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The Effect of the Products' Review on Consumers' Response

Zhou Feng*

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Abstract

Purpose – The purpose of this research is to discover whether the presence of the product average rating introduces biases or change the way people perceive information. We posit that review's overall rating has a predisposition effect on consumers' perception towards detailed review information.

Research design, data, and methodology – To test these hypotheses, we conducted an empirical study on a real-world setting of online shopping platform. We choose the Amazon website to test our results. The data we use were collected by the Stanford Network Analysis Project1 (McAuley et al., 2013).

Results – With a dataset containing reviews of seven product categories from amazon.com., our findings could possess more generalizability as they are produced on the typical and influential online market. Second, as our research provides alternative views of consumers' shopping behavior, it is better to test our hypotheses by data from the same source.

Conclusions – Our study reveals the impact of the collective rating presence on consumers' diagnosticity perception and sheds light upon some of the conflictive results in prior studies. Our research generates implications to both theories and business practices, and suggests future directions for the research question.

Keywords: Collective Rating, Online Product Reviews, Predisposition, Perceived Risk, Perceived Diagnosticity.

JEL Classifications: D30, D70, M70.

1. Introduction

While evaluating products online, people often refer to the product's average rating, which is given voluntarily by all the past consumers and shown by either a number or a distribution diagram (e.g., <Figure 1>). The evaluative mechanism facilitates people when they search for or consider products of their interests. Potential buyers can be disposed by the average attitude of the prior buyers. Some even use the average rating as a filter condition to exclude products with low ratings. For more feature details of the product, people may continue to read product reviews piece by piece.

<Figure 1> Average rating and distribution diagram of customer reviews on Amazon

Many researchers have shown that average rating of a product is positively associated with the product price, sales and the trustworthiness of sellers (Ba et al., 2002; Berger et al., 2010; Chen et al., 2013; Chevalier et al., 2006; Clemons et al., 2006; Duan et al., 2008; Moe, 2009; Park et al., 2009; Zhu et al., 2010). Therefore, to take these advantages effectively, nowadays many websites have already adopted the approach of presenting the appraising information.

Although the economic benefits of collective average rating have been studied intensively, there is limited study of its influence on consumers'perception of other incoming information. Individual reviews, which appear after the collective rating, discover experience of past buyers and their content would greatly influence potential consumers'decisions. Past researchers have found evidence that emotional and negative reviews are more likely to be favored by consumers. But we argue that the collective rating, as a piece of information, might alter or influence the way people digest other information. We ask the following research questions: Will the presence of the product average rating introduce biases or change the way people perceive information? Would consumers be more willing or reluctant to accept other information when disposed to an evaluative diagram?

To answer the questions, in this research, we study the

* Corresponding Author, College of Electronic Information, Shandong Institute of Commerce and Technology, Ji'Nan, Shandong Province, China. E-mail: zhoufengkey@163.com.

effect of products' evaluative information on potential consumers' perception of product reviews. First, we discuss the consumers' perception of information we focus on in this research. Second, building on the ideas that predisposition influences a person's judgment of information (Wilson et al.,1989), and the word-of-mouth (WOM) information functions differently for products with different perceived risks (Arndt,1967). We hypothesize that the information of average score acts two roles by its presence. First, it acts as a predisposition of the product and changes how people perceive other word-of-mouth information –the more deviant the WOM is, the less acceptable it would be. Second, since the evaluative information suggests the performance risk of the product, it also affects the way people perceive deviant information in product reviews. Next, we empirically test our hypotheses using real-world review data from Amazon.com. The results and analysis provide answers to the research questions and shed light upon the impact of average rating through its presence. At last, we discuss the theoretical and practical implications of our research, as well as limitations and future work.

2. Theory Background and Hypotheses

In studying the consumers'perception towards incoming information, we make use of perceived diagnosticity for two reasons. First, as we explain in the following paragraphs, the diagnosticity perception displays a diverse and integrated consumer perception. Second, consumers are familiar with and educated to use the mechanism of expressing their overall diagnosticity perception in online markets. Therefore the notion of perceived diagnosticity fits our research purpose in examining the perception of online information.

The definition of perceived diagnosticity changes according to different contexts and tasks. Hoch et al. (1989) define perceived diagnosticity as the extent to which it helps the consumer assign a product to one (and only one) cognitive category. Jiang et al. (2004) bring the definition into online context and used it to represent consumers'cognitive belief that a website facilitates their product understanding. In the later work of Mudambi et al. (2010), they introduce the concept to online product reviews and interpret helpfulness as a reflection of review diagnosticity.

