Evaluating Online Review Helpfulness Based on Elaboration Likelihood Model: the Moderating Role of Readability

Completed Research Paper

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Abstract

It is important to understand factors affecting the perceived online review helpfulness as it helps solve the problem of information overload in online shopping. Moreover, it is also crucial to explore the factors' relative importance in predicting review helpfulness in order to effectively detect potential helpful reviews before they exert influences. Applying Elaboration Likelihood Model (ELM), this study first investigates the effects of central cues (review subjectivity and elaborateness) and peripheral cues (reviewer rank) on review helpfulness with readability as a moderator. Second, it also explores their relative predicting power using the machine learning technique. ELM is tested in online context and the results are compared between experience and search goods. Our results provide evidence that for both types of products review subjectivity can play a more significant role when the content readability is high. Furthermore, this study reveals that the dominant predictor is varied for different product types.

Keywords: Review helpfulness, Elaboration Likelihood Model (ELM), readability, search goods, experience goods

Introduction

Customer-generated review, as a form of electronic word of mouth (eWOM), has proliferated online due to the recognition that it influences customer's decision-making (Forman et al. 2008). While the abundance of review information makes it easier for customers to assess product features and quality, the numerous reviews can result in the problem of information overload (Fang et al. 2016). Reading all the reviews seems to be impossible. Thus, many e-commerce platforms such as Amazon.com, allow people to evaluate the helpfulness of online customer reviews and sort reviews by helpfulness. Reviews perceived as helpful tend to offer greater value to potential customers and contribute to their confidence in decisions (Liu and Park 2015). Thus, not all the reviews have the same effects and reviews with higher perceived helpfulness tend to be more influential than others (Baek et al. 2012). Prior research has supported the positive influence of the perceived review helpfulness on the customer's purchase decision (Chevalier and Mayzlin 2006). By facilitating customers, review helpfulness can attract and retain more customers to the platform and improve the platform's reputation and performance. For example, review helpfulness function is estimated to bring in approximately $2.7 billion extra revenue to Amazon.com (Cao et al. 2011).

Given the importance of review helpfulness on both consumers and practitioners, identifying factors that contribute to the review helpfulness is critical to the e-marketplace. The existing literature has paid rich attention to various review properties including text-based features and reviewer characteristics (Fang et al. 2016; Liu and Park 2015). However, few studies have investigated helpfulness based on the persuasion theory. The influence of perceived helpfulness reflects the persuasiveness of the review. According to the Elaboration Likelihood Model (ELM)-a dual process theory of persuasion, different information processing routes, namely central route and peripheral route, require different levels of cognitive efforts and the way of processing depends on the recipient's motivation or ability (Petty and Cacioppo 1986). The readability of a review represents the ease of understanding of the content, which may affect customers' willingness and ability to process the information. However, whether review readability can alter the importance of central cues and peripheral cues in review helpfulness is rarely explored. Thus, the first objective of this study is to evaluate online review helpfulness based on ELM with review readability as a moderator.

Moreover, previous studies on review helpfulness focus more on the correlations whereas little is known yet on the comparative influences of factors in predicting review helpfulness. The prediction of review helpfulness enables sellers to identify reviews that may exert considerable influences beforehand. After identifying potential helpful reviews, they can cope with both positive and negative aspects in reviews to alleviate negative influences or promote positive influences. Thus, the second objective in this study is to figure out the relative predicting power of different factors. Additionally, this study divides products into two types-search and experience, as prior research has documented that the effects of online review vary by the product type (Lee and Shin 2014). This study aims to evaluate the influences separately to see how our model works differently under different product types. The data is obtained from Amazon.com using a web data crawler.

Our work is designed to extend past research in the following ways. Firstly, we contribute to the ELM theory by linking the persuasion theory to online review helpfulness and examining ELM in the online context. Secondly, based on ELM, we contribute to the work on the antecedents of review helpfulness by exploring how readability may shape the information processing of central cues (review elaborateness and subjectivity) and peripheral cues (reviewer rank). Our results show that the subjectivity of review content can play a more significant role in review helpfulness when the content readability is high, while the peripheral cue is not affected by readability. Thirdly, we compare the influences under different product types. By examining our proposed relationships respectively for experience and search goods, we confirm the influence of review subjectivity, elaborateness and reviewer rank on review helpfulness for both types of products. We also find that for experience goods the influence of review elaborateness is weakened when the readability is high, while for search goods it is not affected.

