Antecedents of Online Customers Reviews' Helpfulness: A Support Vector Machine Approach

Emergent Research Forum Papers

Mohammadreza Mousavizadeh
University of North Texas
1155 Union Circle #311160
Denton, TX 76203-5017
mohammadreza.mousavizadeh@unt.edu

Mehrdad Koohikamali
University of North Texas
1155 Union Circle #311160
Denton, TX 76203-5017
mehrdad.koohikamali@unt.edu

Mohammad Salehan
California State Polytechnic University, Pomona
3801 West Temple Avenue
Pomona, California 91768
mohammad.salehan@gmail.com

Abstract

Online customer reviews (OCRs) have become an important part of online customers' decision making and People use online reviews to make decision to buy or not to buy products and services. This study aims to answer two research questions: (1) what are the antecedents of helpfulness of online reviews based on their contents? (2) How do content-based cues on OCRs influence their helpfulness? We posit a research model to study the effect of peripheral and central cues in OCRs on online review helpfulness. Online review web pages will be collected from Amazon website using a web crawler. This article will be one of the first studies that investigate OCRs helpfulness based on the central cues in the text of the review. In addition, this research will be the first study that applied the support vector machine as a machine learning method to analyze the text of OCRs.

Keywords: Online customers reviews, Review helpfulness, elaboration likelihood model.

Introduction

Online customer reviews (OCRs) have become an important part of online customers' decision making (Chatterjee 2001). People use online reviews to make decision to buy or not to buy products and services (Korfiatis et al. 2012). In addition, companies can promote their products and services by motivating their customer to write reviews. On the other hand people use online reviews for better understanding of the characteristics of the product and also other customers' experience after using the product or service. According to a consumer review survey in 2014, around 50% of people read online reviews as a part of pre-purchase decision making process (Anderson 2014). According to the survey results, 88% of consumers trust online reviews as much as personal recommendations and 85% of consumers read up to 10 reviews (Anderson 2014).

Although online reviews contain valuable information, users cannot read all of them (Kuan et al. 2015). To present users with the most helpful reviews, online review providers such as Amazon, App Store, and etc. have added a sorting mechanism based on the helpfulness of the reviews (Kuan et al. 2015). A review helpfulness can be determined by readers' votes whether they perceive a review helpful or not (Kuan et al. 2015). While people rate helpfulness of reviews, some reviews may receive less votes because they have not been seen at all and some reviews may receive more votes due to fake voting. Relying on only users' votes regarding helpfulness of reviews, may discourage users from writing reviews if they suspect their comment may not be seen at all.

Huge number of reviews for popular products or services, makes the reading process difficult and as a result consumers prefer to select only a few reviews to make their decision (Cao et al. 2011). Online review helpfulness is designed to provide valuable information that is necessary for decision making (Cao et al. 2011). Many studies have been conducted to understand online review helpfulness based on the characteristics of a review such as its sentiment, length, and readability (Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2011; Korfiatis et al. 2008). There is a gap in the literature about how content of reviews affects their helpfulness. Prior research understood importance of utilitarian and hedonic nature of involvement on customers' purchase intentions (Jiang et al. 2010). However, they overlooked how utilitarian and hedonic involvements with OCRs would influence the perceptions of helpfulness of OCRs.

To fill this gap in the literature we propose the following research question:

- What are the antecedents of helpfulness of online reviews based on their contents?
- How do content-based cues on OCRs influence their helpfulness?

Literature Review and Theoretical Background

Online Customer Reviews

OCR has become an important source of information to consumers, users, and businesses (Chevalier and Mayzlin 2006). An important part of user's decision making behavior is formed by reading online reviews and Research shows both reviewers and reviews affect users' perceptions (Connors et al. 2011). In the literature many measures used to explain characteristics of online reviews so the reviews are comparable to each other. These characteristics are length (Chevalier and Mayzlin 2006; Sridhar and Srinivasan 2012), customers' star rating (Korfiatis et al. 2012), extremity (Kuan et al. 2015; Mudambi and Schuff 2010), valence (Vermeulen and Seegers 2009), and sentiment (Hu et al. 2014). Previous research found that customer purchase behavior is also influenced by content of online reviews (Chevalier and Mayzlin 2006). Online reviews summary statistics such as average star ranking and review helpfulness are mechanisms that influence users' perceptions. In the study by Chevalier and Mayzlin (2006), it is shown that improvement in consumer reviews of books on Amazon.com increases the relative sales. They posit that total number of reviews is correlated with relatively higher sales of the product.

