickens, 1982; Anderson, 1968).

The prevalent influence of the confirmation bias phenomenon has been reported in a number of settings, such as social interaction (Snyder & Swann, 1978), advertising effect (Deighton, 1984), word-of-mouth information processing (Wilson & Peterson, 1989), and investment decision-making (Park et al., 2013).

Explanations of the confirmation bias are given by different streams of research. From an information-processing perspective, people tend to gather information about only one hypothesis at one time and not to consider possibilities simultaneously (Tweney & Doherty, 1983). Since people are more inclined to assume that a statement is true than to assume that it is false (Gilbert, 1991), later searching and interpretation of evidence processes are inevitably prone to confirm the hypothesis. The second explanation posits that the desire to be rational makes it difficult for people to accept new evidence against their expectations objectively. With this account, people tend to value supportive information and discard inconsistent evidence (Festinger, 1962). Thirdly, according to self-enhancement theory, people tend to view themselves in a positive manner and search for information which could validate their prior beliefs (Swann et al., 1987).

Internet is a fertile environment of confirmation bias. The "pull" nature of Internet inherently encourages people to take in whatever information they want while ignoring the rest (Bimber & Davis, 2003), which further affords the opportunity to exhibit confirmation bias towards information. In this paper, we first investigate the existence of confirmation bias in processing online reviews.

According to the account above, we argue that the two approaches adopted in online markets propel people to perceive review information with confirmation bias. First, the collective information provides a prior expectation for potential consumers in evaluating a product. Next, review readers tend to favour the reviews that confirm the expectation.

In practices, product average ratings are often regarded as central tendency of past reviews, providing overall evaluation towards the products. Therefore, we use the average rating as the prior expectation people have on the specific product. We define confirming information as one with high consensus to the expectation, and disconfirming (or deviant) information as one with low consensus to the expectation. Thus, we hypothesize that:

H1. People exhibit confirmation bias in perceiving helpfulness of review information.

2.2 Prior expectation

Reference dependence theory provides explanations that the confirmation bias tendency could be influenced by prior expectation, either favourable or unfavourable. The theory suggests that consumers' reaction towards uncertainty depends on their reference point, which is taken as the status quo, i.e. the assessment of current situation (Kahneman & Tversky, 1979). A decision outcome is framed as a gain when it is above the reference point. Individuals tend to be risk-averse in such situation. On the other hand, an outcome is framed as a loss when it is below the reference point, and people tend to be risk-seeking. In conformity with loss aversion, Meyer (1981), Kahn and Meyer (1991) and West and Broniarczyk (1998) conducted experiments and show that individuals prefer confirming information when the average opinion of the product is favourable (above the reference point), and the preference will be reduced or reversed when the average opinion is unfavourable (below the reference point). In the similar vein, we expect that the prior expectation influence consumers' preference towards confirming information, as it decides whether consumers attribute it as a gain or a loss relative to the reference point.

The choice of reference point can also be influenced by other factors such as aspirations, expectations, norms and social comparisons (Tversky & Kahneman, 1991). In the context of our research interest, reference point could be a norm that is formed through consumers' experience accumulation. A large collection of studies have long been reporting the overwhelmingly positive rating distributions in online shopping markets (Dellarocas, 2003; Hu et al., 2009; Li & Hitt, 2008). Thus, instead of drawing a deterministic threshold of reference point, we posit that a product with high prior evaluation is regarded to be above the reference point and vice versa. In this situation, facing up to highly-evaluated/low-evaluated products, consumers tend to be risk-averse/risk-seeking and consider confirming /disconfirming information as more helpful.

Therefore, we expect that the preference of confirming information varies with regard to their prior expectations towards the product, i.e. the tendency of confirmation bias in helpfulness perception differs in terms of the favourability of the prior expectation. Specifically, we hypothesize that:

H2. People's tendency to exhibit confirmation bias in perceiving review helpfulness is stronger for products with higher expectations than for products with low expectations.

