Do Consumers Trust Online Product Reviews? An Experimental Study of Biases in Online Product Reviews

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The Informational Role of Online Product Review Distributions: An Experimental Study of Biases in Online Product Reviews

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ABSTRACT

Previous studies have identified the impact of self-selection biases in online product reviews on consumer surplus. However, no empirical study has studied how the consumers evaluate the rating distributions of online reviews, especially when credibility of reviews is susceptible to be jeopardized by self-selection biases. This study investigates how the existence of different types of self-selection biases in online product reviews influences consumers' intentions to purchase products and post reviews. A 2×2×2 randomized experiment was conducted to examine the role of two self-selection biases (under-reporting and purchasing biases). Results indicate that subjects exposed to online product reviews that suffer from under-reporting bias and purchasing bias have a significantly lower intention to purchase a product and post a review. Because consumers are not able to fully correct the self-selection biases in online product reviews, this study calls for the need to overcome self-selection biases and formulate strategies to help consumers trust online product reviews.

Keywords

Self-selection biases, trust, purchasing bias, under-reporting bias, purchasing intention, online product reviews

INTRODUCTION

With the burgeoning of user generated content, such as online product reviews, online markets such as Amazon and eBay have been collecting and disseminating online product reviews to help consumers make informed purchasing decisions. Studies find that consumers rely on online product reviews to make purchase decisions (e.g. Chevalier and Goolsbee 2003, Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Godes and Mayzlin 2004, Ye et al. 2009). Online product reviews are widely adopted in an attempt to provide guidance to consumers on products. Examples of sites include IMDb, Epinions.com, Internet Book List, Yahoo! Movies, Amazon.com, BoardGameGeek, TV.com, Ratings.net, and Yelp.com, among others. According to a report conducted by Rainie and Hitlin in 2004, 26% of adult Internet users in the U.S. have rated a product, service, or person using an online rating system. That amounts to more than 33 million people. These online product review systems, also referred to as "reputation systems," are interactive word-of-mouth networks that help consumers make decisions about which products to trust and purchase, or to compare their product evaluatoins relative to those of others. Not only do consumers engage in posting reviews, their purchasing decision and satisfaction is also influenced (Anderson, 1998). According to data from comScore 2007, 24% of online consumers check online reviews prior to making purchase decisions, and more than two thirds of them report that they are heavily influenced by online product reviews. As John Lazarchic, Vice President of Petco said, consumers are highly influenced by the experience of other consumers - far more than they are by direct marketing. In sum, online product reviews have become an important indicator of product quality, seller reputation (Ba and Pavlou 2002) and customer satisfaction.

The mean (average) rating of online product reviews is a visible and clear indicator of aggregate consumer opinions on product quality. Some researchers also use the average rating of online product reviews as a proxy of product quality to predict sales, but whether the average rating of product reviews is a good proxy of product quality is not always consistent. For example, while multiple studies show that the mean rating of online product reviews to have a significant role in sales by reflecting product quality (e.g., Chevalier and Goolsbee 2006, Clemons et al. 2006, Dellarocas et al. 2007, Li and Hitt 2007), many other studies (e.g., Chen et al. 2004, Clemons et al. 2006, Duan et al. 2008, Liu 2006) show that the mean rating of online product reviews does not have a significant effect on sales.

The claim that the average rating of online product reviews indicates true product quality has been questioned by IS scholars. Notably, some studies (e.g., Li and Hitt 2007, Hu et al. 2006) have identified self-selection biases in online product reviews. Using archival data collected from multiple retailers, Hu and his colleagues (2006) show that literally all online product reviews have an asymmetric, positively-skewed, bimodal distribution (or "J-shaped"), which implies that most of the ratings are high (5 stars on a 1-5 Likert-type scale), with only small portion of low (1 star) ratings and barely modest (2, 3, 4 star) ratings. Li and Hitt (2007) found that early reviewers are likely to be homogeneous; therefore the self-selection biases in online product reviews may have an impact on consumer purchasing behavior and consumer surplus. Therefore, one question that emerges is that: due to the self-selection biases, which may jeopardize the credibility of online product reviews, do consumers trust online product reviews when they are faced with biased review distributions?