Review Content Characteristics

Review characteristics play a central role in overall decision making process for online users that is usually referred as review helpfulness. Review helpfulness is a mechanism to represent the users' perceived value of a review (Connors et al. 2011) and facilitate users' decision making (Cao et al. 2011). Online review helpfulness is usually determined by users' rating what extent a review is helpful (Connors et al. 2011). Content of the online review is characterized by length, readability, valence, and argumentation style (Eastin 2001; Kuan et al. 2015). In addition to content of reviews, review extremity and expertise claims are other influential factors of review helpfulness that are presented to users by most of online shopping websites (Kuan et al. 2015). Review length represents word count and ease of reading denotes readability of a review (Mudambi and Schuff 2010). Study by Kuan et al. (2015) shows longer and readable reviews are perceived more helpful.

Review valence reflects its positivity/negativity (Basuroy et al. 2003). While in the literature it is shown that more positive reviews increase purchase behaviors (Basuroy et al. 2003; Zhu and Zhang 2010), but negative reviews are more likely to receive votes and considered helpful (Kuan et al. 2015). Review argumentation indicates the presence of arguments to support the written statements in online reviews (Willemsen et al. 2011). Arguments make the message more persuasive (Price et al. 2006). Willemsen et al. (2011) suggest that argument density and diversity are important predictors of review helpfulness. Review extremity is the rating star of a review voted by customers (Mudambi and Schuff 2010). Online reviews that rates product one-star or five-star (extremes) are perceived to be more helpful (Cao et al. 2011; Skowronski and Carlston 1987). While online reviews tend to be more positive than negative, the most extreme reviews (one-star reviews) have more impacts (Chevalier and Mayzlin 2006). Research showed that reviews written by self-described experts are more helpful than other reviews (Connors et al. 2011). People tend to seek advice from expert sources when making purchase decisions because they believe experts provide more accurate information (Willemsen et al. 2011). In the literature, assessment of the source credibility is based on reviewer expertise (Eastin 2001).

Theoretical Development

Elaboration likelihood model (ELM) of persuasion has been applied in the IS literature in different contexts. ELM suggests that in persuasive communications that one party aims to change or influence the other parties' attitude or behavior, motivation (involvement) and ability to process of information are very important. This theory argues that when individuals are not motivated or do not able to process information they rely on peripheral cues in the communication. On the other hand, individuals who are motivated (involved) and are able to process too much information prefer to prefer more cognitive information (Petty and Cacioppo 1986). According to Petty and Cacioppo (1984) people who are involved in a subject prefer to process simple cues compare to those who are not involved in the subject.

Consumers involvement can be cognitive and affective (Hwang et al. 2011). Jiang et al. (2010) posit that when users interact with websites it would induce cognitive and emotional effects and its effect . Similarly, involvement with websites include affective and cognitive involvement (Jiang et al. 2010). Cognitive involvement is related to the amount of thoughts generated when customers visit websites (Van Noort et al. 2012), based on utilitarian nature (Putrevu and Lord 1994). In addition, affective involvement on websites is derived from value-expressive (Jiang et al. 2010), based on hedonic aspect (Putrevu and Lord 1994). Purchase decision making in online shopping environment is influenced by helpfulness of OCRs (Cao et al. 2011). Consequently, it is very important to consider influencing role of affective and cognitive involvement of users with OCRs. We distinguish between two features of OCRs: central and peripheral cues.