In addition, this paper contributes to the online review research by exploring the comparative importance of central cues and peripheral cues in predicting review helpfulness. Our results highlight that not all the cues are equally important in making prediction. For example, for experience goods reviewer rank is the dominant predictor while for search goods the interaction between review elaborateness and readability turns out to be the most important. Furthermore, we apply scholastic Gradient Boosted Decision Trees (GBDT), a machine learning technique to test the model along with regression. Through illustrating the use of machine learning technique to make predictions based on real data, the study offers insights for practitioners and scholars.

Theoretical Background

Review Helpfulness and Elaboration Likelihood Model (ELM)

Review helpfulness has attracted increasing attention as academics and practitioners start to recognize the importance of review text in shaping consumer attitude and behavior (Schlosser 2011). Previous studies have focused on the determinants of review helpfulness, such as text readability (Korfiatis et al. 2012), subjectivity (Ghose and Ipeirotis 2011), emotions embedded in reviews (Yin et al. 2014) and reviewer characteristics (Baek et al. 2012; Pan and Zhang 2011). There are also some studies that attempt to propose different models for optimizing the prediction of online review helpfulness (e.g., Ngo-Ye and Sinha 2014).

Review helpfulness reflects the persuasiveness of information (Zhang et al. 2010). Reviewers often post reviews with the intention to influence or persuade others. Moreover, people usually consider a review as helpful when it contributes to their evaluations and purchase decisions, which can be associated with the process of being persuaded. Therefore, evaluating review helpfulness can be interpreted as evaluating persuasion effectiveness. One of the important theories to explain persuasion effectiveness is ELM from social psychology literature. ELM is a dual process theory of persuasion. First developed by Petty and Cacioppo (1981), ELM argues that individuals process information through either a central route or a peripheral route, depending on their motivation and ability to elaborate the argument. If individuals are motivated and able to scrutinize information, they will go through the cognitively effortful central route. In this case, issue-relevant argument quality is more important than peripheral cues in persuasion process. Contrariwise, when individuals have low involvement or little knowledge regarding the issue, they will follow the less thoughtful peripheral route and tend to rely more on simple cues such as source expertise and likability than the argument quality (Petty et al. 1997).

ELM has been employed to study the effects of online reviews (Cheung and Thadani 2012; Zhang et al. 2014). Based on ELM, previous studies have investigated the roles of different variables from central and peripheral routes, together with the recipient's involvement and expertise as moderators (see Table 1). However, limited works have incorporated ELM to study review helpfulness. While prior research has already associated helpfulness with persuasiveness, few of them really study helpfulness using persuasion theory. Moreover, previous literature mainly investigates the direct effect of readability on review helpfulness, and this study tries to further explore its moderating role based on ELM.

Central Cues	Peripheral Cues	Moderator	Dependent Variable	Source
Review quality	Review quantity	Involvement	Purchase intention	Park, Lee and Han (2007)
Information quality	Source expertise & trustworthiness	--	Review adoption	Cheung, Lee and Rabjohn (2008)
Type of reviews	Number of reviews	Level of expertise	Purchase intention	Park and Kim (2008)
Quality of negative reviews	Proportion of negative reviews	Involvement	Purchase intention	Lee, Park and Han (2008)
Content of reviews	Review rating, reviewer's credibility	--	Review helpfulness	Baek, Ahn and Choi (2012)
Argument quality	Source credibility, review consistency & sideness	Recipient expertise & involvement	Review credibility	Cheung, Sia and Kuan (2012)

