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# Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics

Mohammad Salehan [a], Dan J. Kim [b,*]

[a] Department of Computer Information Systems, College of Business Administration, California State Polytechnic University, Pomona, 3801 West Temple Avenue, Pomona, CA 91768, USA
[b] Department of Information Technology and Decision Sciences, College of Business, University of North Texas, 1307 West Highland Street, Denton, TX 76201, USA

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A B S T R A C T

Although online consumer reviews (OCRs) have helped consumers to know about the strengths and weaknesses of different products and find the ones that best suit their needs, they introduce a challenge for businesses to analyze them because of their volume, variety, velocity and veracity. This research investigates the predictors of readership and helpfulness of OCR using a sentiment mining approach for big data analytics. Our findings show that reviews with higher levels of positive sentiment in the title receive more readerships. Sentimental reviews with neutral polarity in the text are also perceived to be more helpful. The length and longevity of a review positively influence both its readership and helpfulness. Because the current methods used for sorting OCR may bias both their readership and helpfulness, the approach used in this study can be adopted by online vendors to develop scalable automated systems for sorting and classification of big OCR data which will benefit both vendors and consumers.



## 1. Introduction

Businesses are now using social media to promote their products and services. Many companies maintain Facebook and Twitter accounts to keep in touch with their customers. Customers also use social media to receive information about products/services. In many ways the Internet in general and social media in particular, have changed the way customers shop for goods and services. It's now quite normal for people to find the product they want at brick-and-mortar stores and then order it online. Moreover, online consumer reviews (OCRs) have helped customers to learn about the strengths and weaknesses of different products and to find the ones that best suit their needs. Some studies suggest that customers show more interest toward user-generated product information on the Internet than the information vendors provided [9]. A recent study shows that OCRs are the second most-trusted source of product information after recommendations from family and friends [47]. Compared to vendor-generated product descriptions, OCRs are more user-oriented and describe the product in terms of different usage scenarios and assess it from a user's perspective [13]. Thus, it has even been suggested that consumers who write OCR serve as “sales assistants” for online retailers [13]. Although analysis of OCR can be beneficial to both consumers and businesses, it is challenging to analyze it due to the characteristics such as volume, variety, velocity and veracity.

From a consumer's perspective, the process of examining OCR can be broken into two steps: the decision to read the review, and the actual processing of the information in the review that deems the decision to use it based on perceived helpfulness of the review [1]. Focusing on the two steps of processing OCR, this study proposes two fundamental research questions in the context of OCR:

RQ1: *Which factors determine the likelihood of a consumer paying attention to a review?*
RQ2: *Which factors determine the perceived helpfulness of a review?*

From online business managers' perspective, finding answers to the above questions are quite important steps toward understanding online consumers' perceptions of their products and/or services and ultimately, designing and implementing scalable automated systems for classification and sorting of big OCR data [44,49].

The first research question looks into the characteristics of OCR that absorb the attention of online consumers. Many products receive too many reviews that make it difficult for consumers to read all of them. Thus, most consumers have to read them selectively. In summary, the first research question explores the determinants of the readership of OCR. Although reading a review is the first step in determining its helpfulness, previous research overlooks the readership of OCR.

While the first research question remains largely unexplored, the second one has received some attention. Previous research has found strong evidence that OCRs influence product sales [14,16,18,20,22,23,42,46]. However, three important aspects of the second research question require further investigation. First, most studies only use the

* Corresponding author at: University of North Texas, College of Business, 1155 Union Circle #311160, Denton, TX 76203-5017, USA.
*E-mail address:* Dan.Kim@unt.edu (D.J. Kim).

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numerical review ratings (e.g., the number of stars) and the length of the reviews in their empirical analysis, without formally incorporating the information contained in the text of the reviews. Therefore, a deeper analysis of the textual information contained in the OCR can provide greater insight into what constitutes a useful online review [46]. Although some previous studies have used the text of OCR to predict helpfulness [15,22,37], the effect of sentiment on helpfulness of OCR remains unexplored.

Second, previous research shows that positive statements are considered to be more helpful by consumers [56]. However, research has produced conflicting results regarding the negative comments. For example, Sen and Lerman [58] found that in the case of utilitarian products, negative comments are more useful than positive ones, whereas Schindler and Bickart [56] failed to find any significant relationship between negative statements and helpfulness of a review. By investigating the effect of sentiment polarity (i.e., negative, positive, or neutral) on helpfulness, this study provides insights into the performance of OCR.

Finally, previous research tends to identify the predictors of the performance of OCR without providing many practical solutions for online vendors. Human subjects are largely employed for categorization of OCR based on the textual information contained in them. Although this method provides a descriptive view of the performance of OCR, it does not facilitate the development of scalable automated systems for classification of OCR.

This study investigates the performance of OCR through analysis of textual information contained in the reviews. Previous research has indicated that computer-mediated communications (CMCs) can effectively transfer emotions. Moreover, the emotions contained in a message transferred through CMC significantly influence how the message is processed and interpreted by the receiver [7,54,70]. Sentiment mining can be used for emotional analysis of textual information. Sentiment mining refers to the use of natural language processing and computational linguistics to find and extract subjective information from text data. Sentiment mining is usually done using automated tools that provides benefits such as scalability, effective information retrieval, automated cyber risk management, and increased business profits [4]. It also facilitates processing of large amounts of data. Social media is an important source of big data and is quite suitable for text mining purposes [12,55].

This study contributes to the existing body of knowledge in three unique ways. First, it provides a research model that predicts the performance of OCR in terms of readership and helpfulness of reviews using a sentimental mining approach. Although previous studies have used the text of OCR to predict the performance of OCR such as helpfulness (e.g., [15,22,37]), the effect of sentiment on the performance of OCR still remains unexplored. Thus, this study is expected to provide a novel contribution in this domain. Second, it uses automated tools to analyze a set of secondary OCR data composed of reviews collected from Amazon.com website. In addition, following the directions provided by Chen et al. [12], it uncovers a new application of big data analytics. More specifically, it provides insights to online business managers regarding the design and implementation of scalable automated systems to improve classification and sorting of OCR, which will eventually help them achieve increased sales.

## 2. Theoretical background

### 2.1. Online review performance measures

Different measures have been used by previous studies to evaluate the performance of OCR. Most studies use helpfulness as the single performance measure of OCR [3,46,58]. *Helpfulness* has also been referred to as the value of the review [56]. For studies that use secondary data, helpfulness is measured by dividing the number of people who find a review helpful by the total number of people who voted for that review [46,58].