3 METHODOLOGY

3.1 Data collection

We empirically test these hypotheses on data from an online shopping platform, Amazon.com. We use Amazon because of two reasons. First, it is one of the biggest online markets in the world and consistently has the largest number of posted reviews (Pan & Zhang, 2011). Our findings could be more prevalent if being produced on the most influential online market. Second, previous studies delivered inconsistent results of rating biases by Amazon data. As we provide an alternative view, it is better to test our hypotheses by data from the same source.

The data we used were collected by the Stanford Network Analysis Project[1] (McAuley & Leskovec, 2013). We chose three categories, Books, Music, and Toys & Games, as they are the common categories often used in prior studies. The original dataset spans over thirteen years, including basic review, reviewer, and product information. We discarded products that were launched before the helpfulness voting mechanism was applied, remaining products which were launched between November 1st 2008 and January 31st 2013. Since aggregated evaluation may not be considered representative if a product has few reviews, we dropped the products which have less than five reviews. Therefore, our final dataset contains a sample of 10,585 reviews on 1,713 products in three categories (Table 1).

Categories	N(Review)	N(Product)	N(Review)/N(Product)
Books	1,527	343	4.45
Music	4,013	505	7.95
Toys & Games	5,045	865	5.83
IN TOTAL	10,585	1,713	6.18

Table 1. Dataset description

3.2 Measures

Similar to past studies on product reviews, we use review helpfulness as our dependent variable (*Helpfulness*), and measure it by the ratio of the helpful votes to the total votes received by a review. Besides that, we use $Voting_k$ ($k \geq 1$), a binary variable. It equals to 1 if a review has at least k votes, otherwise it equals to 0.

3.2.1 Collective information

To capture the confirmation bias tendency, we created new measurements of collective information. Following past research, the mean of collective ratings could be used to represent the expectation level. However, with the growing number of reviews, the prior expectation for each potential consumer might change over time. By using the overall average rating, we may misinterpret it as the actual expectation that a potential consumer herself experienced. Therefore, we adopt a novel approach to obtain our measurements.

First of all, we sorted the reviews of each product according to their post time. Next, we calculated the moving average (*Mov.Avg*) of collective ratings for the product at the time when each later review was posted. With this process, the *Mov.Avg* captures the expectation level for the product by the time one potential consumer is reading reviews.

3.2.2 Confirming and disconfirming information

To measure how close the review rating is to the expectation, we introduce information disparity (*InfoDisparity*), which is calculated as the absolute difference between a review's rating and the expectation level (*Mov.Avg*). In this way, *InfoDisparity* represents the dynamic distance from a review's evaluation to the aggregated evaluation at that time.

[1] http://snap.stanford.edu/index.html

3.2.3 Control variables

Following past research, we controlled a series of relevant variables on product level and review level. On product level, we control the following product features. 1). *Mov.Var*: the rating variance of the product; 2). *LaunchTime*: the launching time of the product; 3). *Price*: the product price; 4). *ReviewNum*: the number of reviews under the product.

On review level, we controlled not only reviews' numeric features, but also some textual features. Specifically, we control 1). *ElapsedTime*: the elapsed time of review as a proxy of review age; 2). *WordCount*: the review's word count; 3). *UserExp*: the reviewer's reviewing history of products in the same category, reflecting the expertise of the reviewer; 4). *Readability*: Gunning Fog Index (Gunning, 1969) which has been used for readability in many online review studies of IS discipline (Bao & Chau, 2015; Goes et al., 2014; Kim et al., 2006); 5). *Subjectivity*: the texts' subjectivity level. Following the approach of Ghose and Ipeirotis (2007), we prepared the subjectivity and objectivity classifiers and calculated the subjectivity percentage in review content; 6). *Certainty*, *positivity* and *negativity*: the sentiment level of the three categories in review texts, using a dictionary provided by the Linguistic Inquiry and Word Count (LIWC). It was developed by Pennebaker et al. (2007) and designed to calculate the degree of certain words usage. 7). *Uniqueness*: the textual uniqueness in each review under a particular product item (Bao & Chau, 2015). It was calculated by the percentage of new words that appear in a review and have not been found in the previous reviews for the certain product.

As some of the variable distributions are heavily skewed, we transformed them into log form. Descriptive statistics of the variables are listed in Table 2.

