Association for Information Systems
AIS Electronic Library (AISeL)

CONF-IRM 2013 Proceedings

International Conference on Information Resources Management (CONF-IRM)

5-2013

Biases in Consumer Reviews: Implications for Different Categories of Goods

Makoto Nakayama
DePaul University, mnakayama@cdm.depaul.edu

Biases in Consumer Reviews:
Implications for Different Categories of Goods

Makoto Nakayama
DePaul University
mnakayama@cdm.depaul.edu

Abstract
Consumers frequently read online consumer reviews before purchasing products both online and offline (at stores). Yet, reviews are known to have certain biases. This paper surveys 17 types of biases that previous studies identified. The effects of these biases are intertwined and hard to isolate from one another. It is then difficult to assess the impact of each bias on how consumers rate the helpfulness of reviews. Although extant studies use different terminologies, review biases can be summarized into three basic categories: selection biases, system biases, and attribution biases. Focusing on major categories of goods, the paper then considers the overestimation of review helpfulness due to system and non-system (selection and attribution) biases. Using Amazon.com reviews on six bestselling products and the data from a survey questionnaire to 294 consumers, the paper shows the following: (1) the overestimation of review helpfulness due to non-system biases is smaller in the order of search, experience and credence goods and (2) the overestimation of review helpfulness due to system biases is more pronounced with hedonic goods than non-hedonic goods.

Keywords
Online consumer reviews, review life cycle, biases, survey, search-experience-credence (SEC) paradigm, hedonic goods

1. Introduction
Consumers gain great value from online product reviews written by other consumers (hereafter, reviews) before purchasing products both online and offline (at stores). However, the lack of editorial and quality control leads to a great variance of review quality (Liu, Cao, Lin, Huang, & Zhou, 2007). Some studies investigate what makes reviews more helpful (Korfiatis, García-Bariocanal, & Sánchez-Alonso, 2012; Mudambi & Schuff, 2010). Other studies look into biases involved in writing, reading and evaluating reviews (Hu, Pavlou, & Zhang, 2006; Kapoor & Piramuthu, 2009; Li & Hitt, 2008). One issue observed is that past studies identify same, similar or different biases with different terminologies. This makes it challenging to assess the extent to which consumers overestimate (or underestimate) the helpfulness of reviews due to these biases. This paper first classifies, in the phases of review life cycle, the 17 biases that the previous studies identified. While the individual biases are intertwined and hard to isolate from one another, this study summarizes them into three basic biases: selection biases, system biases, and attribution biases. Then, a preliminary assessment is conducted on the extent of overestimation of review helpfulness arising from system and non-system (selection and attribution) biases by different categories of goods. This paper focuses in particular on the review system used at

Amazon.com because it is one of the largest systems containing reviews for millions of products.[1]

2. Theoretical Background and Hypotheses

Consumer reviews exist in the life cycle of review creation, review organization in the review system, review evaluation and review consumption. Such a life cycle is analogous to the product life cycle model (Day, 1981; Klepper, 1996). This paper uses a conceptual model in which different biases are categorized in the phases of review life cycle (Figure 1).