In fact, self-selection biases underlying online product reviews have been realized not only by researchers, but also by a large proportion of online consumers. According to a recent debate in Amazon customer discussions, many consumers reported that there was serious rating inflation on Amazon product reviews, which referred to typical reviews (let alone extremely egregious cases). Moreover, self-selection biases in movie reviews were widely publicized. A story in New York Times, August 2011, says that many online retailers increasingly depend on online product reviews as a sales tool, that an industry of fibbers and promoters has sprung up to buy and sell raves for a pittance; notably for $5 they can create two more positive reviews for a company. As readers of online product reviews, consumers are also creators of online product reviews. Therefore, it is reasonable to extrapolate that at least some consumers seem to realize the self-selection biases underlying online product reviews. However, it is still unclear whether consumer do realize these self-selection biases, and what are the effects of self-selection biases in online product reviews on consumers' purchasing decisions. In what follows, we survey the literature on self-selection biases in online product reviews, which could create distrust of reviews and product uncertainty for consumers; and consumers' use of heuristics in everyday decision-making. Based on the theoretical underpinnings, we develop our hypotheses about the effect of biased consumer reviews on consumers' intention to purchase and report a review. We then present our experimental methodology and results. Theoretical and practical implications are discussed. We conclude this paper by acknowledging the limitations and suggesting future research directions.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Self-selection Biases in Online Word of Mouth

Even before the emergence of large-scale online communication networks and online product reviews, word-of-mouth was perceived as an important driver of product sales (Rogers 1962). Dellarocas (2003) envisioned online product reviews to be electronic word of mouth that could potentially change consumer purchasing behavior. The extant literature on online product reviews has established that the valence of product reviews can predict sales (Chevalier and Mayzlin 2006; Dellarocas et al. 2007). Recently, Zhu and Zhang (2010) found that the effect of online product reviews on sales was contingent upon product popularity and online shopper experience. Study also found that negative word-of-mouth had a more significant impact than positive reviews (Chevalier and Mazlyn 2003). Though there is great hype on online product reviews, scholars also identified potential problems inherent in online product reviews. Li and Hitt (2007) identified the self-selection problem for online product reviews, and Hu et al. (2006) showed that purchasing bias and under-reporting bias might have driven the presumably normal distribution of product rating towards a "*J*" shape. However, there are scant efforts on understanding whether consumers realize these self-selection biases, and what are the effects of these biases on consumer purchasing decision making.

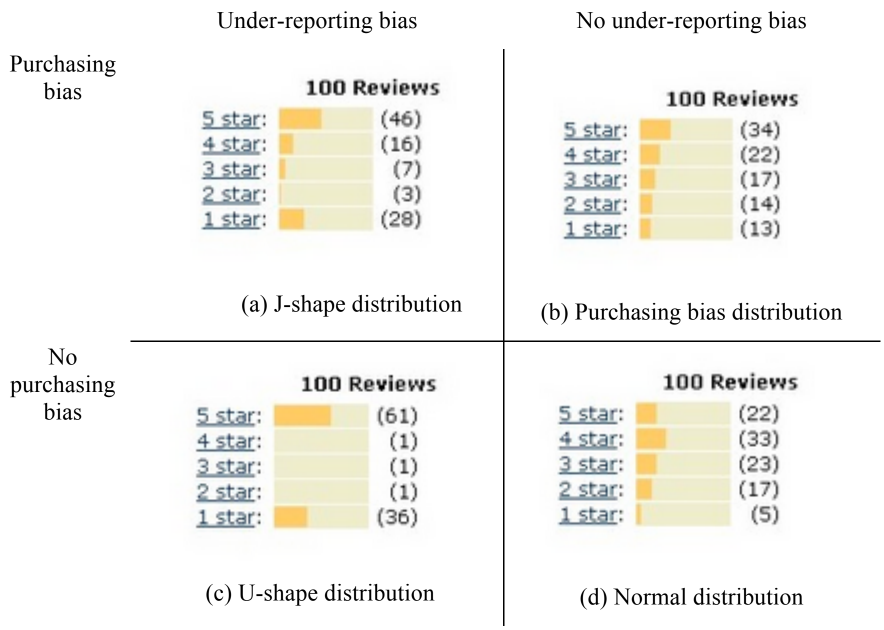


Figure 1. Different Shapes of Distributions of Online Product Reviews and the Proposed Self-Selection Biases