Consistent with the notion of information diagnosticity found in prior research, we define review diagnosticity as the extent to which the information in a review helps people discriminate between good and bad product/service items. Maheswaran et al. (1991) operationalize diagnosticity through the importance of information. However, in online markets, importance alone could not represent consumers'acceptance of the information due to the increased uncertainty. A piece of information could be important to know, but also irrelevant. Therefore, the definition of review diagnosticity might integrate complex dimensions of information, such as importance, relevance, informativeness, accuracy and so on. Also, potential consumers perceive diagnosticity in different stages of online pre-purchase process. Thus, to capture the diagnosticity perception of consumers, we follow the extant studies and adopt the overall helpfulness perception as a proxy of review diagnosticity.

2.1. Prior Belief

Prior belief, or predisposition towards a product, has the potential to affect a person's judgment of WOM information in assessment process (Crocker 1981; Wilson et al., 1989).

Crocker (1981) suggested that for instances within expectations, there are advantages in memory recognition. But for instances that contradict an expectation, prior studies showed mixed results. Processed at a deeper level, the inconsistent information is easier to recall, obtaining an advantage in memory by the additional processing. However, Crocker also stated that if the incongruence can be explained so that it makes sense in the context of the other information, then it is no longer incongruent or the incongruence is qualified and limited. In this way, the incongruent information is likely to be recalled but with little influence on assessment process.

Hoch et al. (1989) explained the impact of predisposition from another perspective. They held the opinion that prior impressions are persistent and hard to be changed by other information, even by contradicted information, because 1) any ambiguous information is interpreted as consistent to expectancies, 2) any consistent information to expectancies increases confidence to expectancies, and 3) any inconsistent information is discounted or ignored (Herr et al., 1991; Hoch et al., 1989).

When investigating the potency of information in different types of expectations, Wilson et al. (1989) showed that individuals' receptivity to both positive and negative WOM information is determined largely by its "fit" with their prior evaluation position. The more the information matches the preposition, the more acceptable it is. Their research builds up the idea that prior information, expected or unexpected, affects people's judgment toward other information.

In studying the conditions where the theory holds, Wilson et al. (1989) found that no matter the predisposition was newly established or well-founded, the results are the same, i.e. once a consumer had a predisposition toward a product, he/she will tend to filter the information that fits the evaluative position. Online markets enable us to various products which we may not have heard of. According to the above, even though consumers are not introduced to the product before, they can be influenced by the collective rating displayed on the product page to formulate an impression. Hence, incoming information which has smaller information disparity with the impression would be more favored. Therefore, we hypothesize that,

<Hypothesis 1> A review whose rating is closer to the average product rating is more likely to be perceived diagnostic.

2.2. Perceived Performance Risk

Besides a predisposition, the collective rating in online markets provides the satisfaction perception of the product/ service item. Since consumer behavior can be viewed as risk taking (Bauer, 1960; Kaplan et al., 1974), it is essential for online consumers to reduce the risk level by pre-purchase information acquisition (Ha, 2002).

Extant research has defined six components of perceived risk, namely financial, physical, psychological, performance, social, and time-related risk (Stone et al., 1993). The collective evaluation of product given by prior product reviews provides a relatively objective evaluation of the product performance. The higher the evaluation is, the more certainty consumers will perceive upon the item and the less the performance risk will be. Since performance risk occurs when the product chosen might not perform as desired and thus not deliver the benefits promised (Horton, 1976), interpreting the collective rating as a measure of performance value is consistent with the notion of the perceived risk in business context.

One might wonder the relationship of performance risk and the product uncertainty concept in Dimoka et al. (2012). Product uncertainty is defined as a buyer's difficulty in evaluating products and predicting how they will perform in the future (Dimoka et al., 2012). In our research, performance risk is different from product uncertainty. A high level of product uncertainty indicates a situation where buyers are more difficult to evaluate the product, while a high performance risk suggests that the product is more likely to have a low quality.

WOM is an important risk reliever for consumers at pre-purchase phase (Ha, 2002; Roselius,1971), but the impact of WOM is different as a function of perceived risk. Arndt (1967) showed that comparing to low-risk perceivers, the high-risk perceivers tended to make more efforts to seek word-of-mouth information. The high riskers are more active in various WOM sources, such as starting pre-purchase conversation, listening to comments, requesting more information and so on. Online markets have made the approaches of obtaining WOM information easier, so online consumers are more likely to initiating searching behaviors.