Research Model and Hypotheses

According to the elaboration likelihood model (ELM) individuals who are more involve in a product are more likely to engage in thoughtful and effortful information regarding those products compare to less involve individuals (Petty et al. 1981). We argue that different people rate the OCRs based on different levels of involvement in the subject of the OCRs. Therefore, to investigate the antecedents of review helpfulness we have to consider both peripheral and central cues of OCRs that a customer see. In addition, previous researches suggested that online customers who are involved in the website seek both hedonic and utilitarian cues on the website (Jiang et al. 2010). Jiang et al. (2010) suggest that hedonic and utilitarian cues on e-commerce websites affects customers' purchase intention. They also found that customers' involvement varies by product type (functional / expressive). Based on the results of these studies the type of the product could be a moderator for the effect of hedonic and utilitarian motives on customers' perceived review helpfulness. Based on the above arguments we suggest our research model (see Figure 1).

Customer involvement literature suggests that individuals seek different types of information on the website (e.g., Dahlen 2002; Dahlen et al. 2003; Petty and Cacioppo 1984; Petty and Cacioppo 1986). One of the sources of information about products on e-commerce websites is the customer reviews. Individuals seek different types of information based on the type of the product they want to buy (Dahlen et al. 2003). Customers perceive more informative reviews as more helpful. Therefore, when a review provide more information about the product that the customer wants to buy they perceive that review more helpful. Reviews that provide more hedonic or utilitarian cues for customers are more informative to those that does not. On the other hand the readability of the review is another important factor that affects its helpfulness (e.g., Korfiatis et al. 2012; Kuan et al. 2015; Salehan and Kim 2014). If a review provide too much information but it is not readable customers are not able to benefit from these information. Therefore, they do not perceive such review as a helpful OCR. So we posit that:

H1: Presence of utilitarian cues on an OCR positively affect the perceived helpfulness of that review.

H2: Presence of hedonic cues on an OCR positively affect the perceived helpfulness of that review.

H3: Readability of OCRs positively affects the perceived helpfulness of that review.

An important peripheral cue on OCRs is the extremity of the review that is shown by vote of the writer of the review about the product. The sentiment of the title of the review is another peripheral cue for online customers. Title sentiment is suggested by previous research as an antecedence of review helpfulness (Salehan and Kim 2014). Finally, Review length is the last peripheral cue we study in our research model.

H4: Review extremity positively affects perceived helpfulness of the review.

H5: Sentiment of the review title positively affects perceived helpfulness of the review.

H6: Review length positively affects perceived helpfulness of the review.