*Purchase intention* is another measure of performance. Customer purchase intention is influenced by both quantity and quality of the reviews [52]. Some studies use sales revenue as a performance measure for online reviews. One study used online reviews from Yahoo Movies website to predict box office revenues and found strong evidence that online reviews influence movie sales [42]. Online reviews have also been used to predict the online sales of books [14]. Product ratings also indirectly influence sales through sentiment [31].

### 2.2. Predictors of online review performance

Different measures have been used to predict the performance of OCR. Some studies have focused on the numeric star rating and word count of the reviews to predict their performance. For example, extreme numerical ratings are positively related to sales of books [14]. Reviews with extreme numerical ratings are also considered more helpful [46]. *Length of a review* may also predict its performance. Length of reviews for a book significantly predicts its sales on Amazon.com [14]. Length of a review is also positively related to its helpfulness [22,37,46,56]. Empirical analysis, however, fails to find any significant relationship between review length and sales of books on Barnes & Noble website [14]. Lu et al. [44] suggest that to predict the performance of OCR, reviews should not be treated as stand-alone documents and contextual information about author's identity and social networks should be use to achieve enhanced prediction accuracy. Several other studies also use reviewer characteristics including total number of reviews written by the user, expertise, experience, writing style, rating pattern, and excellence to predict helpfulness of OCR (e.g., [43,49]).

The difference between the performance of positive and negative reviews is controversial research avenue in the context of OCR. Drawing upon the negativity bias theory, some studies propose that negative reviews are considered more helpful than positive ones. According to the negativity bias theory, people face difficulty in making inferences about the actions of an actor when the actor behaves in an expected fashion. The inference is easier when the actor departs from the norms of behavior [35,36]. Thus, some researchers have argued that negative comments should be considered more helpful than positive ones because they deviate from the accepted norm of staying positive [58]. Several studies test the negativity bias theory in the context of OCR. Their findings, however, are contradictory. While some studies show that consumers find negative reviews more valuable, others find no significant difference between positive and negative reviews. Some others even find that positive reviews are more helpful than negative ones. Sen and Lerman [58] find that positive reviews are generally more helpful than negative ones. However, negative reviews are more useful for utilitarian products (products that focus on task performance) and positive comments are more useful for hedonic products (products that deal with pleasure). Schindler and Bickart [56] find that the number of positive statements is a significant predictor of the value of a review while the effect of the number of negative statements on value is not significant. A recent study suggests that consumer reviews may be subjected to positive social influence bias, also known as inner circle bias [3]. Through an experiment, the author manipulated the helpfulness of OCR and found out that positive manipulations create a positive social influence that last several months. The negative manipulations, however, are offset by a correction effect that neutralizes the manipulation. The findings suggest that corporations can easily manipulate OCR and the reviews should be considered with some level of skepticism.

Recent studies use text of a review to predict its performance. Schindler and Bickart [56] look at the wording of online reviews rather than their source. They divide wording factor into two categories: content and style. They define the content as the information the review provides. Style, by contrast, is defined as the choice of words used to convey the information. They find that proportion of product-descriptive statements and proportion of reviewer-descriptive statements are significant predictors of the value of the review. They also find that while use of negative style characteristics decrease the value of the review, use of positive style doesn't improve its performance. Finally, they didn't find any significant relationship between negative evaluative statements and value of the review. Other significant predictors of helpfulness extracted from the text of online reviews include the amount of objective and subjective information [22], conformity (i.e., deviation from average star rating) [15,37], review completeness (i.e., the amount of optional review content) [49], and readability [22].

*Review sentiment* is another measure used by previous studies to predict the performance of computer-mediated communications (CMC) in general, and OCR in particular. Previous research has indicated that CMC can effectively transfer emotions. The receiver of a message can detect the sender's emotions through verbal cues such as emotion words as well as nonverbal cues such as emoticons [26]. Moreover, the emotions contained in a message transferred through CMC significantly influence how the message is processed and interpreted by the receiver [54,70]. Different methods can be used to extract sentiment out of text. While some studies use human subjects to extract the sentiment of OCR, others use automated sentiment mining to extract sentiment from the text of reviews [4,56,58].

### 2.3. Moderators of performance

Product type is an important factor in the context of online reviews which has mostly been viewed as the variable moderating the relationship between independent variables and helpfulness. For example, reviews on hedonic products are less likely to be perceived as helpful [58]. There are also differences between helpfulness of search and experience goods. For search goods, consumers can obtain information about product quality prior to purchase while evaluation of experience goods requires sampling or purchase. While reviews with extremely high or low star rating are considered more helpful for search goods, the effect is different for experience goods. For experience goods, extreme reviews are considered less helpful than the ones with moderate rating [46]. Product type also moderates the relationship between the number of positive and negative statements with the helpfulness of a review [58]. The length of a review has greater positive impact on its helpfulness for search goods compared to experience goods [46].

Customer involvement is another moderating variable in the context of OCR. While low-involvement customers are more influenced by the quantity rather than the quality of reviews, high-involvement customers are influenced by the quantity of reviews if the reviews have high quality [52].

### 2.4. Theories related to message selection

The *theory of selective attention* posits that people respond to messages selectively because of limited information processing capacity [66]. When people receive multiple stimuli at once, they need to filter some of the messages because they have limited processing capacity. Same thing happens in the context of online reviews. Many products have large number of reviews which makes people to selectively read online reviews. The *theory of selective perception* helps explain the mechanism underlying selective attention. According to selective perception, people develop belief structures which are a simplified representation of the world and use these structures to filter and interpret information [69].

*Attribution theory* explains how people analyze different behaviors. Based on the theory, people identify two types of explanation for different behaviors: actions related to internal (personal) factors and the ones that result from external environment (situational) [19,27]. The theory largely explains the predictors of source credibility and other areas related to consumer perceptions and inference formation [17]. It has also been used to explain the perceptions of the consumers regarding the helpfulness of OCR. Readers consider the motivation of the author of a review when deciding about whether or not to use the information contained in the review. Readers may attribute a review to either external (product-related) or internal (reviewer-related) reasons. If the reader feels that the review is based on external reasons, they are more likely to accept it. If reader believes that the review is based on internal reasons, they are more likely to disregard it [58].