Table 1. Online Review Studies Using ELM

Product Types

Products can be generally divided into two categories based on whether their quality can be evaluated with the information searched before purchase, namely search goods and experience goods (Jourdan 2001). Search goods, such as greeting cards, are products that the quality can be assessed before purchase based on available information. One can easily check the attributes of greeting cards through product description and pictures provided by online sellers and peer customers. Whilst experience goods, such as books, are products that customers cannot verify product trait until they use it for a while. For example, people may refer to peers' comments and book summaries for information, but they can only come up with their own judgment after reading the book. With the help of the Internet, people can easily access product information and online sellers are willing to make such information available (Rentmeester 2007). Thus, for search goods customers are likely to pay attention to the information on specific product features in advance (Ghose and Ipeirotis 2011). In terms of experience goods, though customers cannot confirm product quality, they still can make inference based on secondary experience provided by other users. Therefore, compared to search goods, experience goods may encourage people to pay more attention to online reviews with testimonial evidence rather than those with existing product information (Dillard and Shen 2013). Therefore, this study extends prior research and compares how persuasion works under different circumstances, specifically how the importance of factors weight differently under different types of products.

Research Framework

Central Cues

ELM has highlighted the role of message-based cognitions in persuasion. Central cues which refer to the informational content in the message, are important determinants of attitude when one is motivated and cognitively able to process information (Petty et al., 1983). In the online shopping environment, the arguments in review content provide information that helps customers gain knowledge about products and services, and thus are seen as the central cues in the information processing.

Review Elaborateness

The study of Chevalier and Mayzlin (2006) shows a positive relationship between the length of reviews and product sales. It indicates that the amount of textual information provided in the review, known as review elaborateness, accounts for the customer's decision making (Racherla and Friske 2012). A larger quantity of information often contains detailed product attributes and more arguments, which improves the persuasiveness. Prior literature also suggests that the enriched content available to decision makers boost their confidence in the decisions (Tversky and Kahneman 1974). Thus, reviews with extensive information decrease customers' uncertainties of the product and make them confident in their purchase decisions (Mudambi and Schuff 2010). Moreover, the review elaborateness signals the reviewer's involvement and efforts, and customers are more likely to respond to these enthusiastic reviews (Pan and Zhang 2011). Therefore, review elaborateness is expected to improve the perceived helpfulness of the review. Hence, we propose that:

H1: Review elaborateness is positively associated with review helpfulness.

Review Subjectivity

Apart from the information embodied in the message, the social psychology literature suggests that the influence of linguistic styles in the message should not be overlooked (Ireland and Pennebaker 2010). In terms of the linguistic styles in the online review, it is found that reviewers write both subjective and objective statements (Ghose and Ipeirotis 2011). Subjectivity here refers to the aspects of language delivering personal opinions, speculations or evaluations (Wiebe et al., 2004). Personalness is an essential feature of subjectivity. Subjective statements in online review provide evidence for potential customers through reviewers' personal experiences or evaluations (Ghose and Ipeirotis 2011). Objective information in the review can be similar to the seller's description of product attributes, while subjective argument provides evidence from personal perspective which requires more cognitive efforts and can be perceived as more helpful. Hence, hypothesis is proposed as follows:

H2: Review subjectivity is positively associated with review helpfulness.

Peripheral Cues

Peripheral cues, such as source characteristics, can affect attitude without affecting the argument processing (Petty and Cacioppo 1986). They require less cognitive efforts than central cues in information processing (Chaiken 1980). In the online shopping environment, reviewer characteristics are seen as the peripheral cues which are easy for potential customers to access (Baek et al., 2012).

Reviewer Rank

In the online environment where communication is computer-mediated, verifying source credibility is not an easy task. To reduce the concerns on reviewer credibility in the online marketplace, many platforms come up with the reviewer ranking system which facilitates customers to assess the reviewer. By ranking reviewers based on their past records, the system selects out reviewers with high contributions as top reviewers and differentiates them from others. The rank indicates the reviewer's reputation, reduces uncertainties faced by customers, and in turn promotes trust towards the review (Racherla and Friske 2012). Prior research suggests that customers tend to rely on reviewer reputation as an indication of review quality (Liu and Park 2015). Thus, it is expected that reviews posted by reviewers with higher ranks tend to be perceived as more helpful. In this study, as higher rank is represented by smaller number, the hypothesis is proposed as follows:

H3: The rank number of reviewer is negatively associated with review helpfulness.

