The Effect of Central and Peripheral Cues on Online Review Helpfulness: A Comparison between Functional and Expressive Products

Completed Research Paper

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Abstract

Online customer reviews (OCR) have become an important part of online customers’ decision making. People also use OCR to get better understanding of the characteristics of the product and also learn about other customers’ experience with the product. Drawing upon Elaboration Likelihood Model, this research investigates the predictors of readership and helpfulness of OCR. Our findings show that longer reviews as well as those with extreme star ratings receive more readerships. Moreover, the amount of hedonic and utilitarian cues in a review and its sentiment significantly influence perceptions of online consumers regarding its helpfulness. We also show how product type moderates the effect of utilitarian and hedonic cues on helpfulness. We discuss the implications of our study and provide directions for future research.

Keywords: Online review helpfulness, online customer reviews, elaboration likelihood model, and sentiment mining
Introduction

Online customer reviews (OCR) have become an important part of online customers’ decision making (Chatterjee 2001). People use OCR to make a decision regarding purchasing products (Korfias, García-Bariocanal and Sánchez-Alonso 2012). In addition, companies can promote their products and services by motivating their customers to write OCR. People also use OCR to get a better understanding of the characteristics of the product and also learn about other customers’ experience with the product. According to a recent consumer review survey, around 50% of people read OCR as a part of their pre-purchase decision making process (Anderson 2014). The survey also revealed that 88% of consumers trust OCR as much as personal recommendations and 85% of them read up to 10 reviews whenever they want to shop online (Anderson 2014).

Although online reviews contain valuable information, users cannot read all of them (Kuan, Hui, Prasarnphanich and Lai 2015). To present users with the most helpful OCR, online review providers such as Amazon.com and Apple Store have added a sorting mechanism based on the helpfulness of the reviews (Kuan et al. 2015). Helpfulness of a review can be determined by calculating the proportion of people who perceive it to be helpful (Kuan et al. 2015). While people rate helpfulness of reviews, some reviews may receive fewer votes because they have not been seen at all and some may receive more votes due to fake voting. Relying only on users’ votes regarding helpfulness of reviews may discourage users from writing reviews if they suspect their comment may not be seen at all. A huge number of reviews for popular products or services makes the reading process difficult. As a result, consumers prefer to select only a few reviews to make their decision (Cao, Duan and Gan 2011). Hence, online consumers process OCR in two steps: (1) the decision to read a review, and (2) the decision about whether the review they read was helpful or not. Consequently, following the directions provide by Salehan and Kim (2014), this study proposes the following two research questions:

- What are the antecedents of OCR readership?
- What are the antecedents of OCR helpfulness?

While the first research question remains largely unexplored, the second research question has been investigated by previous studies (Salehan and Kim 2014). Many studies have investigated OCR helpfulness based on characteristics of a review such as sentiment, length, and readability (Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2011; Korfias, Rodriguez and Sicilia 2008; Salehan and Kim 2014). However, the textual information contained in the reviews has not received significant attention from previous research. Therefore, a deeper analysis of OCR textual information can provide greater insights into what makes a helpful online review (Mudambi and Schuff 2010). In terms of the second research question, a recent study looks at how characteristics of the title of a review influences its readership (Salehan and Kim 2014). However, a stronger theoretical development is required to determine the factors that influence readership and helpfulness. Using elaboration likelihood model (ELM) (Petty and Cacioppo 1984), we suggest that people use different pieces of information to make decisions regarding readership and helpfulness of OCR. ELM suggests that there are two types of cues in a persuasive communication: peripheral and central. Peripheral cues are implicit cues embedded in a message. Central cues, on the other hand, are more complex cues in a message that require more cognitive effort from the receiver to evaluate them. Similarly, we suggest that the decision to read a review is based on peripheral cues embedded in a review including its star rating extremity, sentiment of the title, and length of the text. On the other hand, the decision regarding helpfulness of a review follows central cues including utilitarian cues, hedonic cues, sentiment of text, and readability.

This study contributes to the existing body of knowledge in three unique ways. First, it provides a research model that explains different factors influencing the performance of OCR in terms of their readership and helpfulness. Second, it uses textual information of a set of secondary OCR data composed of reviews collected from Amazon.com website to evaluate the proposed research model. Finally, it provides insights to practitioners regarding the design and implementation of new methods of sorting OCR in order to help online consumers make faster and more effective decisions regarding their purchase. Such mechanisms will eventually benefit online stores by providing them with the opportunity to increase sales. The remaining parts of this paper are structured as follows. First, we look at the theoretical background of this study. Then, we propose our research model and hypotheses. Next, we evaluate our research model and show the results of the analysis. Finally we discuss the implications and limitations of our study.
Literature Review and Theoretical Background

Online Consumer Reviews

OCR are comments posted on retail or third-party websites such as Amazon.com and Yelp.com about products and services (Zhu, Yin and He 2014). OCR has become an important source of information to consumers and businesses (Chevalier and Mayzlin 2006). The shift of lotus of control in marketing communication away from marketers to consumers, let consumers to get more involved into the information creation and selection process about products (Burton and Khammash 2010). Ngo-Ye et al. (2014) showed that reviewer engagement is an important predictor of review helpfulness. Reviewer’s recency, frequency, and monetary value (RFM) capture overall engagement of a reviewer. Useful reviews are usually written by reviewers with more effort and involvement. Using text mining approach, RFM dimensions are found to be significant antecedents of review helpfulness (Ngo-Ye and Sinha 2014). Previous research shows that customer purchase behavior is influenced by content of OCR (Chevalier and Mayzlin 2006). A study by Chevalier and Mayzlin (2006) shows that improvement in reviews of books on Amazon.com increases the relative sales. They posit that total number of reviews for a product is correlated with its sales. Purchase decisions of online customers are supported by information existing in OCR (Baek, Ahn and Choi 2012).

Consumers’ response to environment is composed of emotional and cognitive dimensions (Mehrabian and Russell 1974). Mazaheri et al. (2011) find that emotions of online users influence their perceptions regarding informativeness, effectiveness, and entertainment level of a website. Consumers’ involvement can be cognitive and affective (Hwang, Yoon and Park 2011). A study by Jiang et al. (2010), shows that users’ interaction with websites induce cognitive and emotional effects in them. Similarly, involvement with website includes affective and cognitive involvement (Jiang et al. 2010). Cognitive involvement is related to the amount of thoughts generated when a user visits a website (Van Noort, Voorveld and van Reijmersdal 2012) based on the utilitarian nature (Putrevu and Lord 1994). In addition, affective involvement with a website is derived from value-expressive cues (Jiang et al. 2010) are found in hedonic aspects of the website (Putrevu and Lord 1994). Consequently, it is very important to consider the role of affective and cognitive involvement of consumers with OCR. We distinguish between two groups of characteristics of OCR: central and peripheral cues. In the previous literature it has been discussed that content of OCRs influences consumers’ decisions (Danescu-Niculescu-Mizil, Kossinets, Kleinberg and Lee 2009), but there is still a need to classify characteristics of OCRs.