### 2.5. Fake reviews

Because online reviews have the potential to influence customers, they have received significant attention from sellers/providers of goods/services. Some have even tried to influence the perceptions of customers by creating fake reviews [38,61,68]. One study finds that certain hotels distinguished by location and ownership post more fake positive reviews for themselves and more fake negative reviews for their competitors. The independent hotels that are owned by single-unit owners are more likely to post fake reviews than branded hotel chains. Moreover, the hotels close to a hotel with a high incentive to post fake reviews have more negative reviews [45]. Another study reports that 10.3% of book reviews are fake or manipulated [30].

Previous research has used different methods to identify fake reviews. Some studies compare reviews of products on different websites to investigate fake reviews. One study identifies evidence of fake reviews by comparing the reviews of two travel sites with extensive hotel reviews: Expedia.com and TripAdvisor.com [45]. While anyone can write a review on TripAdvisor, one needs to have actually booked at least one night for the given hotel on Expedia to be able to post a review for that hotel. Human subjects and automated tools have also been used to identify fake reviews. One study failed to recognize manipulated reviews using sentiment mining but found that consumers are able to recognize them [30]. Other studies use machine learning methods to identify fake reviews [33,40,50].

## 3. Research model and hypothesis

Following the directions provided by Mudambi and Schuff [46] regarding the need for the analysis of the textual information contained in OCR, we utilize sentiment mining to analyze the text of the reviews and to investigate our two research questions. Each Amazon review has a title and a body text. We extract the sentiment of both the title and the text of reviews and use them to predict performance. We have two measures for OCR performance, readership and helpfulness, each of which corresponds to one of our research questions. Fig. 1 shows the proposed research model.

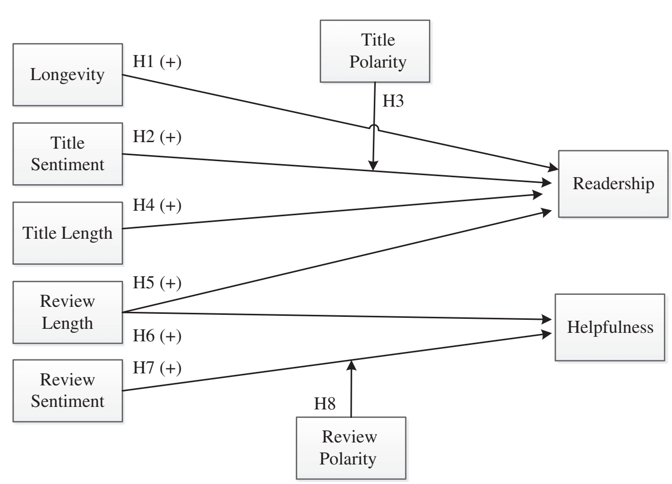


**Fig. 1.** Research model.

In the model, sentiment refers to the total amount of sentiment that exists in a text, both positive and negative. Polarity refers to the direction of the sentiment which can be positive, negative, or neutral. More information on our measures can be found in the methodology section. Liu, Cao, Lin, Huang and Zhou [41] note that the publication date of a review has positive correlation with its total number of votes. This is referred to as ebias. Older reviews receive more votes because older reviews have been on the website for a longer time and hence are more likely to be viewed and read by consumers. On the other hand, reviews that have been recently added to a website are less likely to be read because of their short window of exposure to users. Moreover, most websites, including Amazon.com, sort reviews by “most helpful first” rather than “newest first” [51] which makes new reviews less likely to be exposed to users. Thus, we can expect older reviews to receive more readership than newer ones. Consequently, we hypothesize the following:

**H1.** *Longevity of a review has a positive effect on the readership of the review.*

According to the *theory of selective attention*, people respond to messages selectively because individuals possess limited information processing capacity [66]. We believe that OCRs are no exception to this theory. Many products/services have large number of reviews and reading all of them is very difficult and time consuming for consumers. Hence, people have to pay selective attention toward OCR. We expect people to look for quick signals that enable them to decide about reading a review. Title is a small but important part of a review and provides users with instant information about the general theme of the review. Thus, we expect the title of a review to be an important predictor of its readership. Moreover, sentiment of a message can be effectively communicated through the text and significantly influences the perceptions of the reader [26,54,70]. Finally, affective language in the online environment receives more attention and feedback compared to neutral language [32]. Hence, we expect the total sentiment contained in the title of a review to be positively related to its readership. Consequently, we hypothesize that:

**H2.** *The larger the total amount of sentiment (positive or negative) the title of a review exhibits, the more readership it receives.*

According to the *theory of selective perception*, people use their mental structure to filter information. People tend to absorb information that matches their mental model and filter out the information that don't fit their mental structure [69]. Similarly, we expect people to pay selective attention toward OCR based on their initial attitude about the product. Those with a positive attitude toward the product are expected to look for positive information and those who are more suspicious are expected to look for negative information. Many consumers read OCR to receive reassurance that they have made a good choice [5,24,28]. Reassurance will be gained through positive information rather than negative information. Consequently, we expect a larger number of consumers look for positive reviews rather than negative ones. Thus, we expect reviews with positive titles attract more attention and readership. Considering the above arguments, we expect positive sentiment to have a larger effect on the readership of online reviews than negative sentiment. This leads to the following hypothesis:

**H3.** *Title polarity moderates the effect of title sentiment on the readership of the review. The effect will be larger for positive titles than negative and neutral ones.*

While the total amount of sentiment in the title of a review is an important source of information for consumers, length of the title can also be an important factor related to its readership. Short titles are usually not very informative and do not contain much information. A short title usually communicates the general idea of the author about the product such as “I love it” or “not very high quality.” In contrast, longer titles will give the reader more information about the content of the review which subsequently increases the likelihood of it being read by the consumers. For example, a review entitled “the best LED-lit television at a budget price” signals the reader that it contains information about both quality and pricing of the product which can motivate more people to read it. On the other hand, people usually scan information on the web [48]. In the other words, people look for specific keywords on webpages rather than reading them word by word. A longer title is therefore more likely to contain specific keywords that a reader is looking for. Moreover, length of the title may decrease consumer's search costs through increased information diagnosticity [34]. Hence, we expect length of the title of a review to be positively related to its readership performance. Consequently, we hypothesize that:

**H4.** *The length of the title of a review has a positive effect on the readership of the review.*

Length of a review is an important predictor of its performance [46,56]. Short reviews are more likely to be shallow and lack the comprehensive evaluation of product features. Longer reviews, in contrast, contain more information and are more likely to contain deep analysis of the product, its features, and the context in which it was used. Longer reviews are more likely to receive attention from users. Reading longer reviews may decrease consumer's search costs through increased information diagnosticity [34]. Moreover, longer reviews are more likely to be perceived helpful. An individual's argument is more persuasive when it provides larger amount of information [57]. Increased number of reasons for a choice escalates the decision maker's confidence [67]. Hence, we expect longer reviews to receive more readership as well as more perceptions of helpfulness compared to the shorter ones. As a result, we suggest the following hypotheses:

**H5.** *Length of a review has a positive effect on the readership of the review.*

**H6.** *Length of a review has a positive effect on the helpfulness of the review.*

People tend to find reviews with extreme numerical ratings more helpful [46]. We can expect that reviews with extreme ratings also contain more sentiment because the author is either very satisfied or very unsatisfied. The extreme levels of satisfaction or dissatisfaction are very likely to turn into strong emotions and consequently strong sentiment. The sentiment of a message can be effectively communicated through the text and significantly influences the perceptions of the reader [26,54,70]. One can argue that the sentiment contained in the review is the driver of the perceptions regarding its helpfulness rather than just the numerical rating. Different people have different experiences with the same product. Sentiment is the vehicle for people to convey their emotions to others through text. Thus, sentimental reviews are better conveyer of the experience with the product. Consequently, we can expect high-sentiment reviews to be perceived more helpful by the consumers because they are more likely to convey the experience with the product. Thus, we hypothesize that:

**H7.** *The larger the total amount of sentiment (positive or negative) the text of a review exhibits, the more helpful it is perceived to be.*

The decision regarding the helpfulness of a review is made after the person reads the review [1]. Reviews with larger number of descriptive statements are considered more helpful [56]. One can argue that a good description of an object contains different aspects of it including both positive and negative qualities. This implies that a good review should also contain both positive and negative statements and consequently both positive and negative sentiment. Moreover, the use of positive or negative style characteristics does not increase the value of a review and may even decrease the perceptions regarding its helpfulness [56]. Additionally, extremely sensational content, either positive or negative, may in some cases provoke psychological reactance and lead the receiver to respond unfavorably [10]. In terms of review polarity, this will translate into leaning toward neutral polarity. Neutral polarity does not imply that sentiment is non-existent in the text. It implies that there are balanced levels of positive and negative sentiment. Hence, we expect sentimental reviews with neutral polarity to be perceived more helpful than positive and negative ones. This leads to the following hypothesis:

**H8.** *Review polarity moderates the effect of review sentiment on the helpfulness of the review. The effect will be larger for neutral reviews than for positive and negative ones.*

## 4. Methodology

### 4.1. Measurement

Sentiment mining was done using SentiStrength software [65]. The software is free for academic research and has been tested and validated in previous research [21,25,60,63–65]. SentiStrength is capable of processing different types of information contained in the text including analysis of emoticons and booster words, correction of spelling due to repeated letters, and use of negative words (e.g., not) to flip emotions. It reports two separate numbers for positive and negative emotions. The positive number ranges from 1 (not positive) to 5 (extremely positive). The negative number ranges from −1 (not negative) to −5 (extremely negative). Because both numbers should be considered when evaluating the sentiment of a statement, we use the approach used by Stieglitz and Dang-Xuan [60] to combine the two numbers. We calculate the sentiment polarity of each statement by creating the following measure, which determines the direction of the sentiment as well as its strength:

$$Polarity = positive\ sentiment + negative\ sentiment.$$

Because positive sentiments range from 1 to 5 and negative ranges from −1 to −5, polarity will have a range of −4 to 4. The other approach to combine the positive and negative numbers is to calculate the total amount of sentiment in a statement regardless of the polarity of positive and negative statements. To attain this, the absolute value of positive and negative sentiments should be added up using the following formula:

$$Sentiment = (positive\ \ sentiment – negative\ \ sentiment) – 2.$$

Positive sentiment ranges from 1 to 5 and negative sentiment ranges from −1 to −5. Thus, total sentiment has a range of 2 to 10. Therefore we subtracted 2 from (positive–negative) to normalize the range from [2, 10] to [0, 8].

*Longevity* was measured by counting the number of the days since the review was created. Length of title and review were measured by counting the number of words in the text. Helpfulness of a review was measured as the ratio of "helpful votes" to "total votes" cast by readers in each review [20,22,46]. Because we cannot directly measure the readership of OCR, we use the total number of votes of a review as a measure for its readership. People usually vote for a review after they read it. Hence, total votes can be a good estimate of readership.

### 4.2. Data collection

A group of 35,000 online reviews of 20 different products were collected from Amazon.com website using the crawler software developed by the authors. We selected products that had at least 100 reviews. The examined product types were mobile phones, TVs, laptops, tablets, and TV mounts. We eliminated the reviews that had less than 4 votes to ensure that there is a minimum number of votes accumulated for the review [22]. The final sample consisted of 2616 reviews. Fig. 2 shows the system design of sentiment extraction and mining process.

## 5. Data analysis and results

We first checked the descriptive statistics of the data to determine the proper data analysis approach. Table 1 shows the descriptive statistics of our sample. Variables in our model including review length and total votes represent nonnegative and integer data and their standard deviation is larger than their mean. Hence, the analysis needs to be adjusted for overdispersion using log-transformation [11].

We also checked the distribution of the sentiment measures to find out how people express emotions in the reviews. Fig. 3 shows the distribution of four measures. As you can see in Fig. 3, review polarity, review sentiment, and title polarity are normally distributed with the only exception being title polarity which is skewed to the right. Title sentiment follows a negative binomial distribution with r = 1 [29]. Negative binomial distribution measures the number of failures before a certain number of successes (i.e., r) are achieved.

To analyze hypotheses H1 through H5, we tested the following regression model:Equation 1Predictors of readership.

$$\begin{aligned} \log(Total\ Votes)\ \% \\ &= \beta_0 + \beta_1 Title\ Sentiment\ + \beta_2\ TITLE - POSITIVE + \beta_3\ Title\ Length \\ &+ \beta_4\ Title\ Sentiment \times TITLE\_POSITIVE + \beta_5\ log(Review\ Length) \\ &+ \beta_6\ log(longevity) \end{aligned}$$

We used negative binomial regression to test the first model in order to control for overdispersion assuming that the data follows a negative binomial distribution [29]. Title sentiment refers to the total sentiment (positive and negative) available in the title of the review. We created one dummy variable, TITLE_POSITIVE, to test the moderation effect of polarity on the effect of title sentiment on readership of reviews. The variable has a value of 1 for titles with positive polarity and a value of zero for the others.