Li and Hitt (2007) examined the effect of early reviews on later reviews' rating, finding that idiosyncratic preferences of early buyers can affect long-term consumer purchasing behavior as well as consumer surplus by online product reviews. They also argued that self-selection bias, if not corrected, decreases consumer surplus. Furthermore, Hu et al. (2006) identified the impact of under-reporting biases and purchasing biases on the distribution of online product reviews. Formally, under-reporting bias, is justified by the satisfaction literature (e.g. Anderson 1998) sinceextremely satisfied or extremely dissatisfied consumers are more willing to spend the time and effort to report their product reviews, resulting in more extreme (high or low) ratings. Purchasing bias comes from utility theory that explains that only consumers with high perceived quality of the product are willing to make a purchase, and thus have access to posting reviews, which explains why more high ratings exist in practice. These two self-selection biases shape the distribution of online product reviews to be a J-shaped distribution. Hu and his colleagues focused on describing these two biases and their effect on the shape of the distribution of Amazon's online product reviews, but they did not look at how consumers react to these self-selection biases. In this study, we examine the role of these two self-selection biases (under-reporting and purchasing) on consumers' purchasing decision making.

In a recent study, Sun (2012) examined the informational role of online product reviews, she built a theoretical model in which ratings and the variance of online product reviews can help consumers figure out how much they would enjoy the product. In her study, she interpreted the variance associated with niche products. In our study, we associated the variation in the mean rating and variance as sources of two self-selection biases (variance covaries with under-reporting bias, while the mean rating to purchasing bias). Furthermore, we examined the influence of distributions of online product reviews that reflect different biases on consumer decision-making. Figure 1 presents the different biases and distributions of online product reviews.

Consumers' Use of Statistical Heuristics in Everyday Decision Making

Nisbett and Krantz (1983), in their empirical study, found that in reasoning about everyday problems, people use statistical heuristics, that is people's judgmental tool that are rough intuitive equivalents of formal statistical principles. They bolstered that statistical heuristics improve ontogenetically, and training increases both the likelihood that people take statistical approach and the performance of the statistical heuristics. Similarly, Drake et al. (1998), in studying consumer reaction to political polls, also found that high motivated participants tended to be influenced by consensus only when the poll was reliably large, i.e. highly motivated participants consciously or sub-consciously applied the law of large numbers to infer whether the poll was reliable. A lot of results from previous relevant studies are consistent with heuristic-systematic model that people do refer to systematic reasoning while making decisions and judgments.

According to the descriptive definition of under-reporting bias and purchasing bias and mathematical practice (we generate all possible distributions), we observe that under-reporting bias necessarily brings higher variance, and purchasing bias would inflate mean of ratings. As a matter of fact, these distributions of online product reviews are widely available in different websites (Figure 2).

In Hu et al. (2006)'s study, controlled experimental results showed that, when all respondents (without self-selection biases) were asked to report their ratings for a randomly-selected product, ratings of reviews turned out to follow a uni-modal (approximately normal) distribution. This finding indicates that if self-selection biases are excluded, the ratings of online product reviews are supposed to be normally distributed. Combing with the heuristic-systematic model, we can assume that a portion of consumers would subconsciously expect a normal distribution, and accordingly infer that the ratings are biased from the information contained in product review's distributional characteristics, especially shapes that deviate from a normal distribution, which may reflect potential biases. Consequently, we extrapolate that when consumers read online product reviews, some can get the information to make judgments and refer to their own interpretation of the distributional characteristics to make decisions. In a recent study, Sun (2012) leveraged an archival data set comprised of book reviews and sales rank information Amazon.com, found that higher standard deviation of ratings on Amazon improves a book's relative sales rank when the average rating is lower than 4.1 stars, which is true for 35% of all the books in their sample. She believes that there are other distributional characteristics, such as "skewness", may have an effect on consumer decision-making. In this study, we echo the call to look at online product review distributions from the perspective of biases, i.e. find whether different rating distributions will influence customers' purchasing decisions.

Figure 2: Examples of distribution of online product reviews visible to consumers (from Amazon & Yelp)

