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The effect of product review balance and volume on online Shoppers' risk perception and purchase intention

Jing Yang [a,*], Rathindra Sarathy [b,1], JinKyu Lee [c,2]

[a] Management, Marketing and Information Systems, School of Economics and Business, State University of New York at Oneonta, 330 Netzer, SUNY Oneonta, Oneonta, NY 13820, United States
[b] Management Science and Information Systems, Spears School of Business, Oklahoma State University, Stillwater, 221 Business, Stillwater, Stillwater, OK 74078, United States
[c] Management Science and Information Systems, Spears School of Business, Oklahoma State University, Tulsa, 317 North Hall, 700 N. Greenwood Ave., Tulsa, OK 74106, United States

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ABSTRACT

Online reviews are viewed as an important source of information enabling online shoppers to assess the quality of products/services. An important function of reviews is to reduce the risk and uncertainty that online buyers perceive relating to the product purchase. There are many aspects of reviews that may influence risk perception. This study examines the effect of social consensus in product reviews, represented by review balance and volume, on online shoppers' risk perception, uncertainty, attitude and subsequent purchase intention, using a quasi-experimental design and online questionnaires. Results show that the four proposed risk concerns are good predictors of online shoppers' overall risk in e-commerce; perceived risk is a major determinant of online shoppers' attitude toward purchasing, which in turn determines their purchase intention. However, no significant causal effect between perceived uncertainty and purchase intention was found.

1. Introduction

It is widely accepted that online reviews are crucial components in today's online commerce. Different attributes of online reviews influence product sales. For example, large review volumes normally indicate popularity of products and are associated with increased product sales [1,2]; reviews with five stars stimulate product sales, while those with one star function in the opposite way [3,4]. It is generally accepted that review attributes or cues influence product sales by providing signals relating to the purchasing decision. However, the underlying psychological mechanisms by which cues influence the purchasing decision is not fully understood.

The literature contains several contradictions on the effect of review-related cues on purchase-related variables. For example, consider the effect of review valence (the positivity or negativity of reviews) on perceived helpfulness of reviews. Mudambi and Schuff found that reviews with extreme ratings are considered less helpful than those with moderate ratings when the product in question is an experience product (e.g., books & movies) but not a search product (e.g., computer, camera) [5]. However, Forman et al. suggest that reviews with moderate ratings are less helpful than those with extreme ratings for books [6], which are typical experience goods.

The aforementioned discrepancy is not unique. Chevalier and Mayzlin [2] show that the negative effect of incremental negative reviews on product sales could outweigh the positive effect of incremental positive reviews in the context of book sales; that is, one-star reviews have a stronger impact on book sales than five-star reviews [1]. However, Clemons et al. claim that high-end reviews have a greater impact than low-end reviews in the context of beer sales. Clemons et al. explain that this discrepancy results from the difference in the attributes of these two products. Similarly, another interesting finding is that negative reviews can also lead to sales growth if these reviews are informative as well as detailed. That means if reviewers clearly outline pros and cons of products and provide sufficient information supporting their viewpoints, online reviews will definitely stimulate product sales even though the tone of the review content is negative. The conjecture from researchers was that negative attributes of products did not concern online shoppers as much as they did reviewers [3].

These examples show that the interaction effects of cues may be important when attempting to understand what signals customers attributes to cues. In particular, we choose two specific characteristics — *review balance* (the ratio of positive and negative reviews [7,8]) and *review volume* (the quantity of reviews) — for two reasons. First, we believe that the combination of review balance and volume reflects a *social consensus* towards a product or service that can override the impact of details in review content [12]. The impact of details in reviews on purchases can be mixed. For example, it is claimed that the increase

* Corresponding author at: School of Economics and Business, 330Netzer, State University of New York at Oneonta, Oneonta, NY 13820. Tel.: +1 607 436 3381.
E-mail addresses: jing.yang@oneonta.edu (J. Yang), rathin.sarathy@okstate.edu (R. Sarathy), jinkyu.lee@okstate.edu (J. Lee).
[1] Tel.: +1 405 744 8646.
[2] Tel.: +1 918 594 8254.

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of subjective expression in review content could drive up product sales [3], while this effect would be negative when reviews contain a mixture of slightly objective and highly subjective comments [3]. We believe that when a social consensus toward a product or service is formed, the effect of any specific detail within a review on the purchase decision may be less important. This is supported by the finding that a combination of high average rating together with high volume of reviews forms a good predictor for high product sales [9]. Second, we are also interested in the interactive effect between review balance and review volume. Many papers have addressed the importance of review balance and review volume [1–4,9–11], but make little mention of their interactive effect.

Our second objective is to explore the psychological mechanisms by which the social consensus represented by review balance and volume influences purchase intention. We believe that the social consensus influences potential online buyers' risk perceptions, in turn influencing uncertainty related to the purchase and purchase intention. Uncertainty in e-commerce is believed to arise from the possibility that transactions may not be completed due to fraud, counterfeit products, prolonged product delivery, and so on [13]. Online reviews provide a possible way for online shoppers to acquire information about products or services from a third party and thereby lessen associated uncertainty in purchase intention. Prior studies do indicate that high uncertainty in e-commerce is likely to result in high risk perceptions, in turn hindering online shoppers' intention to engage in transactions [13]. However, unlike most studies that simply treat uncertainty as a background concept, we provide a direct and systematic measure of uncertainty and associated risk perceptions.

The current study contributes to the extant literature in the following ways. First, we explore the effect of social consensus in reviews represented by two important cues relating to online reviews — *review balance* and *review volume*, as well as their interactive effect – on purchase intention. Second, we study the underlying psychological mechanisms by which the social consensus in reviews influences purchase intention. In particular, we posit that it works through mitigating risk and uncertainty perceptions, as well as shaping attitude towards the product. Third, we implement a direct measure of perceived risk in online transactions as well as exploring its potential antecedents. Based on the study by Laroche et al. of risk perceptions in general shopping [14], we measure how risk perceptions — such as perceived financial risk, social risk, performance risk, and psychological risk — constitute online shoppers' overall risk perception of online reviews and, in turn, impact their perception related to uncertainty and purchase intention.

The remainder of the paper is organized as follows. First, we review and discuss the literature related to risk perceptions, uncertainty, review balance and review volume and propose the research hypotheses and model examined in this study. Next, we explain the experiment design and data collection procedure employed in the study. In the following section, we present a summary and a discussion of our results. The paper concludes with a discussion of the contributions and limitations of this study.

2. Theoretical background and hypotheses

2.1. Approaches to studying the effect of online reviews

There are many interesting findings on the effect of reviews on online buyers. For example, negative reviews are considered more informative than positive reviews in the sense of helping consumers discriminate high-quality products from those of low quality [22]. If reviews with substantial supportive evidence are viewed as high-quality reviews and the ones with insufficient information are viewed as low-quality reviews, studies show that high-quality negative reviews have a stronger impact on the attitude toward products than low-quality ones. The attitude toward purchasing becomes less favorable as the number of high-quality negative reviews increases [22]. Negative reviews may trigger sales *growth* if reviewers clearly outline the pros and cons of products and provide sufficient information supporting their viewpoints [3]. This is very interesting because in most of the findings of econometric models, negative reviews seem to always have a harmful influence on product sales growth. Yin et al. find that the discrete emotion, such as anger or anxiety, embedded in seller reviews may affect their helpfulness rating [27]. Baum and Spann show that the consistency between online reviews written by previous consumers and the recommendation from a recommender system are important [28]. All these findings indicate that the psychological processing of cues embedded in online reviews could vary conditionally, although the final outcome may look simple and straightforward.