Review Characteristics

Review characteristics play a central role in the decision making process of consumers that is usually referred to as review helpfulness. Helpfulness is the most widely used measure for predicting performance of OCR (Salehan and Kim 2014). Review helpfulness is a mechanism to represent the users’ perceived value of a review (Connors, Mudambi and Schuff 2011), which facilitates users’ decision making process (Cao et al. 2011). More helpful reviews have stronger effect on purchasing behavior than less helpful reviews (Chen, Dhanasobhon and Smith 2008). Online review helpfulness is usually determined by users’ rating that whether a review is helpful or not (Connors et al. 2011). Other than consumer votes regarding helpfulness of a review, the content of a review can affect its helpfulness.

In the literature many measures have been used to characterize OCR. Content of the online review is characterized by length (Chevalier and Mayzlin 2006; Sridhar and Srinivasan 2012), readability (Ghose and Ipeirotis 2011), valence (Vermeulen and Seegers 2009), sentiment (Hu, Koh and Reddy 2014), and argumentation style (Eastin 2001; Kuan et al. 2015). Review length represents word count and readability denotes ease of reading 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 (Basu Roy, Chatterjee and Ravid 2003). For example, the literature shows that more positive reviews increase sales (Basu Roy et al. 2003; Zhu and Zhang 2010) while negative reviews are more likely to receive votes and be considered as helpful (Kuan et al. 2015). Negative reviews provide less ambiguous information for decision making than positive ones (Hu, Zhang and Pavlou 2009). Review argumentation indicates the presence of arguments to support the written statements in online reviews (Willemsen, Neijens, Bronner and de Ridder
Arguments make the message more persuasive (Price, Nir and Cappella 2006). Willemsen et al. (2011) showed argument density and diversity are important predictors of review helpfulness.

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 extremity is the star rating of a review voted by customers (Korfiatis et al. 2012; Kuan et al. 2015; Mudambi and Schuff 2010). Previous research shows that extreme information are more influential (Skowronski and Carlston 1987). Similarly, reviews with one-star or five-star rating (out of five) are perceived to be more helpful (Cao et al. 2011). While online reviews tend to be more positive than negative, extremely negative reviews (i.e., one-star reviews) have more impact on consumers’ decision making than extremely positive ones (Chevalier and Mayzlin 2006). Furthermore, people tend to seek advice from expert sources when making purchase decisions because they believe that experts provide more accurate information (Willemsen et al. 2011). Previous research shows that reviews written by self-described experts are more helpful than other reviews (Connors et al. 2011). In previous studies, assessment of the source credibility is based on reviewer expertise (Eastin 2001).

OCR Readership

An important part of consumers’ decision making process is formed by reading online reviews and research shows that both reviewer and review characteristics influence consumers’ perceptions (Connors et al. 2011). The findings of study by Burton and Khammash (2010) show OCRs written by more popular authors positively motivate consumers to read them. Decision making becomes more complex when the amount of information provided by OCR increases and the number of product choices is numerous (Baum and Spann 2014). However, customers do not read all of the OCRs, and most consumers read up to 10 reviews to make a decision (Anderson 2014; Cao et al. 2011; Zhang and Tran 2010). The ultimate decision is usually based on fewer reviews (Kuan et al. 2015).

To ameliorate online consumers’ decision making using OCR, many websites provide sorting tools based on different factors such as overall review helpfulness and star rating, and recommendations. Voting mechanism is designed by many retail websites to comfort the voluminous information digesting for consumers. Consumers who read reviews can simply vote up helpful reviews and vice versa (Yin, Zhang and Li 2014). Previous literature shows that inconsistency between recommendations has negative impact on purchase intentions (Baum and Spann 2014). Same argument can be applied to OCR that discrepancies between OCR do not help consumers and it adds up to the perplexities of decision making.

Evidences driven from previous studies shows that customers actually read OCRs rather than relying on summary statistics (Chevalier and Mayzlin 2006; Lee 2009). Customers read OCRs for different purposes and the focus on different sources of information is contingent to the reading purpose (Baek et al. 2012). Customers read OCRs either to find information they are looking for or to evaluate different alternatives (Baek et al. 2012). Findings of Baek et al. (2012) research show when people are seeking information, their focus during reading stage is on peripheral cues while central cues are helpful during alternative comparison. In addition, depending on the type of product the purpose of reading OCRs can be different (Baek et al. 2012). When customers read OCRs, they deal with the uncertainly related to the characteristics of a product and the uncertainty regarding the intentions of OCR writers (Racherla and Friske 2012).

A consumer can vote about helpfulness of a product review after reading it (Zhang and Tran 2011). Automatic prediction of reviews’ helpfulness could help sort reviews more efficiently because newly written reviews usually do not get enough attention (Ghose and Ipeirotis 2011). In the study by Zhang and Tran (2011), an information gain approach is proposed to filter out unhelpful reviews to provide more valuable information for consumer's decision making process. Consumers who have read OCRs can vote whether a review was helpful for their decision making or not (Scholz and Dorner 2013). In the literature, there is little about OCRs' readership and most of the previous research have measured readership only by length of reviews (Mudambi and Schuff 2010).

OCR Helpfulness

Review helpfulness has been the focus of many previous studies (Baek et al. 2012; Cao et al. 2011; Mudambi and Schuff 2010). Measuring helpfulness of OCR is not a trivial task. Most websites simply ask users whether they perceive a review is helpful or not (Cao et al. 2011). As a result, review helpfulness is defined.
as the ratio of “yes” votes divided by total votes on helpfulness of a review (Kim, Pantel, Chklovski and Pennacchiotti 2006). Most of previous studies in this area quantified review helpfulness as number between 0 and 1, the greater the value the more helpful it is (Liu, Cao, Lin, Huang and Zhou 2007). Other studies have quantified helpfulness of a review as a binary variable which simply measures if a review is helpful or not (Forman, Ghose and Wiesenfeld 2008).

A group of studies have discussed OCR helpfulness based on the review content and its context (Mousavizadeh, Koohikamali and Salehan 2015). In a study by Zhu et al. (2014), perceived helpfulness of hotel reviews on Yelp is found to be related to central cues and peripheral cues. Peripheral cues are about the reviewer while central cues are review-related (Pan and Zhang 2011). Riggio and Kirsner (1997) defined peripheral cues as simple indications that influence the early perceptual stages. Central cues are more complex cues that influence the late stage of information processing (Petty and Cacioppo 1986; Riggio and Kirsner 1997). In the context of online hotel reviews, there is a greater tendency toward peripheral cues. The study finds that central cues in review, readability, and length are positively correlated with perceived helpfulness. It also finds that reviewer expertise and attractiveness, as two dimensions of source credibility, are significantly related to perceived helpfulness. Forman et al. (2008) evaluated online review helpfulness on Amazon.com and showed that reviews with self-descriptive information receive more helpful votes than anonymous reviews. They also found that review equivocality shapes the helpfulness of OCR. When a review is more equivocal, the reliance on the source of information is greater (Forman et al. 2008).