Since under-reporting bias causes higher variance and shows larger proportion of two-sided extreme ratings (especially when rating is toward the middle of the scale), consumers may feel uncertainty with their subconscious statistical heuristics ability. When normal distribution (i.e. without any self-selection biases) is used as baseline with the mean and volume of online product reviews controlled, the biased average rating (caused by under-reporting bias) distributions drive up the variance, which causes more dispersed ratings and less centralization. Highly dispersed distribution represents high variance and unstable product quality. Such biases would exacerbate consumers' product uncertainty. Product uncertainty is defined as the buyer's difficulty in evaluating product characteristics and predicting how a product will perform in the future (Dimoka et al. 2011). Due to the temporal and geographical separation betwee buyers and products in online markets, customers are always faced with uncertainty about the quality (Dimoka et al. 2011) and fit (Hong and Pavlou 2010) of products sold online. Additionally, when confronted with obviously skewed distribution of online product reviews with highly dispersion, consumers' uncertainty would increase and thus are less likely to purchase that product. Also since they are less certain about the product quality, they are less likely to post a review, which presumably could mislead other potential customers. Thus, under-reporting bias would cause lower intention to purchase and to post a review. We hypothesize:

H1: The existence of under-reporting bias reduces customers' intention to purchase.

Purchasing bias is one of the reasons that boost mean rating, and cause average rating to be inflated. Accordingly, purchasing bias has both positive and negative effects on consumers' purchasing decision. On the one hand, when the mean rating stays at a reasonable level, moderate extent of purchasing bias would not seem to be the main reason for a high rating for the customers; in this case, consumers will not necessarily attribute high ratings to purchasing bias but to higher product quality. On the other hand, when there is no other information to indicate a high product quality, or the mean rating is perceived to be relatively high, the underlying purchasing bias would be more likely to be realized by consumers. In this case, with online consumers becoming more sophisticated, it is more likely that they will realize the existence of purchasing bias, and would partially attribute the high mean rating to purchasing bias. Also, consumers' perceived usefulness of online product reviews are no longer merely decided by the ratings (Mudambi and Schuff 2010). When faced with purchasing bias, the mean rating on online product reviews remains the same, a proportion of consumers will perceive lower usefulness of the products, and accordingly lower intention to purchase or to post a review for them.

H2: The existence of purchasing bias reduces customers' intention to purchase.

Another scenario is that these two biases co-exist, forming a J-shaped distribution. We argue that these two biases will have either substitution or a complementarity effect. In our study, when faced with the same level of relatively high mean ratings, and without any strong indicating information of high quality, both under-reporting bias and purchasing bias will have negative impact on intention to purchase and to post a review. Thus, from what have been discussed above, we hypothesize:

H3: The coexistence of under-reporting bias and purchasing bias reduces customers' intention to purchase.

RESEARCH METHODOLOGY

Experimental Design

To manipulate the treatment of different groups, four different versions of the experimental interfaces in which the two proposed self-selection biases were manipulated were designed for the study. N (i.e. the control interface) contains normal distribution of consumer reviews, which has neither under-reporting bias nor purchasing bias. P (i.e., purchasing bias group), included purchasing bias, but no under-reporting bias. U (i.e., under-reporting bias group) contained under-reporting bias, yet no purchasing bias. And J (i.e. J-shaped group) contained both self-selection biases. The design of the shape of the distribution resembles Figure 1.

A controlled laboratory experiment with 2 (under-reporting bias condition and a no-underreporting-bias condition) × 2 (purchasing bias condition and no-purchasing-bias condition)× 2 (high variance vs. low variance) factorial design was used to test the impact of self-selection biases on consumer purchasing intentions. The eight distributions were automatically generated by Matlab and the research team selected the most representative ones for the experiment.

To avoid any potential confounds due to brand awareness or price differences, we made up a fictional but realistic product and brand (Senvion USB 3.0 External Hard Drive), and set the list price as $99.99 (comparable to Amazon's list price). To avoid the potential impact of mean rating and review volume, we set the average customer review of eight groups uniformly as 3.5 stars, and the volume of reviews at 100. The pictures used on the website were carefully chosen according to a typical external hard drive's outlook without noticeable esthetical or brand characteristics.

Our main dependent variables (DVs) of interest is purchase intention and intention to post a review. Both DVs were measured with 5-point Likert-type scales. We also amend this measure with two other variables: product quality rating, and recommendation to friends. These measures are shown to be important in capturing consumer perceptions of a product in extant studies (Hu et al. 2008).

Procedures

The study was carried out online in an experiment website. Subjects voluntarily entered this study from the university's psychology study portal and click a URL link that randomly redirects any subject to one of the eight different treatment conditions page. In this way, we seek to hold a truly randomized experiment and alleviate the likelihood that any systematic individual differences would affect the results. All information on the interfaces was kept constant, shown as Figure 3. To eliminate the effect of consumers' expertise or differences in product type, we select a commonly found product – USB 3.0 external hard drive as our product in this study. To reduce the impact caused by respondents' attachment or involvement to certain brand, we made a fictitious but realistic brand name, Senvion. Pre-tests were conducted to ensure that subject would not be systematically affected by the brand name.