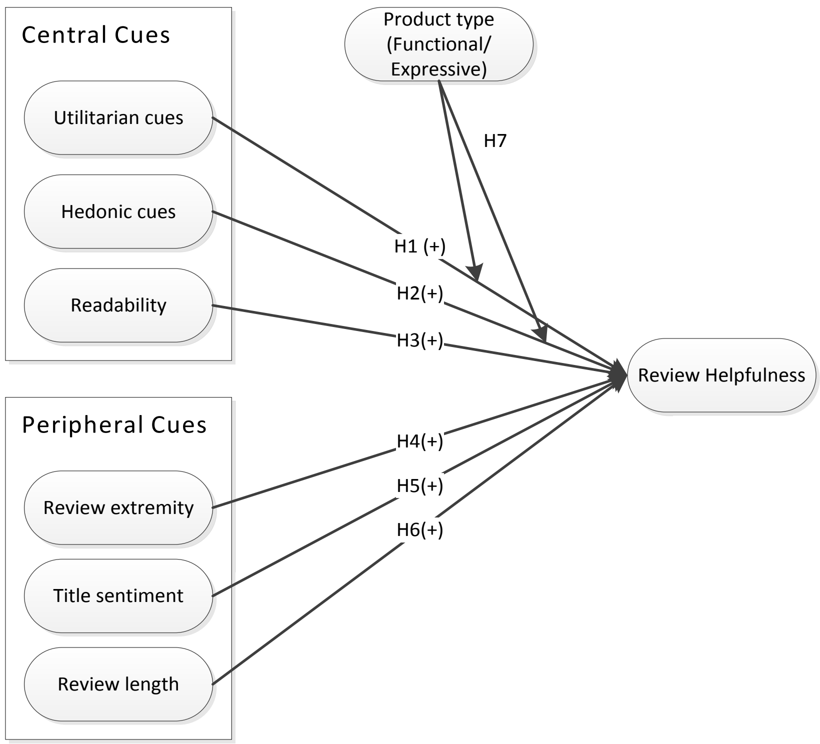

Figure 1: Research Model

According to Dahlen et al. (2003) product type affects our decision process and the type of information we seek. Therefore, a customer who read OCR of an expressive product seek different type of information on OCR compare to another customer who read an OCR of a functional product. Delhan (2002) argues that customers more seek affective (hedonic) motives when they want to buy expressive motives while they seek more cognitive (utilitarian) motives to buy functional products. Therefore we hypothesize that:

H7: Product type moderates that effect of utilitarian and hedonic cues on customers' perceived helpfulness of reviews. The positive effect of utilitarian cues will be stronger for functional products and the positive effect of hedonic motives will be stronger for expressive products.

Research Methodology

Online review web pages will be collected from Amazon website using a web crawler written in Perl programming language. In the next stage, information will be extracted from webpages using C# Regular Expressions. Review length will be calculated by counting the number of words in the text. Review extremity will be measured as the star rating of the review. Review helpfulness will be measured as the ratio of "helpful votes" to "total votes." Sentiment of title will be extracted using SentiStrength software which has be validated by previous research (Garcia and Schweitzer 2011; Gruzd et al. 2011; Salehan and Kim 2014; Stieglitz and Dang-Xuan 2013; Thelwall and Buckley 2013; Thelwall et al. 2012; Thelwall et al. 2010). To measure readability we will use the approach suggested by Senter and Smith (1967):

Readability score = 4.71 * (Total number of characters / Total number of words) + 0.5 * (Total number of words /Total number of sentences) – 21.43

Later we will use two independents raters who are naive to the purpose of the study to rate our training sample in terms of utilitarian and hedonic cues. The raters will first rate the reviews independently and then will meet to work out the ratings for reviews where their ratings did not match. We will use Cohen's Kappa to measure inter-rater reliability (Carletta 1996). After the training is complete, we will use Support Vector Machines to train a text classifier model which is capable of rating a larger group of reviews.

Finally, the suggested model will be analyzed using binomial regression. Because review length is expected to have over dispersion problem, we will use natural logarithm transformation it. The following regression model will be used for data analysis:

$$\frac{Votes\ Helpful}{Votes\ Total}\,\% = \beta_0 + \beta_1 Utilitarian\ Cues + \beta_2\ Hedonic\ Cues + \ \beta_3\ log\ \ (Review\ Length) + \ \beta_4\ Readability + \beta_5\ \ Review\ Extremity + \beta_6\ Title\ Sentiment + \beta_7\ Product\ Type + \ \beta_8\ Product\ Type * \ Hedonic\ Cues + \ \beta_9\ Product\ Type * \ Utilitarian\ Cues$$

Possible Contributions

This study has several possible implications for both theory and practice. In terms of implications for academia this study has at least two possible contributions. First, this article will be one of the first studies that investigate OCRs helpfulness based on the central cues in the text of the review. Previous literature OCR helpfulness focuses on peripheral factor on the review without considering the review text content as an important part of the review. Second, this research will be the first study that applied the support vector machine as a machine learning method to analyze the text of OCRs and measure utilitarian and hedonic clues. Previous researches relied on sentiment analysis approach. SVM enables us to categorize texts based on different criteria using a training data and this method is more effective than other classification techniques (Ye et al. 2009). In terms of implications for practitioners this study will provide a solution for e-commerce websites to sort the reviews not only based on the review helpfulness using SVM approach. This could be more precise than previous methods since in this method we consider the content of the review as an important factor that affects its helpfulness. The results of this study may indicates that ecommerce website has to consider product type as an important factor in prediction of the helpfulness of reviews.

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