Based on a review of studies since 2000, we find that present literature on online reviews can be briefly classified into three main streams. The first stream focuses mainly on the content of reviews and generally employs content-analysis techniques such as text mining to explore linguistic traits in reviews [34,35]. For example, Pavlou and Dimoka uncovered that semantic patterns embedded within seller reviews (reviews focusing on the service provided by sellers) can reveal reviewers' trust over sellers [36]. The second stream of studies normally employs econometric methods to build predictive models [5,37]. For example, Mudambi and Schuff built a Tobit regression model and found that the helpfulness of reviews is a mathematical function of review extremity and review depth moderated by product type [5]. The third stream studies consumer behavior related to online reviews through a psychological lens [38,39]. For instance, Awad and Ragowsky's study reveals that online reviews can alter online shoppers' trust belief by shifting their attitude toward sharing opinions and responding to others, though gender differences exist in this regard [39].

Each stream has its own focus and pros and cons. In particular, text mining methods are mainly used to *uncover underlying patterns* in online reviews while econometric models attempt to *predict* variables such as sales, sales growth, price premiums, product ratings among others based on review characteristics. These two approaches are more prevalent in mainstream studies of online reviews. Causal behavioral models are used to understand people's reaction to certain stimuli pertaining to online reviews and are better suited to *studying the psychological mechanisms* underlying the impact of review characteristics on purchase-related decisions. Our study uses this approach. In particular, we seek to show that social consensus in reviews represented by review balance and volume will influence shoppers' purchase intention by impacting their perceived risk and uncertainty, as well as their attitude toward purchasing the product.

2.2. Uncertainty and purchase intention in e-commerce

Uncertainty is considered an important factor determinant of buyers' willingness to engage in an online transaction and much effort has devoted to look for possible ways to mitigate it. Online shoppers' familiarity of websites impacts their trust in the vendor, and trust, in turn, is assumed to mitigate uncertainty [15]. Gregg and Walczak indicate that improving the quality of e-images or photos on webpages may be another effective way to reduce uncertainty [16]. In the context of online reviews, Weathers et al. [17] investigate the impact of information vividness in reviews on reducing uncertainty, based on comparison of reviews with pictures, no pictures, third party evaluation, and highly-controlled information. They find that for search products such as electronic devices, third-party reviews are comparatively more effective than other information sources in reducing uncertainty and enhancing information credibility; conversely, for experience products such as food, pictures in reviews and merchant-provided product reviews are found to be comparatively more effective. Unlike these studies, which simply treat uncertainty as a background concept without direct measurement, Pavlou et al. measure uncertainty directly, and show that online shoppers' trust, website informativeness, product diagnosticity, and social presence on a website can effectively lessen uncertainty in online transactions [13]. Following Pavlou et al., we implement a direct measure of uncertainty in our study as well. Here, perceived uncertainty is defined as "the degree to which the outcome of a transaction cannot be accurately predicted by the buyer due to seller and product related factors" (p.107) [13]. Since purchase uncertainty is a result of online shoppers' reluctance to engage in transactions, less uncertainty should result in greater intention to purchase [13]. Consequently we hypothesize that:

H1. Perceived uncertainty has a negative effect on online shoppers' purchase intention.

2.3. Risk perception and its measurement

Risk perception is related to uncertainty in e-commerce. The measurement of risk perception varies with context, with no clear consensus. For example, some researchers simply measure overall risk perception without specifying risk types [18]. On the other hand, literature also suggests that risk perception in e-commerce can be understood based on its potential sources, for example, the risk derived from products and the risk derived from vendors' behavior. As posited by principal agent theory, risk in e-commerce may derive from online shoppers' doubt on the potential role of hidden information and hidden actions in transactions [13]. Here, hidden information arises from sellers' intentional actions of hiding information on either products or transactions, while hidden actions derives from sellers' actions of breaking their promises by sending low-quality or counterfeit products to online shoppers. Based on the observation of general customers' shopping behavior, Laroche et al. think that customers' risk perception can also be understood from consumers' concerns on potential financial risk, time risk, performance risk of products, psychological risk, and social risk from friends and family members [14]. Financial risk here refers to online shoppers' assessment of potential financial losses due to the purchase of a product of low quality or potential internet-based fraud [19, 20]. Time risk refers to online shoppers' assessment of potential losses to convenience, time, and effort caused by time researching and purchasing the product [20]. Performance risk is related to online shoppers' assessment of potential problems such as malfunctioning, transaction processing errors, and reliability problems, which cause products not to perform as expected [20]. Psychological risk is defined as online shoppers' assessment of potential losses to their self-esteem, peace of mind, or self-ego due to worrying or feeling frustrated or foolish as a result of buying the product [20]. Social risk measures online shoppers' assessment of potential losses to their perceived status in their social group as a result of buying a product [20]. We believe that this detailed measurement of risk is well suited to study the impact of reviews on risk and uncertainty perception, because potential buyers use reviews for assessing many different types of risks.

Therefore, we measure online shoppers' risk perception in two steps. First, we measure the overall risk perception in the form of perceived risk. Second, we follow Laroche et al.'s measurement model of risk by assuming that the overall risk perception is constituted by five specific risk perceptions such as financial risk, time risk, performance risk, psychological risk, and social risk [20,21]. Our experimental setting excludes time risk since that is often not a factor when online buyers use reviews, and online shoppers normally have plenty of time and flexibility to decide on how much information they would like to acquire from reviews.

Certainly, there might be other risks involved in e-commerce such as risk perceptions related to information privacy and security [13,20]. However, our understanding is that the occurrence of this type of risks heavily relies on the content of information conveyed in reviews. Our special experimental design enables us to get rid of the effect of review content from the study, therefore it would be feasible for us to exclude other potential risk concerns from our examination.

Considering all, we hypothesize:

H2. Perceived financial risk have a positive impact on overall perceived risk.

H3. Perceived performance risk have a positive impact on overall perceived risk.

H4. Perceived psychological risk have a positive impact on overall perceived risk.

H5. Perceived social risk have a positive impact on overall perceived risk.

2.4. Consumers' attitude toward purchasing in the presence of online reviews

Prior literature suggests that online reviews impact buyers' attitude toward products and services. The positive relationship between review valence (positive or negative rating) and product sales [1] indirectly suggests the conformance of review readers to the opinions of review writers, and suggests shaping of their attitude toward purchasing. Besides, Lee et al. find that reviews with substantial supportive evidence have a strong impact on online shoppers' attitude toward products than reviews with insufficient information [22]. Punawirawan et al. suggest that when reviews are perceived relatively useful, the impression created by the content in reviews (positve or negative) affect online shoppers' attitude and intention formation [8].