Since product rating implies the risk of the purchase, it is inferred that high product rating presents a low-risk purchase environment, and low product rating invokes high-risk perception. Therefore in our context, we posit that consumers are less open, and less willing to accept various information when they evaluate products with high ratings, than they are when evaluating products with low ratings.

To summarize, we hypothesize that,

<Hypothesis 2> The deviant information is perceived less diagnostic in reviews under products with high average ratings than in those under products with low average ratings.

3. Methodology

To test these hypotheses, we conducted an empirical study on a real-world setting of online shopping platform.

There are several reasons to choose the Amazon website to test our results. First, Amazon is one of the biggest online markets all over the world and consistently has the largest number of posted reviews (Pan et al., 2011). Many prior studies of online reviews have been conducted on Amazon. Our findings could potentially possess more generalizability as they are produced on the typical and influential online market. Second, previous studies delivered inconsistent results of rating biases by Amazon data. As our research provides alternative views of consumers'shopping behavior, it is better to test our hypotheses by data from the same source.

The data we use were collected by the Stanford Network Analysis Project1 (McAuley et al., 2013). Seven categories were chosen in our pilot test, including Electronics, Gourmet & Food, Health, Home & Kitchen, Musical Instrument, Sports & Outdoors, and Tools & Home Improvement. We discarded products that were launched before the helpfulness voting mechanism was added, resulting products whose launch time are more than 2,500 days from now to be deleted. Therefore, our pilot dataset contains a sample of 213,934 reviews on 52,022 products. Following is a description table for the data we collected.

<Table 1> Data set description

Category	# Products	# Reviews	Avg. #reviews/product
Electronics	7,493	33,668	4.49
Gourmet & Food	3,251	11,294	3.47
Health	7,930	33,563	4.23
Home & Kitchen	9,421	39,188	4.16
Musical Instrument	2,986	11,218	3.76
Sports & Outdoor	8,744	36,264	4.15
Tools & Home improvement	12,724	48,739	3.83
IN TOTAL	52,549	213,934	4.07

3.1. Measures

We use review helpfulness as our dependent variable (*Helpfulness*). We measure review helpfulness by the ratio of the helpful votes to the total votes received by a review.

To measure how close the review rating is to the average product rating, we introduce information disparity (*Info Disparity*), which is the absolute difference from a review's rating to the average product rating at that time. First, we sort the reviews under each product according to their posting time. Second, we calculate the moving average score of the product when each review was posted. Third, the *Info Disparity* for each review is calculated. As we explained above, we measure the perceived shopping risk for each product by the overall average rating score of the product (Avg. Product Score) that the consumers are reviewing.

At the same time, following prior research, we controlled a series of relevant variables on product level and review level. On product level, we use the launched time of product (Launch Time), price (Price) and the number of reviews under the product (Review Num) as control variables. On review level, we use control the elapsed time of review (Elapsed Time) as a proxy of review age, review's word count (Word Count), reviewer's expertise (User Exp.), and also some review's textual features.

Past research has found that many textual features of online review could influence the diagnosticity perception, such as readability, subjectivity, certainty and sentiment. We therefore control them in our research by using various content analysis techniques. First, to control for the reviews' readability level (*Readability*), we calculated the Gunning Fog Index. It estimates the years of formal education needed to understand the text on a first reading (Gunning, 1969), and had been used in many online review studies of IS discipline (Goes et al., 2014; Kim et al., 2006). Second, to measure the texts' subjectivity level (*Subjectivity*), we prepared the subjectivity and objectivity classifiers and calculate the percentage of subjectivity in review content, following the approach of Ghose et al. (2007). Third, we used a dictionary provided by the Linguistic Inquiry and Word Count (LIWC), which was developed by Pennebaker et al. (2007) and designed to calculate the degree to which people use different categories of words across a wide array of words. We applied LIWC to calculate the words that appear in categories of certainty (*Certainty*), positive sentiment (*Positive*) and negative sentiment (*Negative*). At last, we used *Uniqueness* to measure the uniqueness words in each review under a particular product item. 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.

The descriptive statistics and correlations of the variables are listed in <Tables 2> and <Tables 3>.

3.2. Method

Because there are no observations on the mean and standard deviations of helpfulness unless there is at least one vote, a potential selection bias might exist in our sample (Mudambi et al., 2010). We therefore follow the approach of Kuan et al. (2015), using a two step procedure with a Heckman selection model (Heckman, 1979).