Helpfulness is measured as the proportion of helpful votes out of total votes. Hence, we used binomial regression with logit transformation to examine hypotheses H6 through H8 using the following regression equation [6]:Equation 2Predictors of helpfulness.

$$\begin{aligned} \frac{Votes\ Helpful}{Votes\ Total}\ \% &= \beta_0 + \beta_1 Review\ Sentiment \\ &+\beta_2\ REVIEW\_NEUTRAL + \beta_3\ log\ \ (Review\ Length) \\ &+ \beta_4\ Review\ Sentiment \times REVIEW\_NEUTRAL + \beta_5\ \ log\ (Longevity) \end{aligned}$$

We created a dummy variable, REVIEW_NEUTRAL, to test the moderation effect of polarity on the relationship between review sentiment and helpfulness. The variable has a value of 1 for reviews with neutral polarity (i.e., polarity = 0) and a value of zero for the others. We also controlled for the effect of longevity of the review on its helpfulness by including the log transformation of longevity in the model.

We checked the correlation matrix for independent variables to test for multicollinearity. Table 2 shows the correlation matrix for each equation. Because we observed relatively high correlations among some variables, we check the VIF of independent variables. The result of the analysis showed that multicollinearity is not an issue in this study.

Then we proceeded with model analysis. Both models were significant at $p < 0.001$ level. The first model shows a goodness of fit of 1.160 indicating that negative binomial regression was a good choice for analysis of the proposed model. The proposed relationship between longevity and total votes was significant ($b = 0.393$, $p < 0.001$), thus

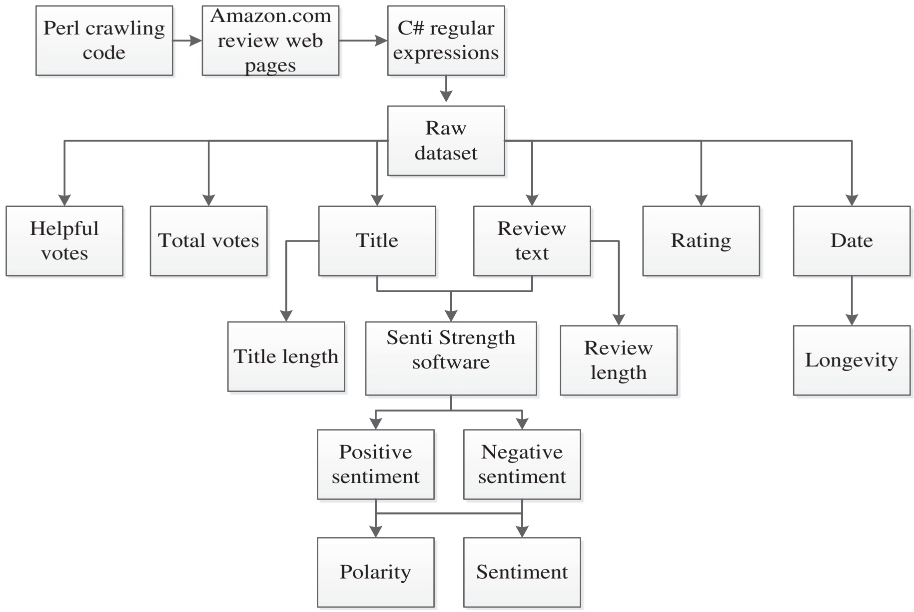


**Fig. 2.** System design of sentiment extraction and mining process.

supporting H1. The relationship between title sentiment and total votes was significant but the coefficient was negative ($b = -0.087$, $p < 0.001$). Therefore we don't find support for H2. However, the coefficient for the interaction term Title Sentiment × TITLE_POSITIVE was positive and significant ($b = 0.439$, $p < 0.001$). Thus we find support for H3. The relationship between title length and total votes was significant but negative ($b = -0.017$, $p < 0.01$). Thus, H4 is not supported. Review length was found to be a significant predictor of total votes ($b = 0.355$, $p < 0.001$), providing support for H5.

In the second model, review length is a significant predictor of helpfulness ($b = 0.407$, $p < 0.001$) providing support for H6. The proposed relationship between review sentiment and helpfulness is significant but negative ($b = -0.068$, $p > 0.001$). Thus, H7 is not supported. However, the coefficient for the interaction term Review Sentiment × REVIEW_NEUTRAL is significant and positive ($b = 0.162$, $p < 0.001$). Thus, we find support for H8. Surprisingly, our control variable, longevity, had significant relationship with helpfulness ($b = 0.416$, $p < 0.001$). Fig. 4 shows the results of the research model analysis. Table 3 summarizes the hypothesis testing.

Because the effect of sentiment on performance did not completely match our expectations, we ran post-hoc analyses to explore the difference between positive, negative, and neutral sentiment. We tested the first model for reviews with positive, neutral, and negative title polarity separately. Then we ran the second model for reviews with positive, neutral, and negative sentiment. The results are summarized in Table 4. Positive sentiment is an important predictor of readership but not helpfulness. Negative sentiment, in contrast, has negative non-significant effect on both measures of performance. The results regarding neutral sentiment are mixed. Neutral sentiment in the text of the review improves perceptions of helpfulness. However, reviews with neutral titles attract fewer readerships.

We also tested the second model for different categories of total votes to control for the effect of readership on helpfulness. We categorized the reviews into three categories based on total number of votes: 1–9 votes, 9–99 votes, and 100 votes or higher. We ran the model for the three categories separately and did not find significant differences between them. The only exception is that sentiment does not have a significant effect on helpfulness of reviews with medium number of votes (10–99). Table 5 shows the results of the analysis.