The study of attitude is consistent with the Theory of Reasoned Action (TRA) which suggests that people's beliefs influences their attitude toward an object [23]. In the consumer behavior domain, perceived risk represents a consumer's belief that certain negative consequences might stem from the purchasing of products [24]. Several studies indicate that this impact is negative. That is, if a consumer perceives more risks from the purchasing of products, their attitude toward this purchasing behavior is less favorable and vice versa. For example, in the purchasing of either symbolic or experimental conterfeit product, consumers' percieved risk has a significant negative impact on their attitude toward the purchasing [24,25]. TRA also posits an indirect role for risk belief in shaping behavioral intention, mediated by attitude. For example, Lee's study shows that risk belief has an inhibiting effect on consumers' intention to trade stocks online mediated by their attitude toward online trading [26].

Therefore, we hypothesize:

H6. Perceived risk has a negative impact on online shoppers' attitude toward purchasing.

H7. Attitude toward purchasing has a positive impact on online shoppers' purchase intention.

Considering that uncertainty arises from the possibility that transactions may not be finished due to the reasons such as fraud, counterfeit products, prolonged product delivery, and so on [13], we believe that high risk perception is likely to lead to high uncertainty, as shown in the study by Pavlou et al. that the potential risk derived from sellers' hidden information and hidden actions may cause an increase of perceived uncertainty [13]. Therefore, we hypothesize:

H8. Perceived risk has a positive impact on perceived uncertainty.

2.5. The effects of review balance and volume

In our experiment, we examine the effect of social consensus in reviews on perceived risk by presenting subjects with reviews that contain a mix of two specific cues: review balance and review volume. Review volume in this study refers to the quantity of reviews and consequently reflects the amount of information exposed to online shoppers. To our understanding, cues pertaining to online reviews can be categorized into two clusters. The first cluster is review-related cues, for example, average consumer rating, dispersion of ratings, review valence, review quantity (or review volume), review length, number of votes on reviews, review content, and so on. Prior studies indicate that product sales grow when products get rated higher by reviewers; that is, a higher average rating normally result in higher sales [1–4]. As important as the average rating, the dispersion of ratings can be viewed as another indicator for future sales [2]. Interestingly, it also finds that if average rating is held constant, the longer reviews are, the lower product sales will be [1].

The second cluster is non-review-related factors, such as product quality, product price, product popularity, product age, and so on. Taking product popularity as an example, all three intrinsic cues in reviews — review volume, average rating, and rating dispersion — are found to have a stronger impact on less popular products than on more popular ones in the market of online games [10]. Products such as MP3 players, music CDs, and PC video games are generally viewed as *experience* products, while others such as cell phones, digital cameras, and Laser printers are viewed as *search* products [5]. Prior studies indicate that assessing the quality of experience products before consumption is difficult; in most cases, the perceived quality of experience products depends on individual expectations [5]. Conversely, the quality of search products can be assessed in an objective way [5]. With regard to online reviews, average review rating normally influences the perceived helpfulness of reviews; however, this effect is moderated by product type. For experience products, reviews with an extreme rating are believed to be less helpful than those with a moderate rating; for search products, ratings have no impact at all [5].

Review balance is related to review valence (positive or negative rating). We measure review balance instead of review valence, because review balance as a ratio of positive to negative reviews, reflects both average rating and dispersion of ratings, making it more efficient than review valence. When close to high end, it means most of reviewers have a positive attitude toward the targeted product or service; vice versa for the review balance close to low end. This pattern can also be reflected by a combination of average rating and dispersion of those ratings.

There is evidence to suggest that review balance and review volume may interact with each other in shaping purchase intention. Prior studies indicate that as the propotion of negative reviews increases, holding review volume constant, the tendency for potential buyers to conform to reviewers' opnions gets stronger [22]. Further, an increase in review volume only causes an increase in product sales (implying lower perceived risk in purchasing the product) when the average rating is positive; vice versa [27]. On the other hand, Anqueveque finds that expert reviews written by professional reviewers can lower consumers' risk perception [28]. Considering all these, we hypothesize:

H9. Review balance has a positive effect on online shoppers' purchase intention.

H10. Review balance has a negative effect on online shoppers' perceived risk.

H11. Review volume moderates the effect of review balance on online shoppers' purchase intention.

H11a. When review balance is low-ended, review volume has a negative effect on online shoppers' purchase intention.

H11b. When review balance is high-ended, review volume has a positive effect on online shoppers' purchase intention.

Online reviews also impact online shoppers' attitude. As mentioned earlier, review valence has a positive effect on product sales, which indirectly reflects the conformance of the readers of online reviews in their attitude toward purchasing. It is also suggested that high-quality negative reviews have a stronger impact on attitude formation than low-quality ones; and online shoppers' attitude toward purchasing turns less favorable when the number of high-quality negative reviews goes up [22]. Therefore, we hypothesize:

H12. Review balance has a positive effect on online shoppers' attitude toward purchasing.

Prior research on the role of amount of information suggests that the evaluative judgment of an object becomes more extreme as the amount of information about that object increases, even when the value of each piece of information is held constant [29]. For example, when clinical patients consider taking influenza vaccination, the more information they get, the stronger the consistency of their atttitude and associated behavior is [30]. Following the logic, we assume that if online buyers are more exposed to more reviews, the consistency of their attitude toward purchasing and associated purchasing behavior will also become stronger. Here, purchase behavior is measured in online shoppers' purchase intention as indicated by literature. Therefore, we hypothesize:

H13. Review volume has a positive effect on the consistency of online shoppers' attitude and their purchase intention.

H13a. If online shoppers hold a negative attitude toward purchasing, a larger volume of reviews will lessen their purchase intention.

H13b. If online shoppers hold a positive attitude toward purchasing, a larger volume of reviews will reinforce their purchase intention.

Integrating all hypotheses, our research model is presented in Fig. 1.

3. Research methodology

This study adopts a quasi-experimental design where paricipants are randomly assigned to different versions of surveys as planned, while the treatments (review balance and review volume) are manipulated. Constructs such as attitude, uncertainty, purchase intention, and so on, are measured using a structured survey questionnaire. The data was collected in two steps from two sample groups — student subjects and general subjects. The effects of review balance and volume are analyzed using MANOVA tests, while the network of causality among the constructs are tested with a PLS-based SEM.

3.1. Product used in experiments

To measure the impact of product reviews on online shoppers' online behaviors, we chose a tablet computer as the product in our experiment for two reasons. First, a large number of prior studies used electronic devices as objects because it is a common product type that is purchased online (e.g. cameras, computers, or cell phones). Second, as discussed before this, it is considered a search product, whose quality of can be evaluated in an more objective approach compared to experience products (whose quality is difficult to assess prior to consumption). All of the information about the tablet computer, including introduction, price, and reviews, is real and taken from Amazon but modified slightly for our research requirements.

3.2. Study design

The manipulation of review balance and volume is presented in Table 1. Adapting from the idea in the study by Park et al. [31], 10 reviews are defined as a low volume while 100 reviews are defined as high volume. A manipulation check over subjects' perceived quantity of reviews was implemented in a pilot study. The significant result of the comparision indicated the success of the manipulation on review quantity.