<Table 2> Descriptive statistics for three categories

Variable	Obs	Mean	Std. Dev.	Min	Max
Helpfulness	213,934	0.36	0.46	0	1
Info Disparity	213,934	0.60	0.74	0	3.82
Avg. Product Score	213,934	4.13	0.78	1	5
Log(User Exp)	213,934	1.15	0.81	0.69	5.89
Readability	213,934	10.03	4.89	0.4	433.12
Subjectivity	213,934	0.89	0.19	0	1
Certainty	213,934	0.01	0.02	0	0.55
Positive	213,934	0.05	0.04	0	1.1
Negative	213,934	0.01	0.02	0	0.97
Uniqueness	213,934	0.59	0.31	0	1
Log(Elapsed Time)	213,934	7.16	0.30	6.76	7.82
Log(Word Count)	213,934	3.95	0.72	0.69	8.27
Launch Time	213,934	1,885.23	444.54	863	2,500
Price	213,934	40.10	72.97	0.01	999.99
Review Num	213,934	52.02	180.96	1	1414

<Table 3> Correlations

1. Helpfulness	1.000														
2. Info Disparity	-0.056	1.000													
3. Avg. Product Score	-0.038	-0.246	1.000												
4. Log(User Exp.)	-0.033	0.013	0.000	1.000											
5. Readability	0.080	0.014	-0.024	0.004	1.000										
6. Subjectivity	-0.050	0.074	-0.074	-0.029	-0.011	1.000									
7. Certainty	-0.013	-0.026	0.054	-0.006	0.010	-0.006	1.000								
8. Positive	-0.082	-0.155	0.189	0.010	-0.123	-0.025	0.132	1.000							
9. Negative	0.020	0.110	-0.114	-0.017	0.022	0.033	-0.025	-0.156	1.000						
10. Uniqueness	0.145	-0.399	-0.028	-0.010	0.077	-0.092	-0.008	-0.035	0.002	1.000					
11. Log(Elapsed Time)	0.396	-0.151	-0.103	0.051	0.054	-0.026	-0.005	-0.034	0.002	0.354	1.000				
12. Log(Word Count)	0.260	0.057	-0.078	0.064	0.305	-0.034	-0.067	-0.338	0.066	0.070	0.134	1.000			
13. Launch Time	0.140	0.233	-0.049	0.055	0.013	0.039	-0.003	-0.020	0.009	-0.441	0.368	0.063	1.000		
14. Price	0.078	-0.042	0.012	-0.017	0.051	-0.030	0.001	0.002	0.001	0.047	0.063	0.147	0.004	1.000	
15. Review Num	0.008	0.089	0.036	-0.046	0.009	0.026	0.011	-0.008	0.007	-0.375	0.023	0.085	0.141	0.058	1.000

Also, it might not be meaningful to calculate the mean and standard deviation of helpfulness percentage when there is only one vote for the review. So we also examine the robustness of results using different minimum numbers of votes to calculate mean and standard error.

The models that we estimate are as follows.

Equation (1): $Voting_k$ = α_1 * Avg. Product Score + α_2 * Avg. Product Score * Info Disparity + α_3 * Info Disparity + α_4 * Log(User Exp) + α_5 * Readability + α_6 * Subjectivity + α_7 * Certainty + α_8 * Positive + α_9 * Negative+ α_{10} * Uniqueness + α_{11} * Log(Elapsed Time) + α_{12} * Log(Word Count) + α_{13} * Launch Time + α_{14} * Price + α_{15} * Review Num + μ

Equation (2): Helpfulness | (Voting ¤ k) = β_1 * Avg. Product Score + β_2 * Avg. Product Score * Info Disparity + β_3 * Info Disparity + β_4 * Log(User Exp) + β_5 * Readability + β_6 * Subjectivity + β_7 * Certainty + β_8 * Positive + β_9 * Negative + β_{10} * Uniqueness + β_{11} * Log(Elapsed Time) + β_{12} * Log(Word Count) + β_{13} * Launch Time + β_{14} * Price + β_{15} * Review Num + ζ+ (λ)

The dependent variable of the first equation $Voting_k$ denotes whether or not there are at least k votes for a review. It equals to 1 if the estimated value is more or equal to k, and 0 otherwise. k is an integer. μ are error terms. (λ) In Equation (2) refers to the inverse mills ratio from the first stage of the Heckman selection model.