To test the impact of consumers' awareness of self-selection biases in online reviews, several fictitious product pages resembling webpages on Amazon.com, were created for the studies. We seek to design the interfaces as realistic as possible. For this reason, the interfaces closely matched Amazon.com with brief product details and customer reviews.

Every participant went through the same procedure across different conditions: firstly, the website was shown to them, and then they were asked questions about their purchasing intention and other aspects of their impression of the product. After the subjects were assigned treatments, they were asked to report their intention to purchase the product. Following the main experiment, subjects were asked to finish a brief questionnaire about gender, age, online shopping experience and manipulation check, etc. At the end of each session, the participants were debriefed, thanked, and released.

Figure 3 Experimental Interface

Participants

Participants included a total of 112 undergraduate students from a psychology study pool at a large public university in North East U.S. Approximately 74% of the participants are female, with an average age of 20.7. According to the Pew Internet & American Life Project (2005), most active Internet users are between 18 and 29 years old. Thus, the sample is relatively representative of active Internet users, making the sample highly appropriate for this context. The respondents received course credit for participation and were entered into a raffle of $100.

RESULTS AND ANALYSIS

Manipulation check

Participants showed stronger purchasing intention against two self selection biases, and mean purchasing intention follow the order: J-shape(2.67) < Under-reporting (2.8) < Purchasing (2.93) < Normal (3.36). Furthermore, although treated in between subjects groups without comparing with other kinds of distributions, 74.11% participants passed manipulation checks, i.e. at the end of the experiment they recalled that they did refer to the shape of customer review ratings while evaluating product.

Table 1 Manipulation Checks

	Purchasing Intention		Review Posting Intention	
Group	Not Referring	Referring to Distribution	Not Referring	Referring to Distribution
J	3.000	2.667	2.462	2.220
N	3.500	3.364	3.000	2.818
P	2.800	2.929	3.800	2.643
U	3.286	2.800	2.286	2.667

Hypothesis Testing

We construct independent sample *t* statistics to test *H1, H2, and H3*. The results are shown in Table 2. As Table 2 attests, first of, intention to purchase and to post a review of the Normal distribution group was significantly higher than that of the under-reporting bias group ($t=1.742$, $p<0.05$), which support *H1a and H1b* that the existence of under-reporting bias reduce customers' intention to purchase and post a review. Secondly, purchasing intention of he Normal distribution group was significantly higher than the purchasing bias group ($t=1.566$, $p<0.1$), indicating that existence of purchasing bias reduces consumers' intention to purchase, therefore *H2a* was supported. Finally, Purchasing intention of the Normal distribution group was significantly higher than the J -shaped group ($t=2.3053$, $p<0.05$), which support *H3a* that the coexistence of under-reporting bias and purchasing bias reduces consumers' purchasing intention. However, although normal distribution groups are consistently more likely to post a review, the t statistics are not statistically significant, therefore, our results mainly support the hypotheses for the effect of self-selection biases on consumer's intention to purchase a product.

Table 2. Results of Hypothesis Testing

Mean		J (18)	N (22)	P (28)	U (15)	
Intention to Purchase		2.667	3.364	2.929	2.800	
Intention to Post a Review		2.222	2.818	2.643	2.667	
t-statistic	J vs. N	J vs. P	J vs. U	N vs. P	N vs. U	P vs. U
Intention to Purchase	-2.305**	-0.942	-0.412	1.566*	1.742**	0.427
Intention to Post a Review	-1.726**	-1.483*	-1.069	0.519	0.333	-0.058

Note: * statistically significant at 10 percent, ** statistically significant at 5 percent.

Results for the other dependent variables (product quality rating, intention to post a review and product recommendation to a friend) are qualitatively same with purchase intention. Since the results are statistically significant, due to limited amount of sample size, we will get further conclusion using larger dataset. We also calculated the statistical power of analysis and the sample size is found to be adequate to detect an effect.