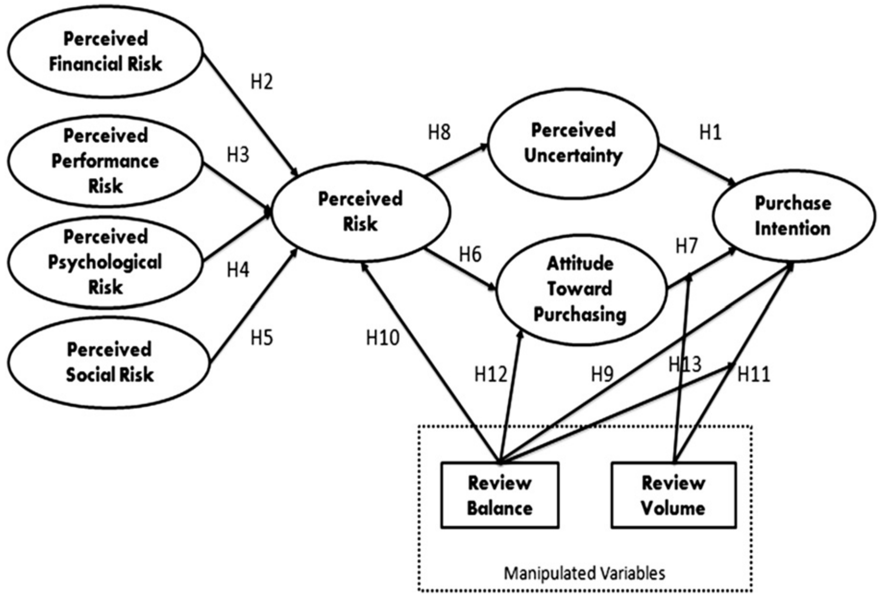


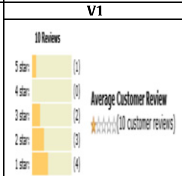
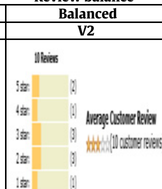
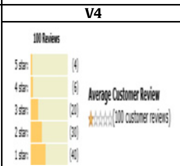
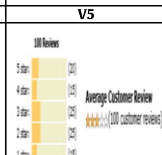
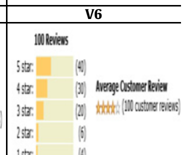
Fig. 1. Research Model.

Review balance is reflected by the distribution of star ratings. In line with general understanding, one- to two- star reviews are viewed as negative, four- to five-star reviews are positive, and three-star reviews as neutral. Review balance changes as one- to five-star reviews are combined in different ways. For instance, a product with 90% positive reviews is considered to have a positive distribution (or high ended) of star ratings and is also viewed favorably; 50% of positive reviews show a neutral distribution (or balanced) and a neutral product; and 10% of positive reviews correspond to an unfavorable product with a negative distribution of star ratings (or low ended). We believe this design will help us better capture the real pattens of online reviews in e-commerce. As illustrated in Table 1, we consequently have six groups of subjects in the experiment.

3.3. Data collection

Our survey questionnaires were posted on Qualtrics.com, a web-based survey software that enables users to develop and collect responses to surveys. All measurement items for the study were adopted and adapted from prior studies. The measurement instruments are presented in Appendix 1. All the statements in the instruments used in the survey were assessed on a seven-point scale anchored at 1 = strongly disagree, 4 = neutral, and 7 = strongly agree. Six versions of the surveys were created. In each version, most of the information, such as product introduction, product price, and information exposure flow (the sequence that the information were exposed to the subjects), stayed the same.

Table 1
Experimental Design.

		Review balance		
		Low-ended	Balanced	High-ended
		V1	V2	V3
Review volume	Low (10 reviews)			
		V4	V5	V6
	High (100 reviews)			

The number of reviews the participants were exposed to varied as the experimental settings changed. To eliminate the influence of review content in the experiment, we applied a randomization technique when the reviews were drawn from a collection of reviews in the surveys. For example, all six surveys shared the same pool of one- to five-star reviews, around 50 of each type of review. A certain number (either 10 or 100 depending on the experiment design) of reviews could be randomly drawn from this pool of reviews according to the experimental settings. Technically, it was impossible for any two participants to be presented with the same set of reviews even though they were taking the same version of the survey.

The data were collected from two sample groups. The first sample group includes student subjects. A call for research participation with a link to one of the online questionnaires was emailed to 500 undergraduate students in the business school at a midwestern university in the U.S. At the start of the email, the participants were told that all the instructions were provided in the survey and that they should read the instructions carefully and complete the survey independently. After deleting incomplete responses, the usable sample size of this first dataset is simply 137 (24.7% of effective response rate).

To improve the generalizability and reliability of the findings in the study, an additional set of data was collected from a more general sample. The surveys were posted for about one week on Amazon Mechanical Turk, which provides access to a global marketplace of more than 500,000 workers from 190 countries. Compared to student subjects, the workers at Mechanical Turk are believed to have more diversified backgrounds. Consequently, the participants from Mechanical Turk are called general subjects in the study. Following the same data cleaning procedure in student subjects, we received 165 usable respnoses from general subjects.

Tables 2 and 3 present the information about sample size and descriptive statistics of the respondents.

From the descriptive statistics in Table 3, it is clear that the majority of the participants in both groups had neither bought nor used the specific tablet computer mentioned in the surveys. More than 90% of them had shopped online for at least once in the past year. All of these indicate that the reviews presented in the surveys are the only source of information for these participants on the product, and additonally they have sufficient knowledge to understand the information presented

Table 2
Sample Size for Two groups of Subjects.

Surveys	Student Subjects Number of Responses	Student Subjects Percentage (%)	General Subjects Number of Responses	General Subjects Percentage (%)
Version 1	22	16.1	27	16.4
Version 2	17	12.4	28	17.0
Version 3	29	21.2	28	17.0
Version 4	24	17.5	26	15.8
Version 5	19	13.9	27	16.4
Version 6	26	19.0	29	17.6
Total	137	100.0	165	100.0

Table 3
Descriptive Statistics.

		Student Subjects Number of Responses	Student Subjects Frequency (%)	General Subjects Number of Responses	General Subjects Frequency (%)
Bought or used the tablet PC before?	Yes	6	4.4	32	19.4
	No	131	95.6	133	80.6
The Frequency of Online Shopping Last Year	Never	9	6.6	13	7.9
	1 ~ 5	44	32.1	76	46.1
	6 ~ 10	25	18.2	33	20.0
	11 ~ 20	29	21.2	16	9.7
	More than 20	28	20.4	27	16.4
Gender	Male	69	50.4	97	58.8
	Female	68	49.6	68	41.2
Age	Average Age	22.7		30.66	
	Std. Deviation	5.379		17.96	

and make a judgment. We combined the two groups of subjects for our analyses.

4. Data analysis and results

4.1. Measurement validation

To assess measurement validity, we calculate means, standard deviations, correlations and average variances extracted for each conceptual construct, and cross loadings of each item on its conceptual construct, as presented in Tables 4 and 5. SmartPLS was utilized as the analytic tool.