**Table 1**
Descriptive statistics.

| Variable | Range | Median | Mean (SD) |
|---|---|---|---|
| Rating | 1–5 | 2 | 2.71 (1.70) |
| Longevity | 15–2196 | 336 | 433 (362) |
| Total votes | 4–912 | 7 | 22.18 (66.89) |
| Helpful votes | 0–873 | 4 | 16 (60) |
| Title sentiment | 0–8 | 1 | 1.02 (1.02) |
| Title polarity | −4 to 4 | 0 | 0.18 (1.26) |
| Review sentiment | 0–8 | 3 | 2.78 (1.48) |
| Review polarity | −4 to 4 | 0 | 0.19 (1.32) |
| Title length | 1–24 | 4 | 5.06 (3.42) |
| Review length | 16–2369 | 84 | 149.9 (202.8) |

## 6. Discussion

This study investigates the effect of review sentiment on readership and helpfulness of online reviews. Using the theoretical lens of the theory of selective attention we suggest that people read OCR selectively. We also use theory of selective perception to show how people decide to read some reviews and ignore the rest. We suggest that because many consumers read OCR to receive reassurance, reviews with positive sentiment in the title are more likely to be read. Despite the proposed positive relationship between sentiment and performance of OCR, we find that sentiment negatively influences both readership and helpfulness of OCR. Emotions have been considered to subvert the rational processes [71]. Similarly, we find evidence that consumers may perceive emotional content to be less rational and therefore less useful. The effect, however, is not consistent across various types of emotions. We find significant positive relationship between positive sentiment in the title and readership of OCR. This observation can be justified using attribution theory. It is likely that people attribute negative sentiment to the author but relate positive sentiment to the product itself. Because negative emotions are attributed to the author, people are less likely to read reviews with negative titles. However, if the author expresses positive emotions in the title of the review, the likelihood of the review getting attention from consumers will increase. This observation also confirms that many consumers look for reviews that reassure them about the choice they have already made [5,24,28].

Unlike our expectation, the effect of sentiment on helpfulness was not significant. This observation may be justified using elaboration likelihood model (ELM) [2]. According to ELM, persuasion occurs through

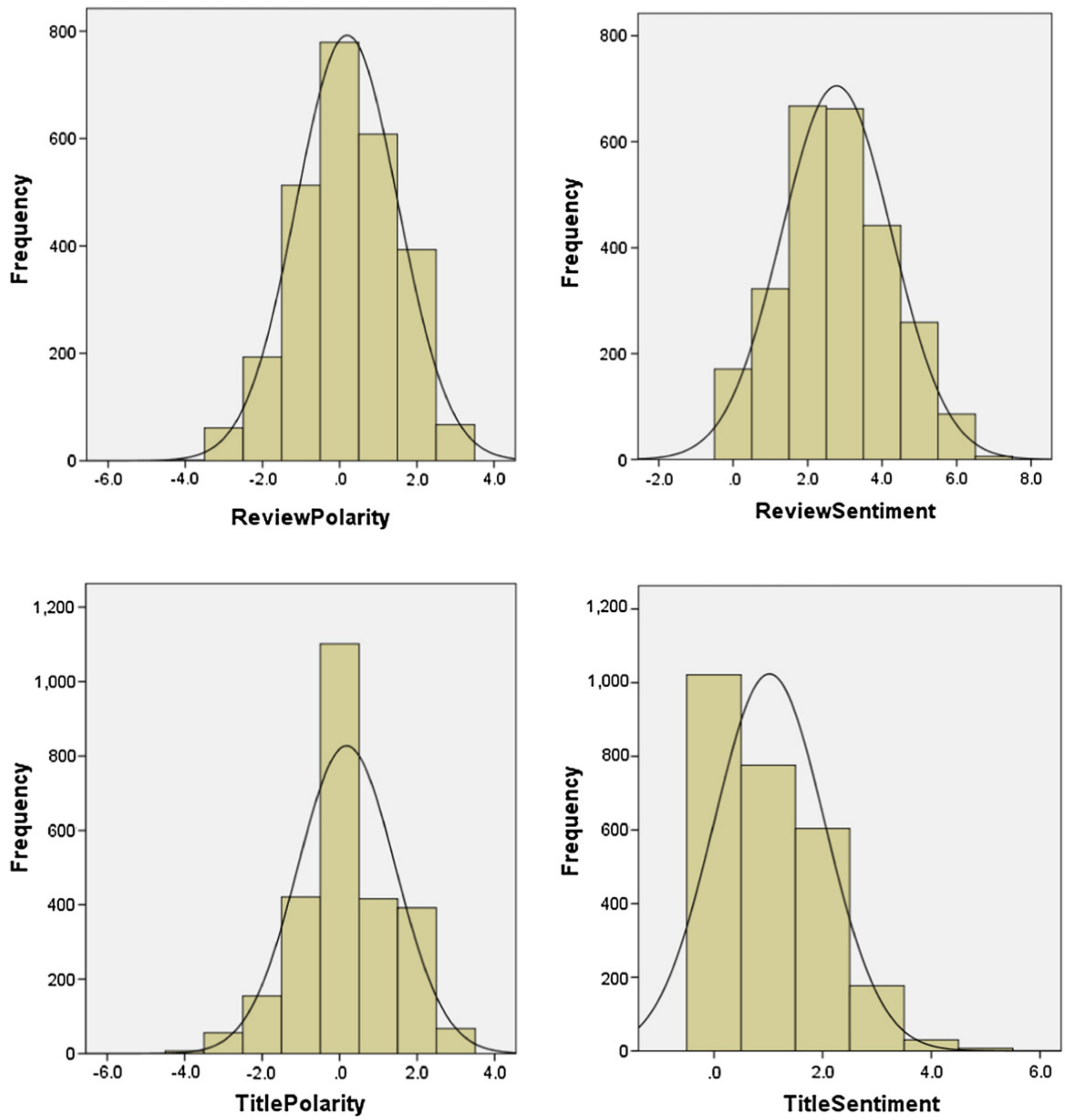


**Fig. 3.** Distribution of the measures.

two routes of influence: the central route and the peripheral route. The central route triggers critical thinking in the audience about the argument of the message and requires high cognitive effort. The peripheral route to persuasion, in contrast, occurs through positive and negative cues and undergoes less cognitive effort [2,8,53]. The perception changes by central route are more stable and long lasting while alterations caused by the peripheral route are less persistent. The sentiment of a message influences users' perceptions through the peripheral route and is expected to be less effective than the cues provided by the central route. However, certain types of sentiment significantly influence users' perceptions regarding the helpfulness of a review. The effect of sentiment on helpfulness was significant and positive for neutral reviews. It can be argued that a helpful review is a neutral one which communicates both positive and negative aspects of the product. Reviews that lean toward either positive or negative may be perceived by consumers as biased and consequently less helpful. Although the use of sentiment

**Table 2**
Correlation matrix of independent variables.

| Equation 1 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Title length | 1 | | | | |
| 2. Title sentiment | 0.09** | 1 | | | |
| 3. Review length | 0.15** | 0.09** | 1 | | |
| 4. Longevity | −0.06** | −0.00 | −0.01 | 1 | |
| 5. Title Polarity | 0.02 | 0.12** | 0.09** | 0.11** | 1 |

| Equation 2 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1. Review sentiment | 1 | | | |
| 2. Longevity | −0.01 | 1 | | |
| 3. Review length | .012** | −0.01 | 1 | |
| 4. Review polarity | −0.11** | 0.07** | −0.06 | 1 |