Variable		# Obs	Mean	Std. Dev.	Min	Max
Helpfulness		10,585	0.27	0.43	0	1
InfoDisparity		10,585	0.76	0.73	0	3.88
Mov.Avg		10,585	4.25	0.64	1	5
Product-level control variables	Mov.Var	10,585	1.19	1.01	0	4.8
	LaunchTime	10,585	2224.92	301.06	973	2794
	Price	10,585	22.28	28.00	0.25	499
	ReviewNum	10,585	32.51	46.75	5	268
Review-level control variables	Log(ElapsedTime)	10,585	7.21	0.30	6.85	7.90
	Log(WordCount)	10,585	3.96	0.78	1.10	7.86
	Log(UserExp)	10,585	1.27	1.08	0.69	10.092
	Readability	10,585	10.42	5.42	0.8	107.85
	Subjectivity	10,585	0.83	0.24	0	1
	Certainty	10,585	0.02	0.02	0	0.35
	Positive	10,585	0.07	0.05	0	0.75
	Negative	10,585	0.01	0.02	0	0.2
	Uniqueness	10,585	0.38	0.17	0	1

Table 2. Descriptive statistics

3.3 Research Model

Based on the hypotheses, we set up the following models. As there would be no observation on the mean and standard deviations of helpfulness unless there is at least one vote, a potential selection bias might exist (Mudambi & Schuff, 2010). We therefore follow the approach of Kuan et al. (2015), using a two-step procedure with a Heckman selection model (Heckman, 1979).

Equation 1. $Voting_k = w_i' \alpha + \mu$

Equation 2. $Helpfulness \mid (Voting_k) = x_i' \beta + \xi + \lambda(\cdot)$

In the first step, we select reviews which had been voted at least *k* times. In the second step, we examine the effects of independent variables on review helpfulness. The *k* (equals 1 by default), is the selection threshold for the minimum number of votes each review receives. $\lambda(\cdot)$ refers to the inverse mills ratio, estimating the average selection effect in the first step. μ and ξ are the error terms. To avoid potentially problematic multicollinearity with the interaction terms, we centered each variable in them.

Also, it may not be meaningful to estimate *Helpfulness* if there is only one vote for a review (when $k=1$ for $Voting_k$). So we test the robustness of our results using different vote thresholds a review receives.

4 RESULTS

First, to address multicollinearity issues, we calculated the variance inflation factor (VIF) for each variable included in the models. The highest VIF across all variables is 1.06, well below the accepted cut-off value of 10. Then, we ran a series of regression analysis. Table 3 reports the results of different model specifications and robustness tests.

Confirmation Bias. To test hypothesis 1, we first ran an analysis with the control variables (Model 1), and then added the two independent variables (Model 2). As shown in Table 3 (Model 2), *InfoDisparity* had a significant effect on helpfulness perception (β = -0.1861, $p < 0.001$). It suggests that reviews with deviant opinions are less likely to be perceived as helpful, and confirming reviews are more likely to be perceived helpful. Therefore, H1a and H1b are supported, i.e. there exists a confirmation bias in the helpfulness perception

Expectation Level. Result in Model 3 indicates that the interaction effect of information disparity with expectation level is significant (β = -0.0709, $p < 0.001$). The negative coefficient shows that the higher the expectation level, the stronger the consensus information is favoured and the stronger the deviant information is discarded. As shown in Figure 2, the confirmation bias is stronger when prior expectation is high than it is when the prior expectation is low. Therefore, H2 is also supported.