There were 6 responses out of 302 (approximately 2%) containing missing values. Instead of simply deleting these responses, all the missing values are replaced by means, using a default function in SmartPLS. As indicated in Table 4, the majority of the construct means have values centered at 4 (meaning a neutral attitude) with standard deviations of around 1.7, indicating that most of the responses are evenly distributed across all seven points.

The only exception is social risk, whose mean is 2.833. Based on the value, it appears that most of the participants held an optimistic attitude toward social risk. The three instruments used to measure social risk represent the participants' attitude toward buying the tablet computer. For instance, if buying the tablet, would the participant be held in higher esteem by his or her friends and family members, or would it cause him or her to be considered foolish by people whose opinion they value? To make the tone consistent in the statements, the ratings of the first two questions were reversed by substracting from 8. After observing the histogram diagrams for these three questions, we found that the responses of all three instruments were right skewed, indicating that most of the subjects did not feel much social pressure to buy the tablet.

The reliability of principal constructs is measured using both composite reliability and Cronbach's alpha. Literature suggests that the composite reliabilities of constructs are considered good if they exceed 0.90, and 0.7 for Cronbach's alpha [13,32,33]. As illustrated in Table 5, all the values for composite reliabilities are over 0.90, and all the Cronbach's alphas are over 0.85. Therefore, we conclude that the reliability for all the constructs in this study is excellent.

Convergent and discriminant validity are tested by looking at AVEs, cross correlations and cross loadings. Prior studies [13,32,33] suggest that 1) all AVEs should be greater than 0.50; 2) the square root of AVEs should be larger than the cross-correlations of constructs; 3) the cross-correlations of constructs should be lower than 0.90, meaning that constructs are distinct from each other; 4) the cross loadings of constructs on themselves should be higher than those on other constructs. Based on these standards, our model in general has a good convergent and discriminant validity, as indicated in Tables 4 and 5.

4.2. Testing the structural model

The structural model was tested using PLS with t-values generated by bootstrapping with 1000 subsamples. As illustrated in Fig. 2, most of the hypotheses are supported at $p < 0.01$ except the path from perceived uncertainty to purchase intention (-0.003, $p = 0.940$). In the left portion of the model, the significance of the hypotheses indicates that online shoppers' concerns on potential financial risk, psychological risk, performance risk, and social risk are effective predictors of general

Table 4
The Means, Standard Deviations, Correlations and AVE.

	Mean (STD)	CR (α)	1	2	3	4	5	6	7	8
1. FR	4.197 (1.806)	0.935 (0.896)	**0.828**							
2. PeR	4.823 (1.632)	0.952 (0.925)	0.754	**0.869**						
3. PsR	3.193 (1.734)	0.972 (0.956)	0.583	0.553	**0.919**					
4. SR	2.833 (1.628)	0.908 (0.860)	0.424	0.382	0.644	**0.767**				
5. Risk	3.798 (1.785)	0.959 (0.943)	0.785	0.775	0.718	0.575	**0.854**			
6. Unc	3.583 (1.556)	0.973 (0.958)	0.537	0.518	0.616	0.528	0.675	**0.923**		
8. Att	3.933 (1.720)	0.974 (0.960)	0.680	0.675	0.438	0.230	0.725	0.450	**0.926**	
9. PI	3.683 (1.852)	0.970 (0.953)	0.634	0.640	0.350	0.185	0.648	0.386	0.890	**0.914**

Note: all the values on the diagonal of correlation matrix represent AVE (Average Variance Extracted). FR = Financial Risk. PeR = Performance Risk. PsR = Psychological Risk. SR = Social Risk. Risk = Perceived Risk. Unc = Uncertainty. Att = Attitude toward Purchasing. PI = Purchase Intention. STD = Standard Deviation. CR = Composite Reliability. α = Cronbach's Alpha.

Table 5
Cross Loading Matrix.

	FR	PeR	PsR	SR a	Risk	Unc	Att	PI
FR1	0.934	0.650	0.496	0.414	0.691	0.468	−0.614	−0.586
FR2	0.894	0.551	0.511	0.392	0.616	0.428	−0.542	−0.488
FR3	0.902	0.673	0.465	0.324	0.662	0.465	−0.564	−0.526
PeR1	0.669	0.935	0.510	0.383	0.699	0.456	−0.627	−0.602
PeR2	0.647	0.937	0.469	0.353	0.658	0.465	−0.577	−0.558
PeR3	0.609	0.924	0.475	0.335	0.667	0.441	−0.574	−0.521
PsR1	0.521	0.505	0.959	0.563	0.683	0.553	−0.412	−0.333
PsR2	0.506	0.481	0.952	0.615	0.633	0.570	−0.388	−0.299
PsR3	0.522	0.510	0.965	0.581	0.648	0.575	−0.407	−0.330
SR1	0.232	0.203	0.438	0.876	0.354	0.413	−0.090	−0.061
SR2	0.255	0.226	0.498	0.871	0.377	0.417	−0.072	−0.023
SR3	0.499	0.475	0.611	0.879	0.642	0.442	−0.392	−0.358
Risk1	0.705	0.697	0.644	0.525	0.941	0.602	−0.658	−0.598
Risk2	0.640	0.657	0.676	0.590	0.930	0.611	−0.618	−0.537
Risk3	0.645	0.643	0.573	0.480	0.903	0.554	−0.606	−0.537
Risk4	0.680	0.679	0.630	0.494	0.922	0.608	−0.669	−0.600
Unc1	0.493	0.480	0.584	0.487	0.642	0.961	−0.424	−0.367
Unc2	0.498	0.487	0.579	0.450	0.627	0.969	−0.437	−0.381
Unc3	0.444	0.432	0.535	0.469	0.580	0.952	−0.382	−0.315
Att1	−0.590	−0.600	−0.424	−0.249	−0.679	−0.432	0.970	0.808
Att2	−0.602	−0.586	−0.371	−0.221	−0.638	−0.396	0.955	0.840
Att3	−0.631	−0.651	−0.417	−0.277	−0.677	−0.421	0.962	0.811
PI1	−0.559	−0.581	−0.273	−0.181	−0.560	−0.351	0.799	0.959
PI2	−0.544	−0.568	−0.376	−0.241	−0.609	−0.343	0.806	0.942
PI3	−0.583	−0.577	−0.311	−0.198	−0.596	−0.368	0.837	0.967

risk concerns in online transactions. Performance risk (0.327, $p < 0.01$) is the most influential risk concern, financial risk (0.292, $p < 0.01$) is the second, psychological risk (0.257, $p < 0.01$) is the third, and social risk (0.162, $p < 0.01$) is the least important precedent. The R^2 pertaining to perceived risk further indicates that these four risk perceptions explain around 71% of the variation in perceived risk.

As hypothesized, perceived risk triggers perceived uncertainty (0.643, $p < 0.01$) and simultaneously depresses online shoppers' positive attitude toward purchasing (−0.691, $p < 0.01$). Online shoppers' attitude toward purchasing dominates the formation of their intention to purchase (0.851, $p < 0.01$). Surprisingly, the path from perceived uncertainty to purchase intention is not significant (−0.003, $p = 0.940$). We interpret this to mean that in a virtual shopping environment, some uncertainty is inevitable. However, as long as the online shopper considers this uncertainty manageable and keeps a positive attitude toward the purchase, his/her intention to buy may still be high. Therefore, although perceived risk effectively shapes perceived uncertainty, this uncertainty perception may have no direct effect on purchase intention.