** Significant at the 0.01 level.

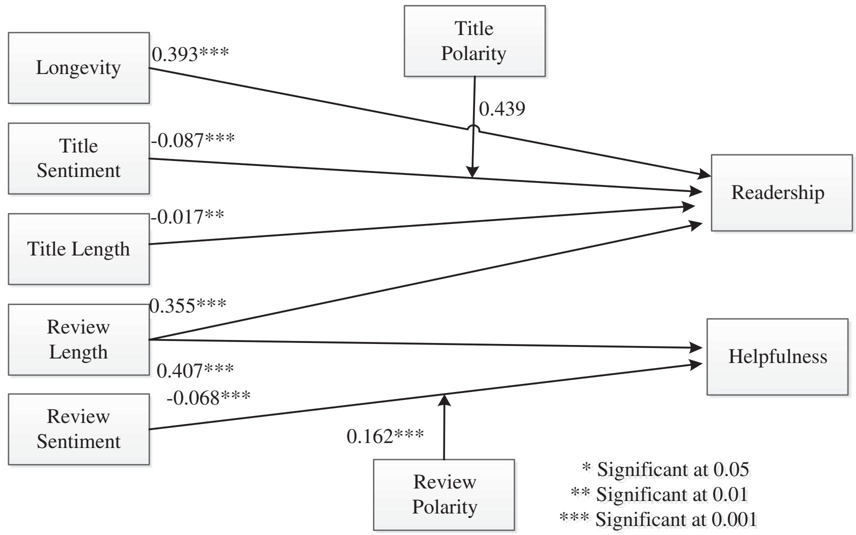


**Fig. 4.** Research model analysis.

may help the authors convey their experience with the product to the audience, emotions are effective as long as they meet the expectations of the consumers.

Despite the significant effect of title sentiment on the readership of online reviews, length of the title was negatively related to it readership. Apparently people use review titles as a quick source of information about the general theme of the review. Reading and processing longer titles take more time and demotivates people to read them. Unlike title length, review length had a positive effect on both the readership and helpfulness of reviews. Review length can be seen as a signal about the amount of information contained in the review. Longer reviews are expected to contain more information and thus attract more readerships. Moreover, longer reviews are more likely to analyze different aspects of the product which leads to increased perceptions regarding their helpfulness.

Surprisingly, longevity has a positive effect on the helpfulness of online reviews. In other words, older reviews are perceived to be more helpful. One reason can be the way Amazon sorts the reviews. By default, users will view the most helpful reviews although it can also be sorted to display the recent ones first. Because older reviews start receiving votes early, they have a better chance of appearing on the first page which will lead to more votes and perhaps better perceptions regarding their helpfulness. Newer reviews, however, stay at the end of the list and are less likely to receive any attention from consumers. Aral [3] has a similar observation. He observed that positive manipulation of helpfulness of online reviews creates a positive social influence. As a result, longevity not only affects readership, it but also influences perception of helpfulness of OCR.

### 6.1. Implications

This study has implications for both theory and practice. From a theoretical perspective, this study introduces a new method of analyzing online consumer behavior. While previous research finds that online reviews significantly influence consumer behavior, few studies have explored the issue using the textual information contained in OCR. We suggest that sentiment mining can be utilized to analyze large amount of OCR that is produced on the Internet every day. Sentiment mining facilitates processing of big data and is highly replicable. This study also contributes to the body of knowledge by studying both readership and helpfulness of OCR. To best of our knowledge this is the first study that analyzes predictors of readership of online reviews. This new performance measure can be used by future studies to further analyze OCR. We also use three important theories (i.e., theory of selective attention, theory of selective perception, and attribution theory) to explain how consumers make decisions regarding reading OCR. Furthermore, although previous research has used the text contained in online reviews to investigate OCR performance, to best of our knowledge this study is the first to also include the title of OCR in the analysis. We show that consumers use the title of a review to receive quick information about its contents. Such information create a quick impression in consumers which may influence their decision regarding reading the review. Finally, this study can be seen as an initial step toward action research in the area of OCR. The findings of this study and future similar studies can be integrated into a single predictive framework to provide a solution for classification and sorting of OCR [59].

**Table 3**
Hypothesis testing results.

| Hypothesis | Hypothesized relationship | Estimates (Wald Chi-square) | Results |
|---|---|---|---|
| H1 | Longevity → readership | 0.393 (227.71) *** | Supported |
| H2 | Title sentiment → readership | −0.087 (11.67) *** | Not supported |
| H3 | Title sentiment × title positive → readership | 0.439 (53.27) *** | Supported |
| H4 | Title length → readership | −0.017 (7.05) ** | Not supported |
| H5 | Review length → readership | 0.355 (311.53) *** | Supported |
| H6 | Review length → helpfulness | 0.407 (1031.03) *** | Supported |
| H7 | Review sentiment → helpfulness | −0.068 (37.21) *** | Not supported |
| H8 | Review sentiment × review neutral → helpfulness | 0.162 (161.38) *** | Supported |

** Significant at 0.01.
*** Significant at 0.001.

**Table 4**
Group analysis.

| Performance measure | Readership | | | Helpfulness | | |
|---|---|---|---|---|---|---|
| Sentiment polarity | Positive title | Neutral title | Negative title | Positive review | Neutral review | Negative review |
| Title sentiment | 0.302*** | −0.209*** | −0.070 | | | |
| Title length | −0.048*** | −0.003 | 0.014 | | | |
| Review length | 0.424*** | 0.379*** | 0.233*** | 0.382** | 0.475*** | 0.450*** |
| Review sentiment | | | | −0.027 | 0.066*** | −0.005 |
| Longevity | | | | 0.461*** | 0.361*** | 0.312*** |

** Significant at 0.01.
*** Significant at 0.001.

We also have implications for practice. Most previous studies just use numerical rating and length of reviews to investigate their performance. Few studies have tried to analyze the textual information contained in online reviews which is usually done using human subjects. Although the use of human subjects is useful in explaining how people use OCR, it barely provides a practical solution for online vendors because the process is neither scalable nor replicable through automated systems. However, we use sentiment mining to analyze the text of OCR. The sentiment mining method used in this study is both replicable and scalable which provides online vendors with a practical solution for analysis of OCR.