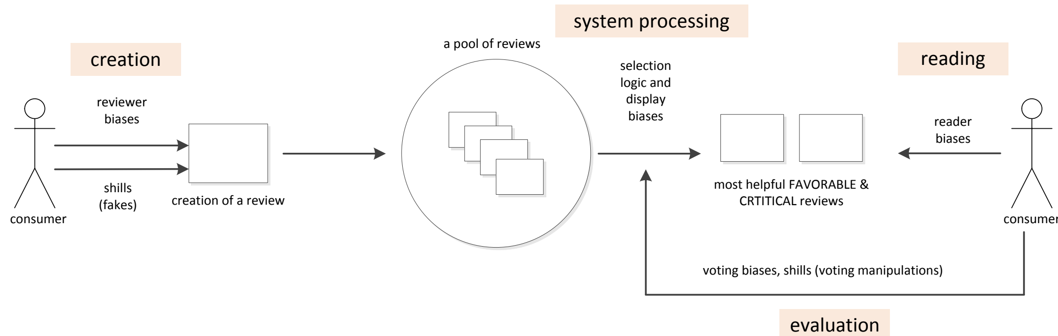

Figure 1. Biases in Phases of Review Life Cycle

The first phase (creation) is when review contributors post their reviews. The second phase (system processing) is when the review system accepts these reviews and displays them according to the internal logic of review prioritization. The third phase (reading) is when the reviews are read by consumers for their product learning and shopping decisions. The fourth phase (evaluation) is when the reviews are continuously evaluated by other consumers. An interesting aspect of the last two phases is that consumers can take the roles of both a reader and an evaluator. A key difference between product life cycle and review life cycle is that the last three stages of review life cycle are not sequential but overlapping with each other. For example, Amazon.com displays reviews in the order of their helpfulness. This order can change dynamically as consumers read and evaluate the reviews.

To compare the findings of previous studies, Table 1 summarizes the definition of each bias and which phase(s) of the review life cycle the bias arises (Table 1).

Bias	Cycle Phase				Definition	References
	C	S	R	E		
self-selection bias	X	X			products are not randomly assigned to reviewers	Li & Hitt (2008)
	X			X	reviewers only rate products they prefer	Clemons et al. (2006)
shills	X			X	manipulated reviews by paid reviewers who praise the products of the firm but bad-mouth those of its competitors	Dellarocas (2006)
purchasing bias	X				since only people with higher product valuations purchase a product, they will not write a (negative) product review	Hu et al. (2009)
under-reporting bias	X				those with extreme ratings (5-star or 1-star) are more likely to express their views to “brag or moan” than those with moderate views	Hu et al. (2009)

[1] In 2011 alone, Amazon.com added millions of products (http://phx.corporate-ir.net/phoenix.zhtml?c=97664&p=irol-presentations).

winner circle bias		X			the higher ranked reviews would attract more eyeballs and therefore gain more people's votes	Liu et al. (2007)
early bird bias		X			some high quality reviews may get fewer users' vote because of later publication	Liu et al. (2007)
sequential bias		X			certain reviews get more exposures as a result of sequential ordering of online product reviews	Kapoor & Piramuthu (2009)
sequential dynamics		X			star ratings of reviews change systematically due to the order of reviews displayed	Godes and Silva (2012)
temporal dynamics		X			star ratings of reviews change systematically due to the age of reviews displayed	Godes and Silva (2012)
correspondent inference bias			X	X	to an observer (reader), negative reviews would have more dispositional value about the actor (reviewer)	Sen & Lerman (2007)
actor-observer bias			X	X	although an actor is more likely to attribute her action to situational factors, the observer is inclined to attribute the actor's behavior to the actor's personal disposition	Sen & Lerman (2007)
knowledge bias			X		consumers find negative expert reviews to be the least persuasive	Vermeulen & Seegers (2008)
negativity bias			X	X	weigh more negatives than positives	Weinberg & Davis (2005)
positivity bias			X	X	consumers who evaluate products associated with promotion consumption goals perceive positive reviews to be more persuasive than negative ones	Zhang et al. (2010)
negativity bias			X	X	consumers who evaluate products associated with prevention consumption goals perceive negative reviews to be more persuasive than positive ones	Zhang et al. (2010)
attritional bias			X		consumers attribute review contents to the reviewers	Park & Han (2008)
imbalance vote bias			X	X	users tend to value others' opinions positively rather than negatively	Liu et al. (2007)

In the cycle phase, the letters indicate creation (C), system processing (S), reading (R), and evaluation (E).