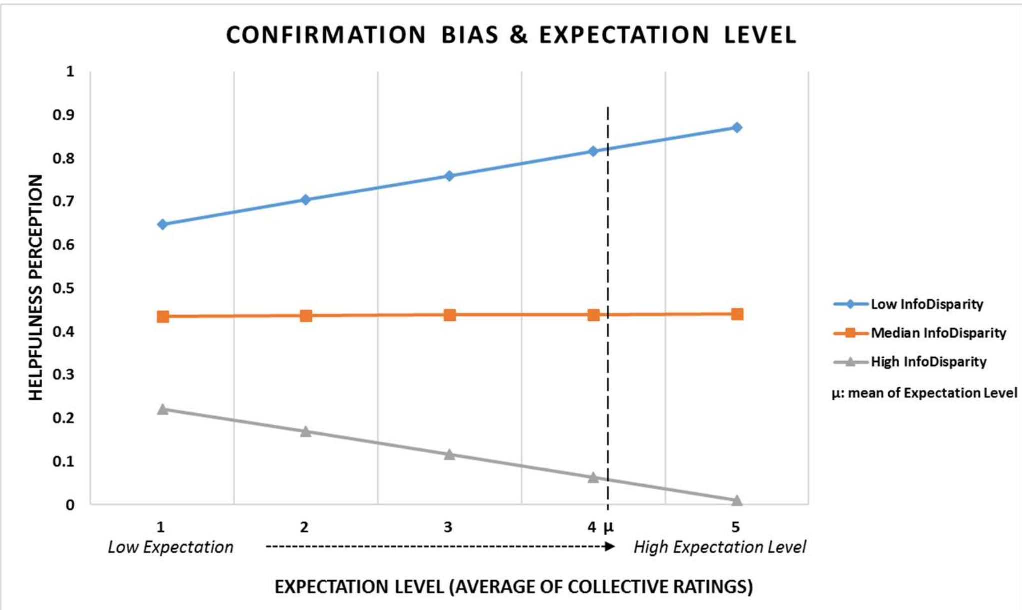

Figure 3. Moderating effects of expectation level

Control Variables. As shown in the models, positive sentiment and review length are positively related to the perceived helpfulness. The review variance, product price, review age, negative sentiment and textual uniqueness are negatively related to the helpfulness perception. Some results are within our expectation because reviews with more depth, and less uniqueness are more likely to be helpful. A recency effect exists in helpfulness perception for a review, that new reviews are receiving more helpfulness perception. We also found consistent positive effect of positive sentiment and negative effect of negative sentiment on helpfulness perception.

DV = *Helpfulness*	Model 1		Model 2		Model 3		Model 4		Model 5	
	Control Variables		Without Interaction		*Mov.Avg* Interaction		Threshold *k = 3*		Threshold *k = 5*	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
InfoDisparity			-0.1861***	(0.015)	-0.1855***	(0.015)	-0.2277***	(0.035)	-0.3263***	(0.067)
Mov.Avg			0.0578***	(0.014)	0.1210***	(0.018)	0.0826**	(0.027)	0.1007*	(0.043)
*Mov.Avg * InfoDisparity*					-0.0709***	(0.012)	-0.0698***	(0.016)	-0.0799**	(0.025)
Mov.Var	-0.0605***	(0.008)	0.0457***	(0.01)	0.0427***	(0.01)	0.0388**	(0.014)	0.0588*	(0.024)
LaunchTime	-0.0001*	(0.00)	-0.0001*	(0.00)	-0.0001*	(0.00)	0.000	(0.00)	0.0001	(0.00)
Price	-0.0008***	(0.00)	-0.0010***	(0.00)	-0.0010***	(0.00)	-0.0020***	(0.00)	-0.0023***	(0.00)
ReviewNum	0.0001	(0.00)	0.000	(0.00)	-0.0001	(0.00)	-0.0004	(0.00)	-0.0005	(0.00)
Log(ElapsedTime)	-0.3458**	(0.118)	-0.2956**	(0.1)	-0.2614**	(0.098)	-0.3608	(0.208)	-0.8605*	(0.388)
Log(WordCount)	0.0783***	(0.015)	0.0792***	(0.014)	0.0846***	(0.013)	0.0615*	(0.024)	-0.0144	(0.049)
Log(UserExp)	-0.0232***	(0.005)	-0.0241***	(0.005)	-0.0231***	(0.005)	-0.0175**	(0.006)	-0.0173	(0.011)
Readability	-0.0011	(0.001)	-0.0011	(0.001)	-0.001	(0.001)	-0.0014	(0.001)	-0.0004	(0.002)
Subjectivity	-0.0477	(0.026)	-0.0101	(0.024)	-0.007	(0.024)	0.0429	(0.033)	0.0531	(0.052)
Certainty	-0.2408	(0.327)	-0.3734	(0.308)	-0.4677	(0.305)	-0.1554	(0.44)	-0.6994	(0.721)
Positive	1.0508***	(0.179)	0.3840*	(0.155)	0.3349*	(0.153)	0.1989	(0.271)	0.9983	(0.565)
Negative	-1.9314***	(0.413)	-0.7022*	(0.357)	-0.5517	(0.352)	-1.1791*	(0.474)	-1.4567	(0.761)
Uniqueness	-0.3105***	(0.064)	-0.2697***	(0.056)	-0.2719***	(0.055)	-0.3390**	(0.104)	-0.5080*	(0.227)
Intercept	3.5092***	(0.987)	3.2089***	(0.841)	2.9016***	(0.823)	3.8552*	(1.766)	8.2821*	(3.345)
Inverse Mills Ratio	-0.2674**	(0.083)	-0.2103**	(0.069)	-0.1861**	(0.068)	-0.2175*	(0.106)	-0.4667*	(0.183)
Wald chi2	312.55106		664.59155		714.16114		555.80158		267.27719	
Prob > chi2	0		0		0		0		0	
R square	0.034		0.117		0.131		0.231		0.186	
Obs	10,585		10,585		10,585		10,585		10,585	