Perceived risk is a major source of perceived uncertainty, explaining around 41% of the variation in perceived uncertainty. Perceived risk also has a strong effect on the formation of online shoppers' attitude toward purchasing, explaining around 47.5% of the variation in purchase attitude. Purchase attitude, in turn, determines online shoppers' final intention to purchase, explaining around 72.4% of the variation in purchase intention.

Overall, the high R^2s and the significance in the majority of the hypothesis tests suggest that our model is a good fit in explaining the impact of consumer reviews on consumers' risk perceptions and purchase intention.

4.3. Testing the effects of review balance and volume

To test the hypotheses regarding review balance and volume, several ANOVA and MANOVA tests were performed for multiple comparisons based on the factor scores generated by IBM SPSS. Given the high

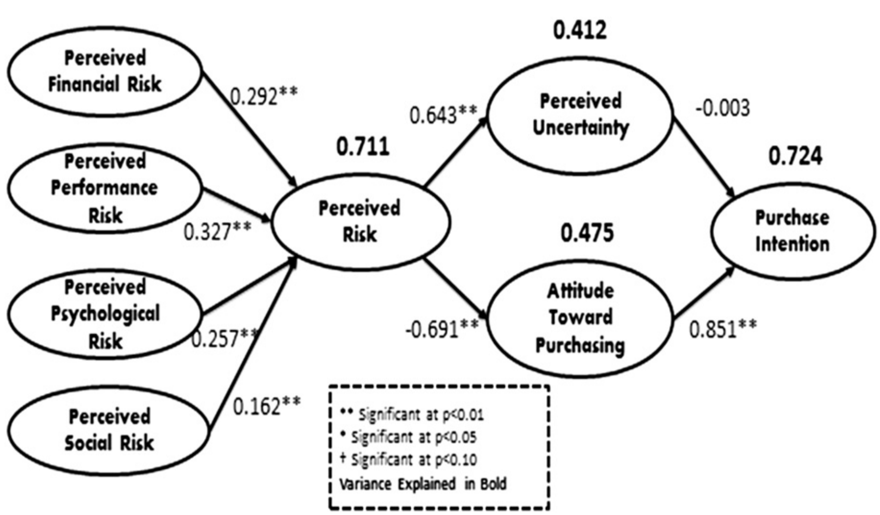


Fig. 2. Standardized Coefficients and R^2 for the Structural Model.

reliability of construct measures (Table 4), factor scores are a good representation of the information contained in each construct.

4.3.1. Effects on perceived risk

MANOVA results show neither a two-way interaction effect of review balance and review volume on perceived risk (F = 0.323, df = 2, p = 0.724) nor a main effect of review volume (F = 1.920, df = 1, p = 0.167). However, consistent with hypothesis H10, the main effect of review balance on perceived risk was found to be significant (F = 11.152, df = 2, p = 0.000).

A LSD test in ANOVA, as illustrated in Table 6, indicates that compared to low-ended reviews, both high-ended (mean difference = −0.635, std. = 0.134, p = 0.000) and balanced reviews (mean difference = −0.339, std. = 0.141, p = 0.017) will cause less risk concerns. That is, the readers of reviews do not sense much potential risk if the reviews are generally positive. There is also a significant difference between balanced reviews and high-ended reviews (mean difference = −0.296, std. = 0.137, p = 0.031).

4.3.2. Effects on attitude toward purchasing

MANOVA findings confirm hypothesis H12 that review balance would have a positive effect on customers' attitude toward purchasing (F = 15.502, df = 2, p = 0.000). An LSD test in ANOVA pertaining to the attitude toward purchasing further indicates that compared to low-ended reviews, the reviews with high-ended (mean difference = 0.717, std. = 0.132, p = 0.000) or balanced distribution (mean difference = 0.532, std. = 0.139, p = 0.000) would result in a more positive attitude toward the purchase, as presented in Table 7. However, there is no significant difference between high-ended and balanced reviews in terms of attitude (mean difference = 0.185, std. = 0.135, p = 0.171).

4.3.3. Effects on purchase intention

The hypotheses on purchase intention are comparatively complex. A MANOVA confirms a main effect of review balance (F = 6.905, df = 2, p = 0.01). This finding is consistent with hypothesis H9. The LSD in ANOVA, as presented in Table 8, further shows that compared to low-ended reviews, reviews with either high-ended (mean difference = 0.505, std. = 0.135, p = 0.000) or balanced distribution (mean difference = 0.293, std. = 0.142, p = 0.040) are more likely to foster online shoppers' purchase intention, with no significant difference between high-ended and balanced reviews (mean difference = 0.212, std. = 0.138, p = 0.127).

Table 6
Multiple Comparisons (LSD) for Perceived Risk.

(I) Review Balance	(J) Review Balance	Mean Difference (I-J)	Std. Error	Sig.
Low-ended	Balanced	0.339	0.141	.017
	High-ended	0.635	0.134	.000
Balanced	Low-ended	−0.339	0.141	.017
	High-ended	0.296	0.137	.031
High-ended	Low-ended	−0.635	.134	.000
	Balanced	−0.296	.137	.031

Table 7
Multiple Comparisons (LSD) for Attitude toward Purchasing.

(I) Review Balance	(J) Review Balance	Mean Difference (I-J)	Std. Error	Sig.
Low-ended	Balanced	−.532	.139	.000
	High-ended	−.717	.132	.000
Balanced	Low-ended	.532	.139	.000
	High-ended	−.185	.135	.171
High-ended	Low-ended	.717	.132	.000
	Balanced	.185	.135	.171

Table 8
Multiple Comparisons (LSD) for Purchase Intention.

(I) Review Balance	(J) Review Balance	Mean Difference (I-J)	Std. Error	Sig.
Low-ended	Balanced	−.293	.142	.040
	High-ended	−.505	.135	.000
Balanced	Low-ended	.293	.142	.040
	High-ended	−.212	.138	.127
High-ended	Low-ended	.505	.135	.000
	Balanced	.212	.138	.127

In addtion, as indicated by H11, review balance and review volume may interact when determining puchase intention. Literature indicates that higher review volume strengthens purchase intention when review balance is positive and weakens purchase intention when review balance is negative. To test this moderating effect, we create an independent PLS model with only three variables: review balance, review volume and purchase intention and ran the model in SmartPLS. However, as illustrated in Fig. 3, all the t tests for the paths and R^2 indicate the lack of the significance of this moderating effect. Thus, there is insufficient evidence to substantiate the hypothesis of a moderating effect (−0.015, p value = 0.786) or that review volume affects online shoppers' purchase intention (−0.062, p value = 0.277). Therefore, we conclude that H11 is not supported.