Another study by Zhiming et al. (2014) investigates the determinants of perceived review helpfulness of movies based on uncertainty reduction theory. The study explains how the overall helpfulness of a review reduces the uncertainties associated with a purchase. The Findings indicate that content quality and source quality influence the perceived helpfulness of reviews. Content quality consists of review extremity, review length, and review timeliness. Source quality is explained by review reputation as one of the significant predictors of movie review helpfulness on IMDB website (Zhiming et al. 2014). In an effort to better describe how the content of OCRs influences perceptions of readers, Chen and Tseng (2011) found high-quality reviews provide detailed explanations about different aspects of products features and as a result receive more helpfulness votes. They examined nine information quality dimensions (believability, objectivity, reputation, relevancy, timeliness, completeness, concise representation, ease of understanding, and appropriate amount of information). However, these dimensions of information cannot explicitly explain the review content characteristics because four different constructs of information quality (intrinsic quality, contextual quality, representational quality, and accessibility quality) are mixed together.

Another school of thought in the literature investigates the effect of emotional valence and arousal on helpfulness of OCRs. The emotional feelings of a person in a situation can be explained in the valence-arousal space (Scherer 2005). Arousal is explained by the level of activation and valence is whether an experience is pleasant or not (Niedenthal 2008; Niedenthal, Winkielman, Mondillon and Vermeulen 2009). In a study by Yin et al. (2014), the emotional valence and arousal of reviews are measured using the Revised Dictionary of Affect in Language. Both emotional valence and arousal positively influence the perceived review helpfulness (Yin et al. 2014). They also find that while reviews with more negative and positive emotions are perceived to be more helpful, in the presence of higher arousal more negative emotions negatively influence helpfulness. Review valence positively influence decision making of online consumers (Chevalier and Mayzlin 2006). Reviews that emphasize the salience of a product may facilitate the overall decision making process (Forman et al. 2008). Zhang et al. (Zhang, Craciun and Shin 2010) study explains how consumption goals moderate the relationship between review valence and persuasiveness. Their findings indicate that for products associated with promotion consumption goals positive reviews are more persuasive than negative reviews. While for products associated with prevention goals the negative reviews are more persuasive than positive reviews. Table 1 summarizes major past research investigating the impact of different variables on review helpfulness.

**Elaboration Likelihood Model**

According to Petty and Cacioppo (1986), there are two types of cues in a persuasive communication. The first type of cues, named peripheral cues, refer to simple cues in a message that can affect the attitude of the receiver. These cues affects receivers attitude temporarily and may not be an indicator of the final judgement of the receiver regarding the message. The second type of cues in a persuasive communication are central cues which refer to the more complex cues in a message that require more cognitive effort for
the receiver to evaluate them. Compared to peripheral cues, central cues have enduring effect on the receiver’s attitude and influence his/her final judgment regarding the message.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Independent variables</th>
<th>Dependent variables</th>
<th>Moderator (s)</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>This study</td>
<td>Peripheral cues (review extremity, review length, title sentiment), central cues (utilitarian cues, hedonic cues, review sentiment, readability)</td>
<td>Readership, review helpfulness</td>
<td>Product type (functional vs. expressive)</td>
<td>Negative binomial and binomial regression</td>
</tr>
<tr>
<td>Cao et al. (2011)</td>
<td>Basic characteristics (posting date, extremeness), stylistic characteristics (average number of words in a sentence), semantic characteristics (overall semantic of a review)</td>
<td>Total number of helpfulness votes</td>
<td>None</td>
<td>Ordinal logistic regression</td>
</tr>
<tr>
<td>Mudambi and Schuff (2010)</td>
<td>Review depth (operationalized with word count), review extremity (measured with star rating)</td>
<td>Helpfulness</td>
<td>Product type (search goods vs. experience goods)</td>
<td>Tobit regression</td>
</tr>
<tr>
<td>Zhu et al. (2014)</td>
<td>Reviewer expertise (Number of “Elite” badges), reviewer online attractiveness (Number of Yelp friends)</td>
<td>Perceived helpfulness</td>
<td>Product price (high-priced vs. low priced), Rating extremity</td>
<td>Negative binomial (NB) regression</td>
</tr>
<tr>
<td>Ngo-Ye and Sinha (2014)</td>
<td>Review words, reviewer engagement characteristics (reputation, commitment, and current activity)</td>
<td>Review helpfulness</td>
<td>None</td>
<td>Text regression</td>
</tr>
<tr>
<td>Wu et al. (2011)</td>
<td>Negativity (measured with star rating),</td>
<td>Helpfulness ratio</td>
<td>Readability, Length</td>
<td>Ordinary least squares (OLS)</td>
</tr>
<tr>
<td>Willemsen (2011)</td>
<td>Expertise claims, review valence, argument density, argument diversity</td>
<td>Usefulness</td>
<td>None</td>
<td>Ordinary least squares (OLS)</td>
</tr>
<tr>
<td>Lee and Choeh (2014)</td>
<td>List price of the product, sales rank of the product, average review rating, review extremity, review length, number of 1-letter words in a review</td>
<td>Review helpfulness</td>
<td>None</td>
<td>Multilayer perceptron neural network</td>
</tr>
<tr>
<td>Korfiatis et al. (2012)</td>
<td>Review readability, review rating</td>
<td>Helpfulness ratio</td>
<td>None</td>
<td>Tobit regression</td>
</tr>
<tr>
<td>Huang et al. (2015)</td>
<td>Quantitative factor (word count), qualitative factors (reviewer experience, reviewer impact, cumulative helpfulness, product rating)</td>
<td>Review helpfulness</td>
<td>None</td>
<td>Tobit regression</td>
</tr>
<tr>
<td>Hu et al. (Hu et al. 2014)</td>
<td>Price of product, age of product, total number of reviews, helpfulness ratio, variance of rating, variance of sentiment</td>
<td>Sales rank, sentiment, rating</td>
<td>Rating, sentiment</td>
<td>Three-stage least square</td>
</tr>
<tr>
<td>(Scholz and Dorner 2013)</td>
<td>Objectivity, prior helpfulness, credibility, ease of understanding, interpretability, timeliness, value-added, amount of data</td>
<td>Probability of review helpfulness</td>
<td>Product type</td>
<td>Tobit regression</td>
</tr>
</tbody>
</table>
According to Petty and Cacioppo (2012), individuals start to process information from peripheral cues and if these peripheral cues do not affect their attitude, they stop analyzing more information. On the other hand, the peripheral cues embedded in a communication may affect individuals’ attitude temporarily and convince them to seek more information. Sundar and Kim (2005) argue that individuals evaluate the central cues in the communication whenever they are motivated to do that and this motivation can be the result of the evaluation of peripheral cues in the communication. Research shows customers who seek information use peripheral cues during reading process and when they make judgments on different alternatives they use central cues (Baek et al. 2012). Consequently, we believe peripheral cues are related to readership and central cues are associated with helpfulness of OCRs.