4. Results

We first estimated a basic model that contained only the control variables. As it is shown in column (1), reviewer expertise, review certainty, positive sentiment, content uniqueness and review length were positively related to the perceived helpfulness. Review readability, subjectivity, negative sentiment, review age, product launch time, price and number of review under certain product are negatively related to the diagnosticity perception. Some results are within our expectation because reviews with more depth, certainty, objectivity and originality, and those written by experienced reviewers are more likely to be helpful. A recency effect exists in helpfulness perception for a review, that new reviews are receiving more diagnosticity value. The negative effect of the number of reviews under a certain product might be resulted by limited attention of potential customers (Kuan et al., 2015). Some effects of textual sentiment are different from past research in our result. We found consistent positive effect of positive sentiment and negative effect of negative sentiment on helpfulness perception, which are opposite to the findings of Kuan et al. (2015). The inconsistency to past research might due to the product categories that we chose for our sample.

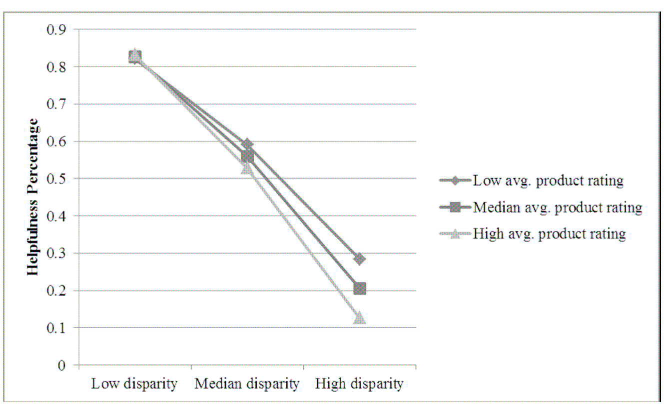
<Table 4> Heckman selection model results

	(1)	(2)	(3)	(4)	(5)
Helpfulness	Base Model	Full Model	Interaction Model	k=3	k=5
Avg. Product Score	0.0275 ***	(0.001)	0.0065 ***	(0.002)	-0.0144 ***
(0.002)	-0.0275 ***	(0.004)	Info Disparity * Avg. Product Score	-0.0726 ***	(0.003)
-0.0979 ***	(0.005)	-0.1140 ***	(0.009)	Info Disparity	-0.1212 ***
(0.003)	-0.1342 ***	(0.003)	-0.1567 ***	(0.006)	-0.1686 ***
(0.011)	Log(User Exp)	0.0125***	(0.002)	0.0076 ***	(0.002)
0.0074 ***	(0.002)	0.0264 ***	(0.003)	0.0348 ***	(0.005)
Readability	-0.0028 ***	(0.0002)	-0.0024 ***	(0.0002)	-0.0024 ***
(0.0002)	-0.0023 ***	(0.0002)	-0.0029 ***	(0.0003)	Subjectivity
-0.0817 ***	(0.006)	-0.0593 ***	(0.006)	-0.0564 ***	(0.006)
-0.0395 ***	(0.009)	-0.02382	(0.014)	Certainty	0.2373 ***
(0.06)	0.2323 ***	(0.058)	0.1945 **	(0.057)	0.1446
(0.082)	0.1257	(0.113)	Positive	1.1562 ***	(0.037)
0.6351 ***	(0.033)	0.5861 ***	(0.032)	0.8107 ***	(0.056)
Price	-0.0001 ***	(0.00001)	-0.0001 ***	(0.00001)	-0.0001 ***
(0.00001)	-0.00017 ***	(0.00002)	-0.0002 ***	(0.00003)	Review Num
-0.0001 ***	(0.00001)	-0.0001 ***	(0.00001)	-0.0001 ***	(0.00001)
-9.7E-05 ***	(0.00001)	-0.0001 ***	(0.00001)	Intercept	2.1823 ***
(0.2006)	2.0505 ***	(0.1897)	2.1201 ***	(0.187)	3.7747 ***
(0.439)	4.5352 ***	(0.7884)	Inverse Mills Ratio: ●(∢)	-0.1970355	-0.1640504
-0.1571807	-0.22863	-0.261753	Wald chi2(15)	4166.93	10752.5
11764.06	8017.88	5221.23	Prob > chi2	0	0
0	0	0	R-Square	0.01911654	0.08114321

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our <H1> states that information disparity negatively influences review's helpfulness perception. The result from <Table 4> (Column 2) lends support to <H1>: the coefficient of information disparity on helpfulness is negative and statistically significant. It suggests that deviant information is less likely to be accepted by consumers. Regarding the result, we also observed that due to the incorporation of information disparity, the effect of uniqueness has changed its direction and remained significant in Column (2). Given that uniqueness and information disparity are negatively correlated in <Table 3>, we propose that the change is because the impact of originality element has been absorbed by the new term information disparity. Since the deviant information has already been controlled, the consensus information is more appreciated by the potential customers.