Table 1. Summary of Biases from Previous Studies

In the first phase, there are self-selection bias (Clemons, Gao, & Hitt, 2006; Li & Hitt, 2008), shills who are reviewers paid by a firm to praise its own products and bad-mouth those of its competitors (Dellarocas, 2006), purchasing bias (Hu, Zhang, & Pavlou, 2009), and under-reporting bias (Hu et al., 2009). Reason to write (e.g., expressing a purchase satisfaction) or not to write (concealing a dissatisfaction or negativity) a review may vary. These biases, however, are essentially rooted in selection biases due to either self-selection by the individuals, or (deceptive/intentional) sample selection decisions (Heckman, 1979). The system related biases in the second phase include winner circle bias, early bird bias, and sequential bias (Godes & Silva, 2012; Kapoor & Piramuthu, 2009; Liu et al., 2007). These are all due to the designs of the review system. As there are many reviews with varying quality, it would be beneficial for consumers to prioritize reviews by their quality. On the other hand, the prioritization may put a newly posted, "possibly great" review buried among other reviews; not many consumers may see such buried reviews including this "possibly great" review. Finally, in the third and fourth phases, many of the biases can be traced back to the fundamental attribution error (Jones, Riggs, & Quattrone, 1979; Ross, 1977). Rather than the content of the review, consumers may rely on who the reviewer is (Park & Han, 2008; Sen & Lerman, 2007), what the reviewer is expected to be (Vermeulen & Seegers, 2009) and what the consumers want to see in the reviews (Liu et al., 2007; Weinberg & Davis, 2005; Zhang, Craciun, & Shin, 2010).

Although previous studies use different terminologies, those 17 review biases can be summarized into three categories: (1) selection biases in the first phase, (2) system biases in the second phase, and (3) attribution biases in the third and fourth phases of the review life cycle model. The next logical question is to what extent these three types of biases influence the purchases of different kinds of goods.

While there are various ways to classify goods, this study will use first the search-experience-credence (SEC) paradigm (Darby & Karni, 1973; Nelson, 1970, 1974), which is often used in marketing and economic studies. The attributes and quality of *search goods* can be evaluated easily before purchase (e.g., printer, camera). In the other hand, those of *experience goods* are hard to know before purchase; only after purchase, consumers can "experience" what they are (e.g., music CD, restaurant). Consumers can hardly be certain about the benefits of *credence goods* even after buying and using them for some time (e.g., vitamins, certain medical treatments). If the attributes of search goods are examined easily, there is less room for subjective biases. However, consumers can hardly review objectively on credence goods. Therefore, the study hypothesizes:

H1: The extent of overestimating review helpfulness due to non-system biases is smaller in the order of search, experience and credence goods.

Another typology of goods is utilitarian (usefulness) vs. hedonic (pleasure) (Richins, 1994; Sethuraman & Cole, 1999). To review *hedonic goods* such as music and dining, consumers cannot focus on measureable attributes but rather on the subjective experience of enjoyment from them. The subjective nature of reviews may be more sensitive to system biases such as review display orders, because consumers cannot objectively differentiate good reviews from poor reviews.

H2: The extent of overestimating review helpfulness due to system biases is pronounced more with hedonic goods than non-hedonic goods.

H1 concerns the first and third categories of biases whereas H2 addresses the second category.

3. Method and Preliminary Results

The study uses two printers and two music CDs as search and experience goods (Mudambi & Schuff, 2010) while choosing two products in the category of "vitamins and supplements" as credence goods (Nakayama, Sutcliffe, & Wan, 2010). Two products were randomly drawn from those listed on the first page of Amazon.com's "Best Sellers" page for the three product categories in January 2012. Then two "most helpful" reviews were collected on the six products. The same reviews were also sampled in September 2012 for comparison regarding their helpfulness votes. After pretesting at two U.S. Midwestern and Southwestern universities, the survey questionnaire was developed to test how general consumers rate the helpfulness of the 12 reviews for the 6 products. Volunteers were sought with a modicum incentive via Dealsea.com and the two universities. There were 294 participants.