Elaboration likelihood model (ELM) of persuasion has been applied in the IS literature in different areas. ELM suggests that in persuasive communications that one party aims to change or influence the other parties’ attitude or behavior, motivation (involvement) and their ability to process information are important. This theory argues that when individuals are not able to process information, they rely on peripheral cues in the communication. On the other hand, individuals who are able to process more information prefer to use more cognitive information (Petty and Cacioppo 1984).

We argue that OCR, as a persuasive communication between consumers, contain peripheral and central cues. Peripheral cues of an OCR are those which can be found on the online vendor’s webpage without too much cognitive effort. Central cues are the information contained in OCR which require consumers to spend more time and cognitive effort to evaluate them. The process of evaluating a review consumers can be broken into two steps: (1) the customer decides to read the review, and (2) the customer decides to rate the review as a helpful one (Ahluwalia 2000; Salehan and Kim 2014). When customers analyze the peripheral cues in OCR, they may or may not be involved in that review. According to ELM, the more a customer is involved with a review, the more he/she is likely to read the review that contains central cues which require more cognitive effort compare to peripheral cues.

Research Model and Hypotheses

In order to address our research questions we propose a research model based on different cues embedded in OCR. This research model aims to investigate the effect of peripheral and central cues of OCR on consumers’ decision to read (readership) and subsequently rate a review as helpful. Each review on Amazon.com website contains a number of cues that may affect its performance (Figure 1). Our research model (see Figure 2) classifies these cues in two different categories based on ELM and evaluates the effect of these cues on OCR performance. This study investigates the effect of review extremity, review length, and title sentiment as peripheral cues embedded in OCR. To investigate the effect of central cues on performance of OCR, we focus on the content of the review which requires more cognitive effort to be analyzed by people. The central cues used in this study are utilitarian cues, hedonic cues, review sentiment, and readability of the review. Moreover, this study examines the moderating effect of product type on the effect of utilitarian and hedonic cues on perceived helpfulness.

Customers are able to rate products on most online shopping websites from a very low rating (one star) to very high rating (five stars). One star shows extreme negative attitude of the person about the product while a five-star rating reflects a very positive attitude about the product (Mudambi and Schuff 2010). The extremity of a review refers to the deviation of the buyer’s attitude from midpoint of an attitude scale (Krosnick, Boninger, Chuang, Berent and Carnot 1993). Customers are able to process rates and quickly conclude whether the review is extreme or not. Therefore, review extremity is considered as a peripheral cue on OCR that affects consumers’ decision to whether read the review or not. There are conflicting results in the literature about the effect of review extremity on individuals’ attitude. Schlosser (2005) found that arguments that contain both negative and positive arguments are more credible. Some other researchers argued that extreme reviews are more influential (Forman et al. 2008; Pavlou and Dimoka 2006). In the context of online reviews, reviews that contain a large number of arguments are generally longer than others with lower number of argument (Mudambi and Schuff 2010). These reviews affect readership because through review length. In fact in the first look a review may not seem to be extreme based on the extremity rate but generally it is long and this longevity affects readership. Thus, both arguments in the literature are valid in the context of online reviews. We posit that customers are more likely to be interested in reading...
extreme reviews than moderate reviews. According to Mudambi and Schuff (2010), customers are seeking information regarding the product that they want to buy and read reviews to reduce uncertainty. Mudambi and Schuff suggest that extreme reviews are more likely to contain information about a product. Therefore, this is more probable that online customers read extreme reviews. As a result, we hypothesize:

**H1:** Review extremity positively influences readership of a review.

Length of a review is an important indicator of its helpfulness (Mudambi and Schuff 2010; Salehan and Kim 2014). Longer reviews are more in depth and contain more product-related information compared to shorter reviews (Mudambi and Schuff 2010). Customers are able to find out the review length easily by looking at the review and it does not require much cognitive effort for them. Therefore, we argue that review length should be considered as a peripheral cue. Review length affects consumers’ attitude about the review. Hence, consumers are more willing to read longer reviews. Longer reviews are more likely to contain persuasive arguments and more reasons for that may decrease consumer’s uncertainty (Schwenk 1986; Tversky and Kahneman 1974). Customers’ attitude regarding longer reviews is more positive than shorter reviews since they believe that these reviews are more informative (Mudambi and Schuff 2010). However, the final evaluation of the helpfulness of a review is based on its content not its length. Thus, we posit that length of a review will be positively related to its readership. Longer reviews are more likely to be read because they have higher potential to contain deep information about the product. Hence, we posit the following:

**H2:** Review length positively influences readership of a review.

People look for quick signals on the review that would convince them to read it (Salehan and Kim 2014). One quick signal on the review is the title of the review which is a short combination of words and does not require much cognitive effort to be processed by people. Each message may contain positive and negative emotions that indicate the temper of the author (Riordan and Kreuz 2010). Title of the review is a small part of a review but it reflects the overall attitude of the author of the review about the product. Total sentiment of a message is a signal that could be communicated in the text and affects the perceptions of the reader regarding the message (Harris and Paradice 2007; Riordan and Kreuz 2010). The total amount of sentiment in the title of a review is the sum of the positive and negative emotions. Hence, high sentiment in the title indicates review’s emotional extremity. Therefore, a review title with large amount of sentiment will be more likely to attract readers than the one with less sentiment. Consequently, we hypothesize:

**H3:** The total amount of sentiment in the title of a review positively influences its readership.

Customers need to spend time and cognitive effort to understand the reviewers’ comments about a product (Korfiatis et al. 2012). There are different pieces of information on the review that should be evaluate and comprehend altogether by the reader. The final attitude of the reader about the product is the result of
processing all of these information. Each product has a number of utilitarian and hedonic attributes and these attributes affect consumer’s overall evaluation of that product (Dhar and Wertenbroch 2000). The author of a review provides information regarding these attributes. These information may persuade or dissuade consumers from buying the product by decreasing their level of uncertainty. A review may contain arguments about both hedonic and utilitarian attributes of a product. According to ELM, the arguments embedded in a review are considered as central cues and influence reader’s attitude about the product (Cheung, Sia and Kuan 2012).