Additional Analysis

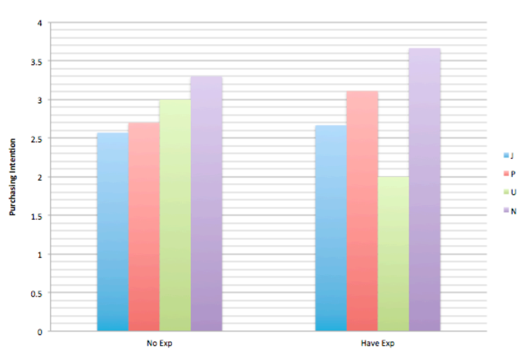
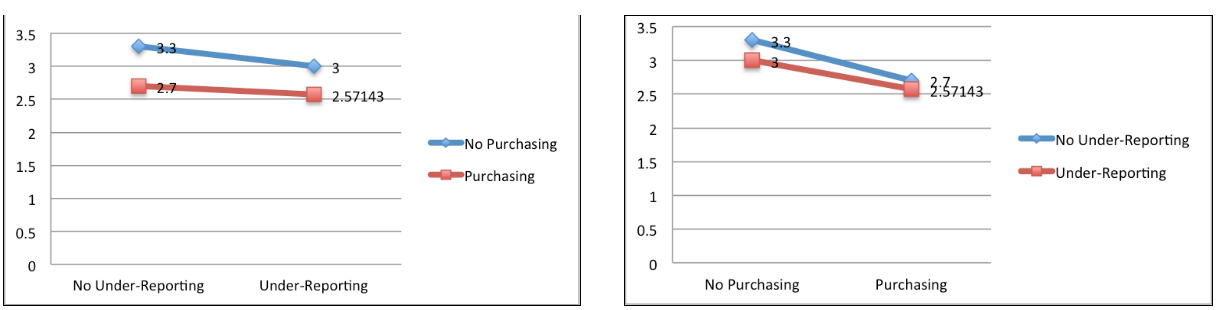


Figure 4. Potential Interaction Effects

Additionally, in our experiment, we also investigated the respondents' experience in online shopping and posting reviews on Amazon.com. And we examined the interaction effects among under-reporting bias, purchasing bias, between consumers who have experience on Amazon reviews and those who do not. The results implicate that, two types of self selection biases have an interaction effects among respondents with experience in posting reviews on Amazon, as shown in Figure 5.

No Amazon review Experience



Have Amazon review Experience

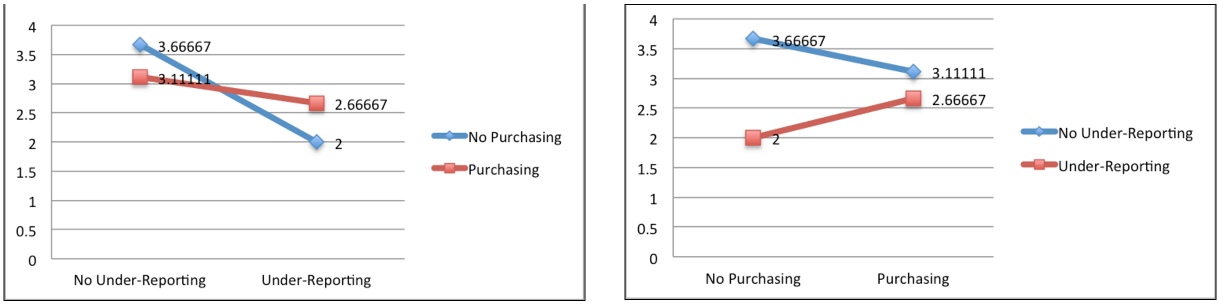


Figure 5 Interacting Effect of Amazon Review Experience

Robustness Checks

Confounding Factor of Variance

To rule out the alternative explanation that it is the variance instead of the biased rating distribution caused less purchasing intention. We constructed *t* statistics to compare the difference of purchasing intention for high and low variance groups within the 4 treatment groups (4 different distributions).

Table 3 Purchasing Intention in different Group with different Variances

group	Variance	Purchasing Intention	*t*-statistic
J shape	Low: 2.350	2.875	0.865
	High: 2.839	2.500	
Normal	Low: 1.329	3.364	0.000
	High: 1.690	3.364	
Purchasing bias	Low: 1.245	3.067	0.830
	High: 1.991	2.769	
Under-reporting bias	Low: 2.989	2.818	0.120
	High: 3.648	2.750	

As we can see from Table 3, in each group, purchasing intentions of different variance are not significantly different across variances (even in under-reporting group where variance is supposed to be a major influence of the distribution shape), indicating that the main factor influence customers' purchasing intention is the shape of the distribution, and not the variance.