Hypothesis H13 was based on literature suggesting that review volume might reinforce the consistency of online shoppers' attitude toward purchasing and associated purchase intention. Therefore, we split the dataset into two subsets based on the factor scores of the attitude toward purchase. If the composite score is greater than 0, we consider the subject as holding a positive attitude, and vice versa. We then conducted two one-way ANOVA tests to examine the effect of review volume on purchase intention. As illustrated in Table 9, the effect of review volume is not significant in either case. That is, no matter what attitude the subject holds toward the purchase, an increase in review volume would not change their purchase intention. Therefore, H13 is unsupported, which to some extent is in accordance with H11.

5. Summary and discussion of findings

A summary of all related hypotheses and their results is presented in Table 10.

As discussed in the introduction, our goals were three-fold:

(1) Explore the effect of social consensus in reviews represented by *review balance* and *review volume*, individually and interactively, on purchase intention.
(2) Study the behavioral mechanisms by which the social consensus in reviews influences purchase intention. In particular, we posit that it works through mitigating risk and uncertainty perceptions, as well as shaping attitude toward the product.

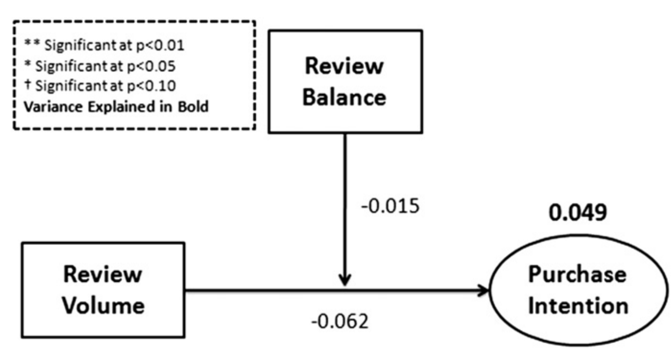


Fig. 3. A PLS Model Testing on the Moderating Effect of Review Balance in H11.

Table 9
ANOVA Tests on the Positive Effect of Review Volume in H13.

Subgroup	N		Sum of Squares	d.f.	Mean Square	F	Sig.
Positive Attitude	156	Between Groups	.006	1	.006	.012	.914
		Within Groups	72.398	154	.470		
		Total	72.403	155			
Negative Attitude	145	Between Groups	.229	1	.229	.554	.458
		Within Groups	58.981	143	.412		
		Total	59.210	144			

(3) Identify which antecedents of perceived risk impacted by the social consensus in reviews, (based on Laroche et al.'s study [14] of risk perceptions in general shopping), — financial risk, social risk, performance risk, and psychological risk — are important in determining overall perceived risk in the online purchasing context.

6. Discussion of findings

6.1. Effect of review balance and volume on purchase intention

Our findings suggest that review balance has a significant effect on purchase intention (H9), but is not moderated significantly by review volume (H11). This is contrary to suggestions in the literature. In addition, literature suggests a moderating effect of review volume. For example, an increase in review volume should cause an increase in sales for average rating above a certain anchor point (depending on context) and vice versa [27]. However, our study fails to confirm this moderating effect of review volume. It also failed to support any significant effect of review volume on attitude (H13). It is possible that our choice of 10 reviews as "low-volume" and 100 reviews as "high-volume" constituted insufficient manipulation of review volume. Park et al.'s study [31] found that 5 to 6 reviews were considered a "moderate" number, so perhaps 10 reviews were inappropriate to be considered as "low-volume". It must be noted that our manipulation check over subjects' perceived quantity of reviews in a pilot study did validate our categorization.

Table 10
A Summary of the Hypothesis Tests.

	Hypotheses	Significance
H1	Perceived uncertainty has a negative effect on online shoppers' purchase intention.	Unsupported
H2	Perceived financial risk haa a positive impact on overall perceived risk.	Supported
H3	Perceived performance risk has a positive impact on overall perceived risk.	Supported
H4	Perceived psychological risk has a positive impact on overall perceived risk.	Supported
H5	Perceived social risk has a positive impact on overall perceived risk.	Supported
H6	Perceived risk has a negative impact on online shoppers' attitude toward purchasing.	Supported
H7	Attitude toward purchasing has a positive impact on online shoppers' purchase intention.	Supported
H8	Perceived risk has a positive impact on perceived uncertainty.	Supported
H9	Review balance has a positive effect on online shoppers' purchase intention.	Supported
H10	Review balance has a negative effect on online shoppers' perceived risk.	Supported
H11	Review balance moderates the effect of review volume on online shoppers' purchase intention.	Unsupported
H12	Review balance has a positive effect on online shoppers' attitude toward purchasing.	Supported
H13	Review volume has a positive effect on the consistency of customers' attitude toward purchasing and their intention to purchase.	Unsupported

We also found that low-ended reviews reduced purchase intention significantly compared to balanced or high-ended reviews. We found similar results of the effect of review balance on perceived risk (H10) and (H12), whereby low-ended reviews had significantly different effects than balanced or high-ended reviews. These results are interesting and are in line with the findings that one-star reviews have a stronger impact on book sales than five-star reviews [1]. Our results suggest that negative ratings (low-ended balance) convey important information, and once the distribution veers away from a negative shape, it lowers perceptions of risk, and shapes attitude and intention positively. In other words, shoppers primary concern seems to be whether social consensus is negative or not.

6.2. Effect of review balance and volume on purchase intention – behavioral model

In contrast to the econometric models, our goal was to provide an explanation of *how* reviews impact purchasing intention (by impacting perceived risk, and subsequently uncertainty and attitude). We manipulated review balance and review volume to test the behavioral model that perceived risk (and its antecedents) determine perceived uncertainty (H8) in purchasing the product online and shape attitude (H6) toward the product purchase. These, in turn, determine intention to purchase the product (H1 and H7).

We found that perceived risk explains around 41% of the varibility in perceived uncertainty and 48% in attitude toward purchasing. Those, in turn, explain 72% of the variability in purchase intention. Thus, overall our model was successful in explaining the impact of perceived risk on purchase intention. The social consensus underlying review balance and volume impacts online buyers' risk perception significantly, shapes their attitude toward the online purchase, and significantly impacts their purchase intentiion. Perceived risk also significantly impacts perceived uncertainty. However, contrary to our expectations, perceived uncertainty does not significantly affect online shoppers' purchase intention, when attitude toward purchasing is also considered in the model. A possible explanation for this might be that with the prevalence of e-business, most online buyers have already taken into account the uncertainty in online transactions in developing an attitude toward online purchases. We believe that this represents an interesting avenue for future research.

6.3. Effect of review balance and volume on perceived risk and its antecedents – behavioral model

Our model tested the effect of the experimental manipulation of review balance and volume (shown in Table 1) on perceived risk and its antecedents. We modeled the antecedents of risk perceptions along four dimensions (H2 through H6). In accordance with our expectations, online shoppers' concerns regarding potential financial loss, product performance, psychological risk and social risk are significant predictors of overall risk perception in online transactions, accounting for about 71% of the variability in perceived risk. The magnitude of the standardized coefficients indicates that performance risk plays the most important role, financial risk is the second, and psychological risk is the third. To our knowledge, this is the first study that examines individual components of perceived risk in online product purchasing. The results of our study appear to suggest that online purchasers are most concerned about the product not performing as expected.