Table 3. *The selection stage results of the Heckman model are not reported for brevity. Standard errors are reported in parentheses under coefficients. * p<.05; ** p<.01; *** p<.001*

Robustness Check. Our hypotheses are also supported by various robustness tests (Models 4-5). Therefore, in summary, the empirical evidence is consistent with the hypotheses we proposed. On the Amazon platform, the collective review information of product predisposes consumers to accept the reviews holding similar evaluation, resulting in a confirmation bias. Meanwhile, the effect of confirmation bias is moderated by the expectation level.

5 CONCLUSION

The purpose of our research is to discover whether the presence of product collective rating introduces biases or change the way people perceive information. We extend our knowledge of collective ratings from new perspectives – exhibiting confirmation bias to prior expectation. We suggest that 1) collective rating introduces confirmation bias to consumers; 2) the tendency to show confirmation bias becomes greater as the expectation level is higher. Therefore, we conclude that collective rating presence directly and indirectly influences the way people perceive information.

5.1 Theoretical & Practical Implications

A main contribution of our study is to extend the current research of reviews helpfulness perception. Our work on the collective rating presence intends to supplement and reconcile the past inconsistent research findings. We provide evidence that potential consumers are prone to confirmation bias when perceiving review information. Second, the present research will also contribute to the studies of collective rating presence. We suggest that, consumers' tendency to exhibit confirmation bias in review perception increases with collective evaluation level. Third, this research affords a better understanding towards consumer behaviours of information seeking and interpretation. In making purchase decision, consumers' information handling and seeking behaviours are constantly affected by their risk perception, echoing the underlying mechanisms in prospect theory studies (Kahneman & Tversky, 1979).

Our research also sheds light upon online marketing practices. To further benefit sellers' and platforms' welfare, managers of such online markets should recognize the existence of confirmation bias and improve the usage of collective ratings. Noticing that lower ratings do not necessarily lead to the agreement of bad product performances, one approach is to decide when and how to offer collective rating information to potential consumers. For the goodness of potential consumers, understanding confirmation bias is essential in helping them make purchase decisions, so that fewer consumers would behave with herds and buy products of poor quality, or miss a good one because of its reported feedback.

5.2 Limitations & Future Work

The emphasis of the present research is limited to the phenomenon of confirmation bias on the review helpfulness perception. We did not reveal the underlying reasons of such bias. Second, our study only explores the perceptual benefits of review information, but later research could extend our idea on economic or social benefits of such information. Also, we did not consider effects of potential consumers' prior knowledge or expertise in studying the confirmation bias tendency, which might be a potential moderator to influence the tendency. Finally, in order to further generalize our idea, future research could also use multiple methodologies or apply to other contexts to investigate the idea of present study.

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