Table 2 summarizes the results from the survey and review data collection in eight months. The two columns – Amazon H-VR and Survey H-VR – show how the helpfulness ratings vary between the Amazon.com website on Jan 5, 2012 (1/5) and the data collected from the survey participants. The differences were all significant except for the critical review on the Canon Printer. The average differences are -4.67%, -25.53% and -13.76% each for search, experience and credence (SEC) goods. To interpret these numbers, however, we need to take into account the fact the experience goods this study chose are hedonic goods at the same time. The System Factor column lists the average differentials by SEC goods based on the difference regarding Amazon H-VR between 1/5 and 9/23. The experience goods have the highest differential of -3.67%. The column for Amazon H-VR (9/23/12) shows that the individual differentials for the hedonic (also experience) goods were all significant. This supports H2. Using the system factor results, we can estimate the SEC differentials by adjusting the raw differentials between 1/5 and the survey. The adjusted figures are based on *raw differential* divided by *relative system factor* where the relative system factor is defined by the relative magnitude differentials (e.g., regarding the system factor for search goods as 1.00, that for experience goods is 1.98 = -3.97% divided by -1.94%). The right-most column shows the adjusted SEC differentials. The results support H1, as the credence goods have the highest differential of -19.48% and the search goods have the lowest of -4.67%.

SEC	Product	Valence	Star Rating	Amazon H-VR (1/5/12)	Amazon H-VR (9/23/12)	Survey H-VR	System Factor (1/5 vs. 9/23)	Adjusted by System Factor (survey vs. 1/5/12)
S	Canon MP280 Printer	Favorable	5	92.4%	90.6%*	84.10%**	-1.94%	-4.67%
		Critical	3	76.2%	70.4%	78.10%		
	HP LaserJet Pro 1102w	Favorable	5	98.7%	98.7%	91.80%***		
		Critical	3	98.5%	98.4%	93.10%***		
E	Adele 21 (Music CD)	Favorable	5	96.1%	88.2%***	82.22%***	-3.67%	-13.48%
		Critical	3	87.5%	66.7%***	22.64%***		
	El Camino (Music CD)	Favorable	5	73.8%	87.2%***	52.05%***		
		Critical	3	76.7%	77.3%*	75.00%*		
C	Viviscal Extra Strength Vietary Supplement	Favorable	5	96.8%	96.2%	87.70%***	-1.37%	-19.48%
		Critical	1	85.7%	87.0%	69.20%***		
	Nature Way Coconut Oil	Favorable	5	100.0%	98.0%***	83.60%***		
		Critical	3	94.7%	90.6%*	81.70%**		

H-VR: helpfulness vote ratio = YES votes divided by total votes
*'s in the column Amazon H-VR (9/23/12) show the statistical difference between Amazon.com data on 1/5/12 and those on 9/23/12.
*'s in the column Survey H-VR show the statistical difference between this survey's H-VR and Amazon.com H-VR on 9/23/12.
*: p < .10, **: p < .05, ***: p < .01

Table 2. Survey Results of Review Bias Assessment

4. Implications and Conclusion

This paper reviewed the different biases that previous studies examined regarding online consumer reviews. In the review life-cycle phases, this study mapped these biases along each phase of the model. While the previous studies named the biases differently, three basic biases are identified: (1) selection bias, (2) system bias, and (3) attribution bias. Using the SEC paradigm and utilitarian-vs.-hedonic goods, the study investigated how certain goods are likely to have more biases than other goods. The highlights of the results are as follows. Hedonic goods are subjected to more system biases than non-hedonic goods. The extent of system biases is 1.5 to 2 times more for hedonic goods than non-hedonic goods. The influence of self-selection and attribution biases is seen in the creation, evaluation and use phases. Votes indicating the helpfulness of reviews are an aggregate measurement for these influences. The order in which votes regarding review helpfulness on Amazon.com were overestimated is search, experience and credence goods, from smallest to largest. Consumers should be aware that they are seeing overestimated helpfulness votes when reading reviews. They should also know that such overestimation depends on the types of goods this paper used. Future studies should increase the number of product samples to further validate this study's results. In addition, we should extend this research by considering different price ranges of goods.