In Column (3), we list our results of Equation 2, including the interaction term. Info Disparity *Avg. Product Score ($p<0.001$) was statistically significant. The average product score moderates the effect of review's information disparity, supporting <Hypothesis 2>. To further understand the interaction, we draw the following plot. For products with high rating, the effect of information disparity is stronger than it is for products with low rating, lending supports to our <H2a>.



<Figure 2> Interaction effect of information disparity and average product rating

People can vote for reviews at any time. With our method of calculating Info Disparity, we tested our hypotheses in a scenario that each review was voted after disposed to a prior collective evaluation, regardless of the later information. But in online setting, for an old review, the collective evaluation might be different from the one we measured by the absolute difference between review rating and the moving average of the prior reviews. Therefore, we used the latest average rating as a substitute of moving average rating, and generated a new *Info Disparity*. Then we tested our model again with *Info Disparity* and obtained very similar results.

Besides, we also conduct additional tests using alternative thresholds of the number of votes on reviews. Column (4) and (5) show the results of our interaction model with review samples that received at least 3 and 5 votes respectively. From the table, our results remain the same at different thresholds.

Overall, the empirical evidence is consistent with the hypotheses we proposed. In Amazon platform, the collective review information of product predisposes consumers to accept the reviews holding similar evaluation to the overall rating. Also, the deviant information receives less diagnosticity perception when product ratings are high than when they are low.

5. Discussion & Conclusion

The purpose of this research is to discover whether the presence of the product average rating introduces biases or change the way people perceive information. We extend our knowledge of review rating from new perspectives – forming predisposition and risk perception of each product. We posit that review's overall rating, as displayed at the top of all product reviews, has a predisposition effect on consumers' perception towards detailed review information. Also, since the review average rating also portrays the risk level of product performance, we propose that the acceptance of deviant/similar information is influenced by the average rating.

In summary, as an answer to our research question, the presence of the product average rating changes people's favor towards the similar information, and the higher the average rating, the stronger the effect.

5.1. Theoretical Implications

A main contribution of our study to theoretical development is its demonstration of the deviant information in online review context. The results provide evidence that predisposition influences review feedback perception, resulting that the consensus information is more likely to be favored. Earlier researchers showed the perception of online review as a function of review rating within each review unit. They found inconsistent results, i.e., positivity bias (Pan et al., 2011) and negativity bias (Kuan et al., 2015; Sen et al., 2007). The two ideas have received substantial discussion over the past decade, but either of them provides explanation of the opposite results. Our work on average product rating supplements their research findings and helps reconcile and explain the inconsistency between the two opinions.

The present research also contributes to the current knowledge of online consumers' perception towards word-of-mouth information. First, potential consumers tend to follow the collective evaluation before they make purchase decision. Second, our research presents that consumers' behaviors towards online information are influenced by their risk perception, which extends the role of perceived risk on adoption behavior of information technologies (Pavlou, 2003). Under a risky shopping situation, consumers are less willing to take words of consensus information and more acceptable to various types of information.

5.2. Practical Implications

Our research also sheds light upon online marketing practices. With the phenomenal effects of overall product rating, marketers or executives should think about how to apply them on their product pages. Given the impact of risk perception, in order to make the most use of positive WOM, marketers or sellers should provide more security or safety cues to potential consumers. On the other hand, sellers of products with neutral or negative evaluation need not to worry too much, if they supplement consumers with sufficient deviant information onsite or from other sources. Consumers will make decision after obtaining comprehensive information about the products.

Additionally, as the overall negative impact of lower ratings'presence, sellers should think of ways to minimize the disadvantages. Instead of offering a variation diagram of average rating, it is worth trying to separate the one rating into several dimensions, such as ratings on product appearance, duration, sellers' service, package delivery and so on.

5.3. Limitation and Future Work

The emphasis of present research is limited to the diagnostic perception of online consumers. However, future work could extend our idea on the adoption behaviors and the economic benefits of consensus word-of-mouth information. Also, in this study, we examine the moderation effect of performance risk on the relationship between WOM information and consumers' perception. We acknowledge that other risk dimension is left uninvestigated. Future research may address the problem by other risk dimensions and explore their role on the consumers' perception or behaviors towards information. 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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