7. Conclusions

7.1. Contributions and implications

Our study confirms the important role online reviews play, especially negatively distributed reviews, in determining purchase intention. It shows that the mechanism by which online reviews shape buyer's intention is by impacting their risk perception and shaping their attitude. The remarkably high proportion of variability explained in purchase intention (nearly 72%), the fact that our sample consisted of both students and members of the general population, and the simplicity of the final model involving risk and attitude, shows that our model has the potential to be robust. We found that even though perceived risk in the online transaction significantly impacts their uncertainty in the transaction, this uncertainty does not influence the purchase intention when their attitude is taken into account. In our opinion, this means that any model that attempts to understand the influence of online reviews on purchasing should take into account attitude toward the purchase. We consider this an important contribution of our study.

Our study should also enrich researchers' understanding of risk perception in e-commerce. Our findings confirm our inital beliefs that the four risk perceptions are good predictors of online shoppers' overall risk perception in e-commerce. Our results appears to suggest that performance risk may be uppermost in online buyers' minds, followed by financial risk. This, however, may be influenced by product type and may be a potential source of study in the future.

The findings in our study may also benefit practitioners. The possibility that performance and financial risks may significantly influence an online buyer provides guidance on how to highlight their products on the web site. The relative power of negative reviews, compared to positive ones, sends a message that vendors need to pay attention to negative reviews in particular. Our findings suggest that it is more productive for recommender systems and web designers to rank products by review balance instead of review volume.

In additon, our findings on risk perceptions may benefit text miners who are interested in linguistic patterns in review content. When extracting lingusitic cues from review content, text miners may want to focus on the narratives pertaining to performance or financial risk in particular.

7.2. Limitations

Given the already large scope of the present study, we did not take into account several aspects that deserve consideration. First, there is room to improve the measurement of risk perceptions to account for both product risk (as we have done) and seller risks. In fact, a heavier focus on consumers' satisfaction over sellers' behavior (for example, whether products are delivered on time, in a good package, or as good as advertised) may be a useful future research direction. Pavlou et al. find that sellers' activities such as sending fake or low-quality products to consumers, have a straight negative effect in e-business [13]. The findings in this study are limited to the impact of product reviews.

Second, the narrative features pertaining to *review content* have not been considered. A large number of studies indicate the importance of review content and find that an increase of subjective expression in review content may lead to a growth of product sales. Conversely reviews with mixed objective and subjective comments would lessen product sales [3]. In this study, we isolated the effect of review content by a randomization of reviews presented to the subjects. However, the inclusion of review content would permit greater generalization of our findings.

Third, this study neglects the influence of product type, which may cause some problems of generalizing findings across different products. In this study we chose a search product (an electronic device) as the object in the experiment, because we believe that the objective nature of this product may help us better measure people's perceptions in the experiment. However, this choice also may limit the generality of some findings. As indicated in Mudambi and Scuff's study [5], product type may moderate the effect of review valence on perceived helpfulness of reviews. They find that when assessing experience products, reviews with extreme ratings (e.g., five star or one star) are perceived to be less helpful than those with moderate ratings (e.g., three star); however, for search products, ratings have no impact on the perceived helpfulness at all [5]. Hence it may be inferred that if an experience product was taken in the experiment, our understanding might be different. Therefore, a comparison of experience products, search products, and even services could be a good topic for future research.

Appendix 1. Survey Instruments

Risk adapted from [14]

<u>Financial risk</u>

- If I bought this tablet PC for myself, I would be concerned that the financial investment I make would not be wise.
- Purchasing this tablet PC could involve important financial losses.
- If I bought this tablet PC for myself, I would be concerned that I would not get my money's worth.

<u>Performance risk</u>

- If I were to purchase this tablet PC, I would become concerned that the item will not provide the level of benefits that I would be expecting.
- As I consider the purchases of this tablet PC soon, I worry about whether it will really “perform” as well as it is supposed to.
- The thought of purchasing this tablet PC causes me to be concerned for how really reliable the product will be.

<u>Psychological risk.</u>

- The thought of purchasing this tablet PC gives me a feeling of unwanted anxiety.
- The thought of purchasing this tablet PC makes me feel psychologically uncomfortable.
- The thought of purchasing this tablet PC causes me to experience unnecessary tension.

<u>Social risk.</u>

- If I bought this tablet PC, I think I would be held in higher esteem by my friends. (Reversed).
- If I bought this tablet PC, I think I would be held in higher esteem by my family. (Reversed).
- Purchasing this tablet PC would cause me to be considered foolish by some people whose opinion I value.

Perceived risk adapted from [14]

- There is a good chance I will make a mistake if I purchase this tablet PC.
- I have the feeling that purchasing this tablet PC will really cause me lots of trouble.
- I will incur some risk if I buy this tablet PC in the near future.
- This tablet PC is a very risky purchase.

Perceived Uncertainty adapted from [13]

- I feel that purchasing this tablet PC online involves a high degree of uncertainty.
- I feel that the uncertainty associated with purchasing this tablet PC online is high.
- I am exposed to many transaction uncertainties if I purchase this tablet PC online.

Attitude toward purchasing adapted from [40]

- Purchasing this tablet PC is good.
- Purchasing this tablet PC is valuable for me.
- Purchasing this tablet PC is a wise move.

Purchase Intention adapted from [41,42].
Given a chance,

- The likelihood of purchasing this tablet PC is high.
- I would consider buying this tablet PC.
- My willingness to buy this tablet PC is high.

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Jing Yang
• School of Economics and Business, State University of New York at Oneonta, 330 Netzer Administration Building, Oneonta, NY 13820, USA
• jing.yang@oneonta.edu
• 1-607-436-3381
• **Jing Yang** is an Assistant Professor at School of Economics and Business, State University of New York at Oneonta. She received her Ph. D. from Oklahoma State University, Stillwater. She has published refereed journal and conference articles in AMCIS, DSI, IGI, Decision Support Systems and so on. Her current research interests include e-commerce, m-commerce and data mining.

Rathindra Sarathy
• Spears School of Business, Oklahoma State University, 221 Business Building, Stillwater Campus, Stillwater, OK 74074, USA
• rathin.sarathy@okstate.edu
• **Rathindra Sarathy** is the Ardmore Chair in Business Administration in the Department of Management Science of Information Systems in the Spears School of Business at Oklahoma State University. He received his Ph.D. from Texas A&M University. He has published in many journals including ACM Transactions on Database Systems, Decision Sciences, Decision Support Systems, Information Systems Research, Information Systems Journal, Journal of Database Management, Management Science, and Operations Research. His current research interests include privacy and confidentiality, data masking, data and information security, e-commerce and behavioral modeling.

JinKyu Lee
• Spears School of Business, Oklahoma State University, 317 North Hall, 700 N. Greenwood Ave., Tulsa, OK 74106, USA
• Jinkyu_lee@hotmail.com
• **JinKyu Lee** is an Associate Professor at Spears School of Business, Oklahoma State University. He obtained his Ph.D. from The State University of New York at Buffalo. His work has been published in various journals such as Decision Support Systems, Information Systems Journal, Communications of the ACM, and Information Systems Frontiers. His current research interests include end-user security training effectiveness, information security workforce development, and information quality for e-commerce and e-government applications.