References

Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry. *Journal of Management Information Systems, 23*(2), 149-171.

Darby, M. R., & Karni, E. (1973). Free Competition and the Optimal Amount of Fraud. *Journal of Law and Economics, 16*(1), 67-88.

Day, G. S. (1981). The product life cycle: analysis and applications issues. *The Journal of Marketing*, 60-67.

Dellarocas, C. (2006). Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms. *Management Science, 52*(10), 1577.

Godes, D., & Silva, J. C. (2012). Sequential and temporal dynamics of online opinion. *Marketing Science, 31*(3), 448-473.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153-161.

Hu, N., Pavlou, P. A., & Zhang, J. (2006). *Can online reviews reveal a product's true quality? Empirical findings and analytical modeling of online word-of-mouth communication*. Paper presented at the Proceedings of the 7th ACM conference on Electronic commerce, Ann Arbor, Michigan, USA.

Hu, N., Zhang, J., & Pavlou, P. A. (2009). Overcoming the J-shaped distribution of product reviews. *Commun. ACM, 52*(10), 144-147. doi: 10.1145/1562764.1562800

Jones, E. E., Riggs, J. M., & Quattrone, G. (1979). Observer bias in the attitude attribution paradigm: Effect of time and information order. *Journal of Personality and Social Psychology, 37*(7), 1230-1238.

Kapoor, G., & Piramuthu, S. (2009). Sequential Bias in Online Product Reviews. *Journal of Organizational Computing & Electronic Commerce, 19*(2), 85-95.

Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *The American Economic Review*, 562-583.

Korfiatis, N., García-Bariocanal, E., & Sánchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications, 11*(3), 205-217. doi: 10.1016/j.elerap.2011.10.003

Li, X., & Hitt, L. M. (2008). Self-Selection and Information Role of Online Product Reviews. *Information Systems Research, 19*(4), 456-474. doi: 10.1287/isre.1070.0154

Liu, J., Cao, Y., Lin, C.-Y., Huang, Y., & Zhou, M. (2007). *Low-Quality Product Review Detection in Opinion Summarization*. Paper presented at the Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning.

Mudambi, S., & Schuff, D. (2010). What Makes A Helpful Online Review? A Study of Customer Reviews on Amazon.com. *MIS Quarterly, 34*(1), 185-200.

Nakayama, M., Sutcliffe, N., & Wan, Y. (2010). Has the web transformed experience goods into search goods? *Electronic Markets, 20*(3), 251-262.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy, 78*(2), 311-329.

Nelson, P. (1974). Advertising as Information. *The Journal of Political Economy, 82*(4), 729.

Park, D. H., & Han, I. (2008). *Integrating conflicting reviews: Attributional hypotheses of consumer response to information uncertainty depending on prior brand attitude.* Paper presented at the The 41st Annual Hawaii International Conference on System Sciences.

Richins, M. L. (1994). Valuing Things: The Public and Private Meanings of Possessions. [Article]. *Journal of Consumer Research*, *21*(3), 504-521.

Ross, L. (1977). The intuitive psychologist and his shortcomings: Distortions in the attribution process. *Advances in experimental social psychology, 10*, 173-220.

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing*, *21*(4), 76-94.

Sethuraman, R., & Cole, C. (1999). Factors influencing the price premiums that consumers pay for national brands over store brands. *The Journal of Product and Brand Management*, *8*(4), 340-351.

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123-127.

Weinberg, B. D., & Davis, L. (2005). Exploring the WOW in online-auction feedback. *Journal of Business Research*, *58*(11), 1609-1621.

Zhang, J. Q., Craciun, G., & Shin, D. (2010). When does electronic word-of-mouth matter? A study of consumer product reviews. *Journal of Business Research*, *63*(12), 1336-1341.