Consumers read reviews to find the information they need and decrease their uncertainty regarding the purchase decision. The more information about the product is available in the review text, the less the search cost of the consumer will be (Johnson and Payne 1985; Mudambi and Schuff 2010). Therefore, when a review provides more information about a product, the consumers perceive it to be more helpful. Utilitarian cues embedded in a review provide information about the product. Utilitarian and hedonic benefits of a product have been suggested as an important indicator of consumer’s satisfaction and loyalty with the product (Chitturi, Raghunathan and Mahajan 2008). Therefore, these two dimensions of a product are important in consumers’ decision making process to buy or not to buy the product. More specifically, the hedonic and utilitarian cues about a product positively influence consumer’s intention to buy a product (Overby and Lee 2006). Presence of the hedonic and utilitarian cue in a review accelerates and facilitates consumers’ decision making and reduces their search cost. On the other hand, a review that does not have enough information about the product also dissatisfies the consumers because the consumer spends time to read the review without finding any useful information. As a result, we suggest the following hypotheses:

H4: The amount of utilitarian cues in a review positively influences its perceived helpfulness.

H5: The amount of hedonic cues in a review positively influences its helpfulness.

Sentiments of a message influence the perceptions of the receiver of the messages (Harris and Paradice 2007; Riordan and Kreuz 2010). An individual’s comprehension of the text of a review involves high level of cognitive effort (Korfiatis et al. 2012). Therefore, the total sentiment of a review is considered as a central cue (Baek et al. 2012). The total sentiment of a review reflects the level of satisfaction of the author with the product (Salehan and Kim 2014). Consequently, a review with large total sentiment provides more information for the reader about the degree of the satisfaction of the author compared to a review with little sentiment. A review with large total sentiment decreases consumer’s search cost and accelerates his/her purchase decision. Therefore such reviews are considered more helpful compared to neutral reviews which do not contain neither positive nor negative sentiment. This leads to the following hypothesis:

H6: The total amount of sentiment in the text of a review positively influences its perceived helpfulness.

Readability of a review refers to the extent to which a review is easy to read by the reader (Korfiatis et al. 2012). Korfiatis et al. (2012) argue that the level of cognitive effort that the reader should spend to comprehend a review increases when the text is less readable. Hence, the level of readability of text affects reader’s level of understanding of that text. Inability of a consumer to comprehend a review may dissatisfy him/her. The reason is that the person spends time to understand the review and find the information that he/she is seeking. When the consumer cannot find these information on the review because of low level of readability of the review, he/she will be dissatisfied with that review. Hence, we suggest the following hypothesis:

H7: Readability of the text of a review positively influences its helpfulness.

Product type has been studied by several studies as a moderator of the effect of different dependent variables on review helpfulness (Salehan and Kim 2014). Product type influences the way consumers seek and process information about a product (Dahlen 2002; Mittal 1989; Rossiter and Percy 1991). Products available on online shopping websites can be classified as functional and expressive products. The inherent characteristics of functional products are more important for the customer (Mittal 1989) and the decision to buy these products is logical and based on functional information about the product (Dahlen 2002). On the other hand, expressive products are more evaluated based on feeling of the consumer about those product (Dahlen 2002; Dahlen and Bergendahl 2001). Therefore, any cues on a review that helps the reader to understand the feeling of the author will increase reader’s satisfaction with the review. people who seek information about an expressive product are less likely to search for product-related information compared
to those who are looking for a functional product (Dahlén, Rasch and Rosengren 2003). Hedonic cues in a review are the emotions and feelings of the author about the product while utilitarian cues are functional features of the product. Hence, we argue that consumers who seek information about expressive products find reviews with high amount of utilitarian cues more helpful. Moreover, those who look for a functional product find reviews with high amount of utilitarian cues more helpful. The reason is that these reviews satisfy their need for information and decrease their search cost. Thus, we hypothesize that:

H8: Product type moderates the effect of utilitarian cues on perceived helpfulness of a review. The positive effect of utilitarian cues will be stronger for functional products.

H9: Product type moderates the effect of hedonic cues on perceived helpfulness of a review. The positive effect of hedonic cues will be weaker for functional products.

Research Methodology

Data Collection

We collected data from Amazon.com website by using a crawler software developed by the authors. A total of 9257 reviews of 17 different products were downloaded. We selected products with more than 200 reviews since generally a very small proportion of reviews of a product are rated by consumers. Following Dhar and Wertenbroch (2000), we downloaded reviews of microwave (functional product) and jewelries (expressive product). We later excluded reviews that had less than 5 votes (Kim et al. 2006; Wu et al. 2011). The final sample consisted of 589 reviews. Figure 2 summarizes the system design of our data collection and mining process.

Coding

Following the content analysis research process by Krippendorff (1980; 2012), we qualitatively hand coded 589 reviews to measure utilitarian and hedonic cues. Four Master’s students read all of the 589 Amazon customer reviews. To build our coding book two meetings were held to explain the hedonic and utilitarian cues of different products to our coders. A different sample of reviews were randomly chosen by the authors and we did not use the reviews of the same product for our content coding purpose. The coders were unaware of the purpose of the study and did not know our proposed set of hypotheses. Moreover, we selected coders from four different departments. To reduce errors, the coders were given only 50 reviews to do the coding every even day.

Coding Scheme

Detailed coding scheme for variables is provided in Appendix 1. To develop the coding scheme for independent variables, we first defined each variable. Two coded independent variables were hedonic cues and utilitarian cues. These variables were quantified using a dichotomous scale from 0 to 9 in which greater values indicate the richer review content in terms of hedonic and/or utilitarian cues.

Inter-Coder Reliability

To evaluate the reliability of coding, we calculated the Cohen’s Kappa statistic which is an indicator of inter-coder reliability (Berry and Mielke 1988). Inter-coder reliability is often used to understand how independent coders reach the same conclusion when utilizing the content coding (Lombard, Snyder-Duch and Bracken 2002). Kappa value greater than 0.70 is a representative of high agreement between coders (Carletta 1996; Fleiss, Levin and Paik 2013). All four coders were assigned to code the same randomly selected reviews from all product types. Then, we calculated Kappa value for each of the coded variables. The calculated Kappa values ranged between 0.87 and 0.95 (p-value<0.000). The resulting inter-coder reliability values indicate an excellent agreements between the coders (Fleiss et al. 2013; Landis and Koch 1977).
Table 2. Measurement Variables Instrumentation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Possible range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Review extremity</td>
<td>The absolute value of difference between an average of reviews’ rating and rating of a review (Cao et al. 2011)</td>
<td>Greater than zero</td>
</tr>
<tr>
<td>Review length</td>
<td>Number of words of a review (Huang et al. 2015)</td>
<td>Greater than zero</td>
</tr>
<tr>
<td>Title sentiment</td>
<td>Total sentiment of a title (Salehan and Kim 2014)</td>
<td>From 0 to 8</td>
</tr>
<tr>
<td>Readership</td>
<td>The overall votes of a review (Salehan and Kim 2014)</td>
<td>Greater than zero</td>
</tr>
<tr>
<td>Utilitarian cues</td>
<td>Information about useful and functional premises of a product presented in the content of a review (Palazon and Delgado-Ballester 2013)</td>
<td>From 0 to 9</td>
</tr>
<tr>
<td>Hedonic cues</td>
<td>Information about pleasurable and experimental premises presented in the content of a review (Palazon and Delgado-Ballester 2013)</td>
<td>From 0 to 9</td>
</tr>
<tr>
<td>Review sentiment</td>
<td>Total sentiment of a review (Salehan and Kim 2014)</td>
<td>From 0 to 8</td>
</tr>
<tr>
<td>Readability</td>
<td>Minimum level of the US second education level required to understand a review (Senter and Smith 1967)</td>
<td>Greater than zero</td>
</tr>
<tr>
<td>Review helpfulness</td>
<td>The total number of helpful votes a review received (Zhu et al. 2014)</td>
<td>Greater than zero</td>
</tr>
<tr>
<td>Product type</td>
<td>Classification of product based on different characteristics (Jiang et al. 2010)</td>
<td>Functional or Expressive</td>
</tr>
</tbody>
</table>