Our study finds two weaknesses of the current method used for sorting OCR. First, we find that older reviews attract more readerships. Many products have thousands of review many of which never receive any attention from consumers because they stay at the end of a long list of reviews. Out of the 35,000 reviews we collected for this study, 92.5% had less than five votes and 69.7% had no votes. New reviews may contain up-to-date information about the product and the recent changes made by the manufacturer such as the software updates which may be overlooked by the current sorting method. Second, we observe that older reviews are more likely to be perceived helpful than the recent ones. In other words, perceptions of helpfulness are biased toward older reviews. These two observations indicate that many potentially useful reviews receive little or no attention from consumers because they are barely seen by consumers. Hence, improving the sorting algorithms of online reviews seems to be necessary. An intelligent system capable of detecting potentially useful reviews can help both vendors and consumers. It helps consumers by providing them with more valuable information and by saving their time and energy. It also helps vendors to satisfy their customers' need for information which will allow customers to decide more quickly and may eventually lead to increased sales for the vendors. The findings of this study can be used by online vendors to develop systems that analyze and classify online reviews based on their expected performance.

### *6.2. Limitations and future research*

Like any other studies, this study has limitations. Although automated sentiment mining is quite useful in analyzing big textual information, it still has limitations. First, the software we used in this study can process different types of textual information. However, it lacks processing capability for alternate styles of writing such as sarcasm. While there are many areas for improvement in the field of natural language processing, future research can provide better insights regarding the information contained in online reviews using more advanced technology. Future research can also look at how explanation of different aspects of the online shopping experience such as service quality, product quality, and price influence OCR performance.

Second, the sample used in this study was collected from Amazon.com website and was mainly limited to reviews of electronic products. While the reviews we used in this study are limited to products and do not include services, other websites such as Yelp.com allow their users to write reviews on services such as restaurants. Because there are significant differences between products and services [39], the findings of this study may not be generalizable to reviews of services. Future research may further investigate the issue by analyzing reviews of services of other platform. Additionally, while previous research shows that product type has an important moderation effect on the performance of online reviews, our conclusions may remain limited to certain product types used in this study. Future research can use a sample consisting of different product types and test the moderation effect of product type on the performance of reviews.

Third, the votes casted by readers in each review is subject to imbalance votes bias which indicates that many reviews voted as helpful by consumers do not contain deep information about the product [41]. Hence, the perceived helpfulness measure may not precisely reflect the actual helpfulness of the reviews.

Fourth, we used the same elements for the calculation of sentiment in two different ways: polarity and total sentiment. Using the same elements for the calculation of these variables may make them subject to functional dependence and possibly leading to biased estimation of the relationships in the research model. Although we believe that functional dependence of these variables is not a concern in this study, we should be cautious about the application of these variables.

Finally, our sample lacks language and cultural diversity. The reviews were collected from Amazon US website and all are in English. Different cultures express emotions differently. For example, it is believed that people in individualistic cultures express negative emotions more freely than those living in collectivist cultures [62]. On the other hand, language as the vehicle of information may play in significant role in communicating the message to the reader. Future research may utilize reviews written in other languages to include the effect of language and culture on the performance of online reviews. Future research may also look at the differences in expression of emotions between the real life and the virtual space.

**Table 5**
Group analysis of helpfulness based on total number of votes.

| Total votes | 1–9 | | | 10–99 | | | >99 | | |
|---|---|---|---|---|---|---|---|---|---|
| | B | Wald Chi-Square | Sig | B | Wald Chi-Square | Sig | B | Wald Chi-Square | Sig |
| Review length | 0.30 | 95.36 | 0.00 | 0.43 | 459.10 | 0.00 | 0.28 | 141.97 | 0.00 |
| Review sentiment | −0.07 | 10.00 | 0.00 | −0.01 | 0.25 | 0.62 | −0.18 | 67.14 | 0.00 |
| Longevity | 0.29 | 115.08 | 0.00 | 0.30 | 208.64 | 0.00 | 0.16 | 22.09 | 0.00 |
| ReviewSentiment ∗ ReviewTextNeutralD | 0.16 | 26.54 | 0.00 | 0.09 | 19.33 | 0.00 | 0.16 | 42.30 | 0.00 |

## 7. Conclusions

This research provides insights regarding the predictors of performance of online reviews using a sentiment mining approach. We find that sentiment negatively influences the performance of online reviews with two exceptions: positive sentiment in the title and neutral sentiment in the text of the review. We also find that longer reviews are more likely to attract readership and to be perceived as helpful. This research can be used by online vendors to create scalable automated systems for sorting and classification of OCR.

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**Mohammad Salehan** is an Assistant Professor of Computer Information Systems at California State Polytechnic University, Pomona. He holds a Ph.D. in Business from the University of North Texas, an MBA from Sharif University of Technology, and a Bsc. in Software Engineering from Shahid Beheshti University. His research has appeared in Computers in Human Behavior journal and proceedings of International Conference on Information Systems (ICIS), Americas Conference on Information Systems (AMCIS), and Pacific-Asia Conference on Information Systems (PACIS). His research interests include business analytics, social networks, and mobile computing.

**Dan J. Kim** is a professor of Information Technology and Decision Sciences (ITDS) at University of North Texas (UNT). He earned his Ph.D. in MIS from SUNY at Buffalo. He also holds a MBA degree with management science concentration and MS degree in computer science. His research interests are in multidisciplinary areas such as information security (InfoSec) and privacy, information assurance, and trust in electronic commerce. Recently he has focused on InfoSec Self-Efficacy, Web Assurance Seal Services (WASS), and Trust in e-collaborations. His research work has been published or in forthcoming more than 120 papers in refereed journals, peer-reviewed book chapters, and conference proceedings including *Information Systems Research*, *Journal of Management Information Systems*, *Communications of ACM*, *Communications of AIS*, *Decision Support Systems*, *International Journal of Human-Computer Interaction*, *Journal of Organizational and End User Computing*, *IEEE Transactions on Professional Communication*, *Electronic Market*, *IEEE IT Professional*, *Journal of Global Information Management*, *and International Journal of Mobile Communications*, *ICIS*, *HICSS*, *AMCIS*, *INFORMS*, *ICEC*, *ICA*, *and so on*. He has been awarded the National Science Foundation CyberCorps: SFS grant for multi-years, 2012 Emerald management Review Citations of Excellence Awards, 2010 Best Published Paper Award in ISR, an Emerald Literati Network 2009 — Outstanding Paper Award, the ICIS 2003 Best Paper-First Runner-up Award, and the AMCIS 2005 Best Research Paper Award at AMCIS 2005.