Manipulations

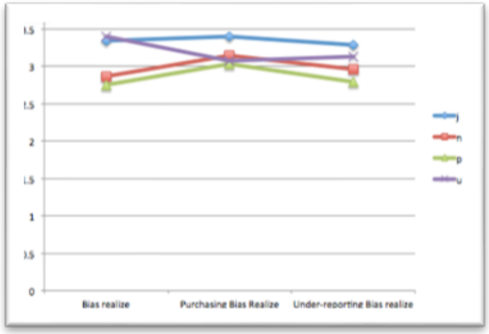


Figure 6. Additional Manipulation Checks

Three different measures were collected to further check whether participants accurately perceived the manipulations of the independent variables (i.e. self selection biases): (1) Realized any biases: "when you initially made your choices, did you think that the distribution (shape) of customer reviews was biased"; (2) Realized purchasing bias: "did you think that the distribution (shape) of customer reviews reflected a bias towards positive reviews (e.g. 5-Star reviews)"; and (3) Realized under-reporting bias: "did you think the distribution (shape) of customer reviews reflected a bias towards extreme reviews (e.g. either 1-Star or 5-Star reviews)?"

The validity of the manipulation of the agregate of the two self-selecttion biases was tested using a J-shaped distribution (i.e. containing both biases) and N (i.e. control interface), and the difference was significant ($p<0.1$). Also, the treatment of purchasing bias was tested by the J and the U group (i.e. that contains under-reporting bias, yet no purchasing bias), more subjects realize purchasing bias for J-shaped distributions than U-shaped distributions of online product reivews. Finally, the manipulation of under-reporting bias was tested using J and P (i.e. contain purchasing bias but no under-reporting bias), and the difference was significant ($p<0.05$). Thus, it offers evidence that the manipulation of the independent variables was accuratedly executed.

KEY FINDINGS AND IMPLICATIONS

From the results of the manipulation check and hypothesis testing, we draw the conclusion that, a large proportion of the consumers are aware of the existence of under-reporting bias and purchasing bias. And the results also strongly support our contention that biased distributions of online review ratings will influence consumers' purchasing decisions. Furthermore, when the mean rating remains the same moderate level, existence of purchasing bias or under-reporting bias can cause lower purchasing intention, and the coexistence will also decrease purchasing intention.

Moreover, according to the data, we find that prior experience reinforced the influence of under-reporting bias on purchasing intentions. In other words, among consumers with experience in posting reviews on Amazon, under reporting bias would have a relatively stronger effect in decreasing consumers' purchasing intention.

This paper's main theoretical implication is to fill the research gap of the lack of understanding about the impact of exposure of online rating distribution of online reviews on consumers' purchasing decision making. Rating distribution and the underlying self-selection biases are shown to play an important informational role in consumer decision-making. When the mean rating (indicator of product quality) is controlled for, different distributions indicator self-selection biases underlying the rating, i.e. consumers can interpret more information from distributional characteristics than merely comparing different mean ratings. With the same level of mean ratings, the distribution of online product reviews can be viewed as an important predictor of consumer demand and product sales.

For online retailers and business involved in online rating systems, merely being obsessed with raising their mean rating will not necessarily increase consumers' purchasing intention and accordingly improve sales. Instead, while trying to raise the valence of their ratings of online reviews, the sellers should also pay attention to the normality and self selection bias control, since with a similar level of mean rating, an obviously biased distribution would decrease consumers' purchasing intention.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

In this phase of the study, we primarily tested the significant influence of the existence of two self-selection biases on consumers' purchasing intention. But due to the sample size and power of analysis, we were not confident about testing the interaction effects between under-reporting and purchasing biases, or the interaction between self-selection biases and consumers' own characteristics (e.g., risk aversion, online shopping experience and online review experience).

Since we theorize that uncertainty plays an underlying role in the effect of self selection biases on consumer purchase decision, it will be beneficial to test the potential mediating relationship in a structural model.

The impact of self-selection biases on consumer decision-making process and product attitudes may also be moderated by product type. For example, for experience goods, under-reporting bias may cause larger damage on product image than search goods do. On the other hand, purchasing bias may play a negative role in search goods, while have a positive impact with experience goods. In the future research, using archival data, we may test the moderating effect of product type on influence of self-selection biases.

Our study takes an initiative in theorizing and empirically testing the effect of two primary self-selection biases on consumer purchasing decision-making, and calls for more IS research and practice to address such concerns.

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