Readability

We used automated readability index (ARI) to measure readability (Senter and Smith 1967). Unlike many other measures, the ARI is calculated based on the number of characters in a word which makes it an efficient indicator for readability of a document (Hu, Bose, Koh and Liu 2012). The ARI value can be interpreted as the minimum level of education to comprehend a text. We used an R package (koRpus) version 3.1.1 to measure readability of reviews.

Sentiment

To understand the helpfulness of OCRs, it is very important to detect emotional sentiments in the content of OCRs. Sentiment is the level of emotions in OCRs (Hu et al. 2014). Sentiment is also known as polarity and it is used to identify negative and positive language in the text (Hu et al. 2012). Prior studies have used sentiment lexicons containing a list of positive and negative words (Duric and Song 2012). In this study we used SentiStrength software (Thelwall, Buckley, Paltoglou, Cai and Kappas 2010) which is free for academic
research. SentiStrength reports two separate numbers by analysis of a text. One positive number that indicates positive emotions and one negative number that indicates negative emotions exists in the text. We used the approach suggested by Stieglitz and Dang-Xuan (2013) to combine these two numbers and calculate the total sentiment associated with each review.

**Data Analysis and Results**

We used SPSS to check the descriptive statistics of our sample and based on that determine the appropriate data analysis approach. As shown in Table 3, review length represents a positive integer number which is overdispersed because it’s mean is smaller than its standard deviation. Hence, we used natural logarithm transformation to adjust it for over-dispersion (Cameron and Trivedi 2013).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Range</th>
<th>Median</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product rate</td>
<td>1-5</td>
<td>3</td>
<td>2.71 (1.70)</td>
</tr>
<tr>
<td>Review length</td>
<td>2-1184</td>
<td>67</td>
<td>106.84 (138.31)</td>
</tr>
<tr>
<td>Total votes</td>
<td>4-590</td>
<td>7</td>
<td>20.37 (53.52)</td>
</tr>
<tr>
<td>Helpful votes</td>
<td>0-568</td>
<td>5</td>
<td>17.77 (50.47)</td>
</tr>
<tr>
<td>Title sentiment</td>
<td>0-6</td>
<td>1</td>
<td>1.08 (1.07)</td>
</tr>
<tr>
<td>Review sentiment</td>
<td>0-7</td>
<td>3</td>
<td>2.72 (1.42)</td>
</tr>
<tr>
<td>Readability index</td>
<td>0.2-14.6</td>
<td>4.4</td>
<td>4.85 (2.79)</td>
</tr>
<tr>
<td>Utilitarian cues</td>
<td>0-9</td>
<td>4</td>
<td>4.79 (2.11)</td>
</tr>
<tr>
<td>Hedonic cues</td>
<td>0-9</td>
<td>3</td>
<td>4.01 (1.94)</td>
</tr>
</tbody>
</table>

According to Hilbe (2011) negative binomial models are appropriate for the analysis of data in which the dependent variable is overdispersed and count variable (Hilbe 2011). Readership, as one of the dependent variables in our model, is the count of the people who have voted for a review. As shown in Table 3, the standard deviation of total vote is significantly larger than its mean (Mean = 20.37, SD = 53.52). To statistically test whether the data is over-dispersed we used the approach suggested by Cameron and Trivedi (1990). To perform the test we used an R package, AER version 3.1.1. The results of the test show that the total votes is significantly over-dispersed (z statistics =3.06, p = .001). Therefore, we conclude that the dependent variable is highly dispersed. Thus, negative binomial regression is a proper candidate for testing the relationship between the independent variables and readership. Moreover, figure 3 represents the log distribution of total vote with a negative binomial distribution. We test the following negative binomial regression to analyze hypotheses 1 to 3 by using Log link function as suggested by Hilbe (2011):

$$Total \, votes = \beta_0 + \beta_1 Review \, extremity + \beta_2 \ln(Review \, length) + \beta_3 Title \, sentiment + \varepsilon$$ (Equation 1)

The second indicator of the OCR performance in the model is review helpfulness. This study measures review helpfulness as the proportion of helpful votes out of total votes of a review (Salehan and Kim 2014). According to Baum (2008), binomial regression with a Logit link function is an appropriate statistical modeling approach for models in which the dependent variable is a proportion. Binomial regression also accounts for the selection bias, suggested by Mudambi and Schuff (2010), in the sample (Greene 1994). Therefore we used binomial regression to test the hypotheses 4 to 9 (see Equation 2). To test the moderating effect of product type on the effect of utilitarian and hedonic cues on review helpfulness, we created a dummy variable entitled “Product type”. This variable has a value of one for functional products and a value of zero for expressive products.

$$Review \, helpfulness \% = \beta_0 + \beta_1 Utilitarian \, cues + \beta_2 Hedonic \, cues + \beta_3 Review \, sentiment + \beta_4 Readability + \beta_5 Product \, type \times Utilitarian \, cues + \beta_6 Product \, type \times Hedonic \, cues + \varepsilon$$ (Equation 2)
Before testing the two models we checked the Pearson’s correlation among our independent variables to test for multicollinearity in equation 1 and 2 (see Table 4). Because of high correlation between a numbers of independent variables, we checked the Variance Inflation Factor (VIF). The VIF values shows that multicollinearity is not an issue in this study.

<table>
<thead>
<tr>
<th>Table 4. Correlation Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equation 1</strong></td>
</tr>
<tr>
<td>Review extremity</td>
</tr>
<tr>
<td>Review extremity</td>
</tr>
<tr>
<td>Title sentiment</td>
</tr>
<tr>
<td>Review Length</td>
</tr>
<tr>
<td>* p &lt; 0.05 (two-tailed significance)</td>
</tr>
</tbody>
</table>

Finally, we used SPSS to test the hypotheses in both equations. The SPSS results revealed that the negative binomial regression was significant (Chi-Square = 164.27, df = 3, p < 0.001). Therefore, negative binomial model was an appropriate approach to test our hypotheses. Binomial regression model was also significant (Chi-Square = 427.03, df = 6, p < 0.001) which shows that the binomial regression model was appropriate to test the model. The results of testing equation 1 revealed that review extremity (b = .260, Wald χ² = 15.45, p < 0.001) and review length (b = .548, Wald χ² = 154.44, p < 0.001) significantly influence readership while title sentiment is not a significant predictor of readership (b = -.014, Wald χ² = 11, p = .737) (See Table 5).

<table>
<thead>
<tr>
<th>Table 5: Regression Output for Equation 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
</tr>
<tr>
<td>(Constant)</td>
</tr>
<tr>
<td>Review extremity</td>
</tr>
<tr>
<td>Review length</td>
</tr>
<tr>
<td>Title sentiment</td>
</tr>
</tbody>
</table>

*** p < 0.001 (two-tailed significance); NS: Non-significant

The results of binomial regression test revealed that utilitarian cues (b = .100, Wald χ² = 8.66, p < 0.01), hedonic cues (b = .237, Wald χ² = 152.15, p < 0.001), and review sentiment (b = .085, Wald χ² = 13.04, p <
Effect of Central and Peripheral Cues on Review Helpfulness

0.001) significantly influence review helpfulness. In contrast, the effect of review readability on review helpfulness was not significant (b = .008, Wald $\chi^2 = .52, p = .473$). As shown in figure 4, the moderating effect of product type on review utilitarian cues (b = .116, Wald $\chi^2 = 11.78, p < .001$) and review hedonic cues (b = -.267, Wald $\chi^2 = 71.25, p < 0.001$) was significant (See Table 6). The significant moderating effect of product type reveals that the positive effect of utilitarian cues on review helpfulness is stronger for functional products and the significant effect of hedonic cues is stronger for expressive products. Figure 4 shows the results of model testing.

### Table 6: Regression Output for Equation 2

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>.689***</td>
<td>.084</td>
<td>67.90</td>
</tr>
<tr>
<td>Utilitarian cues</td>
<td>.100***</td>
<td>.034</td>
<td>8.66</td>
</tr>
<tr>
<td>Hedonic cues</td>
<td>.237***</td>
<td>.019</td>
<td>152.15</td>
</tr>
<tr>
<td>Review sentiment</td>
<td>.085***</td>
<td>.024</td>
<td>13.04</td>
</tr>
<tr>
<td>Readability</td>
<td>-.008NS</td>
<td>.011</td>
<td>.52</td>
</tr>
<tr>
<td>Product * Utilitarian cues</td>
<td>.116***</td>
<td>.034</td>
<td>11.78</td>
</tr>
<tr>
<td>Product * Hedonic cues</td>
<td>-.267***</td>
<td>.032</td>
<td>71.25</td>
</tr>
</tbody>
</table>

*** p < 0.001 (two-tailed significance); NS: Non-significant

### Post-hoc Analysis

Online customers may not read too long reviews because it takes too much time and effort to read them. According to Cao et al. (2011) some reviews are too long to absorb the attention of customers and may not be read by them. This study examine for the quadratic relationship of the review length on readership to test whether too short or too long reviews are less likely to be read by the customers. We used negative binomial regression (See Equation 3) to add the quadratic relationship of review length to equation 1.

$$\text{Total votes} = \beta_0 + \beta_1 \text{Review extremity} + \beta_2 \ln(\text{Review length}) + \beta_3 (\ln(\text{Review length}))^2 + \beta_4 \text{Title sentiment} + \varepsilon \text{ (Equation 3)}$$

The negative binomial regression model was significant (Chi-Square = 168.02, df = 4, p < 0.001). The results of the negative binomial regression model revealed that review extremity and review length have positive significant effects on readership. The test results also show that title sentiment and square of review length does not have a significant influence on readership (See Table 5).
Table 7: Regression Output for Equation 3

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>.919***</td>
<td>.012</td>
<td>13.02</td>
</tr>
<tr>
<td>Review extremity</td>
<td>.264***</td>
<td>.066</td>
<td>16.14</td>
</tr>
<tr>
<td>Review length</td>
<td>.163***</td>
<td>.034</td>
<td>151.38</td>
</tr>
<tr>
<td>Title sentiment</td>
<td>-.009NS</td>
<td>.043</td>
<td>.04</td>
</tr>
<tr>
<td>Review length^2</td>
<td>.046NS</td>
<td>.028</td>
<td>2.59</td>
</tr>
</tbody>
</table>

*** p < 0.001 (two-tailed significance); NS: Non-significant

Discussion

This study investigates the effect of peripheral and central cues on OCR performance. The results of this study reveal that consumers tend to read extreme reviews. Moreover, we find that longer reviews are more likely to be read by consumers than shorter ones. Surprisingly, in the post-hoc analysis, we found that there is no quadratic relationship between review length and readership. This shows that review length positively influences the readership of the review even the review is too long and it takes too much time and effort to be read. One possible explanation for this finding is that the reviews in our sample are not that long (Mean = 106.84, SD = 138.31) (See Table 3). Additionally, we find that sentiment of the title of a review does not have a significant effect on its readership. The results confirm that consumers read reviews based on rational thinking and not emotions (Wang 2006). In fact, customers prefer to read those reviews that seem to be more informative not emotional.

The results of this study also show that reviews containing more utilitarian and hedonic cues are perceived to be more helpful. These observations confirm the findings of previous studies that more informative reviews are perceived to be more helpful by consumers (Johnson and Payne 1985). We also find that reviews with high amount of sentiment are perceived more helpful by the consumers. This contradicts the findings of previous studies suggest that total sentiments on a review does not affect its helpfulness (Salehan and Kim 2014). By default, customers read reviews to understand the opinion of others about a product. Sentimental reviews better reflect the experience of the author compared to neutral ones.

Surprisingly, we find that readability of the text of a review has no significant effect on its helpfulness. One possible reason is that ARIs for almost all reviews were low enough (Mean = 4.85, Median = 4.34, SD = 2.79) to be understandable for consumers (Senter and Smith 1967). Thus, the effect of readability on helpfulness was not significant. Finally, the results of this study show that consumers looking for functional products perceive reviews containing utilitarian cues as more helpful. In contrast, consumers looking for expressive products perceive reviews containing hedonic cues more helpful.

Implications

This study has implications for both academia and practice. From a theoretical perspective, this study successfully applies ELM in the context of OCR performance that was not done by previous studies. Using ELM, we investigated the concept of OCR performance in two steps. The first step is a consumer’s decision to whether or not read a review which is influenced by peripheral cues. The second step is to decide whether the review was helpful or not which is affected by central cues. Hence, we show how ELM can be used to study different dimensions of performance of OCR. Moreover, to best of our knowledge this study is the first to examine the effect of utilitarian and hedonic cues on review helpfulness. Prior researches mostly investigated the effect of factors such as total word count, review extremity, reviewer expertise and credibility, and review sentiment (e.g., Cao et al. 2011; Huang et al. 2015; Mudambi and Schuff 2010; Zhu et al. 2014). We examine utilitarian and hedonic cues embedded in the text of a review. Hence, unlike most of the previous studies, we use the textual information contained in reviews to predict their performance. Future studies may look at other subjective information that could be extracted from the text of reviews in order to predict helpfulness. Finally the findings of this study contributes to the existing literature by introducing product type as a mediator of the effect of utilitarian and hedonic cues on review helpfulness. Few previous studies have examined the moderating effect of product type (e.g., Mudambi and Schuff 2010). This study shows that people expect different types of information based on the type of the product they want to buy.
This study also has implications for practice. First, this study suggests that consumers who want to buy functional products are looking for utilitarian cues while those looking for expressive products are prefer reviews that contain hedonic cues. Thus, online shopping websites may allow their users to sort reviews based on the amount of utilitarian or hedonic cues embedded in them. Machine learning approaches can be used to extract such information from text of reviews. Moreover, the results show that different people look for different information in reviews. Hence, we suggest online shopping websites to provide their users with multiple methods to sort OCR. Multiple sorting methods will reduce search costs and improve the shopping experience of online consumers.

**Limitations and future research**

Our study suffers from a number of limitations. First, coding procedure could impose information loss (Oh, Agrawal and Rao 2013). To capture exact definitions of different constructs it was an inevitable choice to use the coding technique. In the future research, other methods such as text mining can be used to extract peripheral and central cues to overcome the hand coding limitation. Text mining technique is an appropriate method when we want to compare contents of large amount of textual information together (Koohikamali and Kim 2015). The judgment of coders is always derived subjectively. However, the shared beliefs across coders could accurately represent the information. Second, in our study the number of coders was four. According to previous studies, to allow calculations of reliability test the minimum number of coders is two (Lombard et al. 2002; Neuendorf 2011). However, to minimize subjectivity of coders the future research can consider more coders with greater diversity.

Third, we only analyzed reviews about products available on Amazon. We could include reviews about businesses and services to better understand performance of online reviews. We believe that all of the OCR helpfulness aspects identified in our study could be further examined. Previous research in this area showed that there are still many aspects of helpfulness that should be determined. In this study we only focused on the variables about the review itself. Therefore we did not studies other variables suggested by previous researches such as reviewer experience and impact (Huang et al. 2015) and etc. These unexplored area provide directions for future research. Specific conclusion of this study is that there are much remained to be explained in this area. First, the influence of review manipulation on review helpfulness is an interesting area of research. In addition, our study defined review helpfulness and readership as indicators of review performance. Other antecedents of performance of OCR and their relationship could be considered in future studies. Third, information available on reviewers' profiles (e.g. wish list items, waiting list items, purchase history) can be used to understand helpful votes they receive. Finally, the reviews we analyzed in this study lack language and cultural diversity. Different cultures express emotions differently (Takahashi, Ohara, Antonucci and Akiyama 2002). Thus, we suggest future studies to include online shopping websites containing reviews from other languages and cultures to increase diversity.

**Conclusion**

This study serves as initiative attempt to investigate the performance of OCR. Results show two indicators of OCR performance are readership and helpfulness that are influenced by peripheral and central cues. Peripheral cues (review extremity and review length) influence the readership of OCR. On the other hand, central cues (utilitarian cues, hedonic cues, and review sentiment) have significant effects on helpfulness of OCR. Two indicators of OCR performance could be used in sorting mechanisms of reviews.
References


Greene, W.H., 1994 "Accounting for excess zeros and sample selection in Poisson and negative binomial regression models."


## Appendix 1. Coding Scheme

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
</table>
| **Utilitarian cues** | An online customer review on Amazon that explicitly contain cues about inherent product features, product functionalities, and practical use of products highly contains utilitarian cues (Schulze, Schöler and Skiera 2014). Utilitarian cues indicate functional and instrumental cues of products (Mano and Oliver 1993). Based on this perspective when customers use a product they objectively view symbols of products (Palazon and Delgado-Ballester 2013). Overall, hedonic cues provide information about useful and functional premises (Jiang et al. 2010; Palazon and Delgado-Ballester 2013). **Examples.**  
1. My review here is pretty simple as we've only had our ... for a few weeks. ... I've not played around with the functionality much but can say that the sensor reheat function works very well for reheating things. Just put the item in, hit sensor reheat + start and it does the rest. That being said, be careful when reheating certain liquids such as milk or cream. Likes - (in no order) A - Size (a good compromise and perfect for our needs - two adults, no kids) B - Functionality C - Looks. Dislikes - (in no order) A - Interior light works when unit is on but not when you open the door!? B - Brushed stainless finish looks nice but shows finger prints and smudges very easily. C - Sometimes when you push the button, the door doesn't always 'pop' open all the way, instead it kind of opens 'halfway' and you have to put your finger underneath to finish the job. Overall, I would definitely recommend this unit to others. As it's been less than a month, I cannot say how reliable it will end up being though but am keeping my fingers crossed. If we have any problems, I'll update this review.  
2. I bought this microwave at Best Buy. The inverter technology works great. It is the best cooking microwave I have ever owned. It cooks frozen entrees and vegetables very well and without the burned edges you frequently get in traditional magnetron microwaves. ...While the inverter cooking technology may be a big step forward, the unit itself is cheaply made and has several issues. Here they are in no particular order: It's a loud beast. Easily twice as loud as any other microwave I've ever owned. The small LED display is difficult to read from any angle other than straight on. ... The interior light does not come on when the door is open. It only lights up when the unit is operating. The door doesn't open/close smoothly. ... You have to continuously press the power level button until it cycles around to the power level you want. ... Overall, I like the unit despite the many faults I've listed. ... |
| **Hedonic cues**   | Hedonic values imitate different feelings of excitement when using a product (Grange and Benbasat 2014). An online customer review on Amazon containing information about fun, exciting, delightful, thrilling, and enjoyable experiences of customers encompasses hedonic cues (Schulze et al. 2014). Hedonic cues usually reflect emotions and feelings (Hirschman and Holbrook 1982; Palazon and Delgado-Ballester 2013). Based on this perspective when customers use a product they subjectively view symbols of products (Palazon and Delgado-Ballester 2013). Overall, hedonic cues provide information about pleasurable and experimental premises (Jiang et al. 2010; Palazon and Delgado-Ballester 2013). **Examples.**  
1. I was blown away by how beautiful this necklace is in person, it's as beautiful as or more so than it is in the picture. I particularly love the chain that comes with it. When light hits it, the chain and the purple amethyst both sparkle and they look amazing together! I feel like I need to start wearing nicer clothes, because I intend on wearing this every day and it looks a bit too fancy to be worn with jeans and a t-shirt. Definitely worth the money and then some. I got free super saver shipping from Amazon with my order, and I received my necklace in three days when it should have taken five to seven. I am very pleased.  
2. I bought two of these for my daughters. I would love one myself. It was such a great buy. The pendant is beautiful and the necklace is stunning by itself. Usually you get a "throw away" chains, but this one is shiny and expensive looking, plus it is sturdy. |