Readability as Moderator

Readability can be defined as the extent to which a written text is easy to understand, and its main determinant can be the complexity of wording (Senter and Smith 1967). According to ELM, central route demands cognitive efforts to process information. Hence, without certain level of cognitive capability, customers may be reluctant to comprehend the information (Dainton and Zelley 2014). The ease to understand a text decides whether readers are willing to make more efforts in comprehending information of the statement. It has been investigated that text readability can amplify the impact of argument (Armstrong 2010). A brief and clear statement allows people to capture the meaning of argument easily no matter the argument is strong or weak. If the statement in a review has poor readability, readers are less capable and less motivated to process the contained information. In that case, they may refer to peripheral cues such as information source which require less efforts in order to assess information quality more intuitively. Hence, it is expected that which route of ELM is the main way to comprehend the statement depends on the level of readability. Thus, the hypotheses for moderating effects are proposed as follows.

H4a: Readability strengthens the association between review elaborateness and helpfulness.

H4b: Readability strengthens the association between review subjectivity and helpfulness.

H4c: Readability weakens the association between reviewer rank and review helpfulness.

Figure 1 presents the research framework.

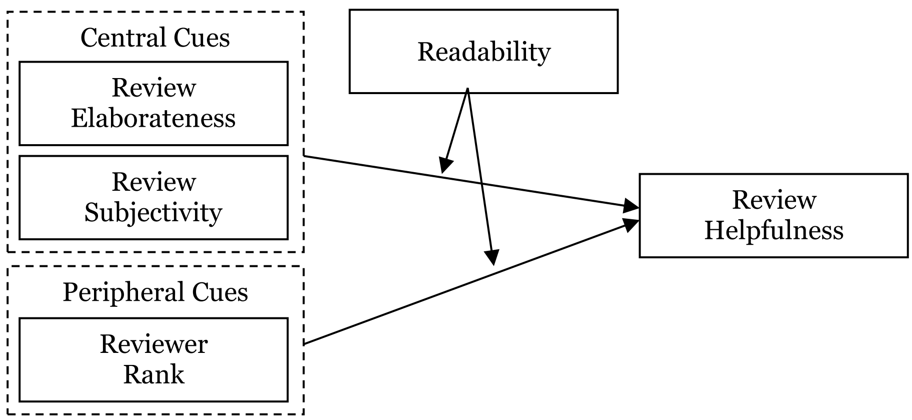

Figure 1. Research Framework

Methodology

Data Collection and Variable Operationalization

Data used in this study was collected from Amazon.com. Books were selected as the representative experience goods while greeting cards were chosen to represent search goods (Chen 2008; Franke et al. 2004). We used web data crawler to extract review and reviewer information. In total 1,493 online reviews of 88 books and 1,295 online reviews of 137 greeting cards were extracted for analysis. The operationalization of variables is listed in Table 2.

Variable	Operationalization	Reference
Review Helpfulness	Number of people who found the review helpful	Liu and Park (Liu and Park 2015)
Review Subjectivity	Self-referencing words such as *I, me, my,* calculated using Linguistic Inquiry and Word Count (LIWC)	Pennebaker (2001)
Review Elaborateness	Number of words in the review	Racherla and Friske (Racherla and Friske 2012)
Reviewer Rank	Rank number of reviewer listed in Amazon.com. Smaller number represents higher rank, while larger number represents lower rank.	Baek et al. (Baek et al. 2012); Ngo-Ye and Sinha (Ngo-Ye and Sinha 2014)
Readability	The Automated Readability Index (ARI) $\text{ARI} = 4.71 \times \frac{total\ number\ of\ characters}{total\ number\ of\ words} + 0.5 \times \frac{total\ number\ of\ words}{total\ number\ of\ sentences} - 21.43$	Hu et al. (2012)

Table 2. Operationalization of Variables

Data Analysis

To develop a comprehensive understanding of how factors influence review helpfulness, this study uses both regression analysis and machine learning technique. Regression analysis is applied to test the model by examining the significance of correlations between the factors and review helpfulness. Whereas machine learning method is used to test prediction effects and compare the predictive importance of the factors. In terms of the regression model, the dependent variable-the number of helpful votes is a count data variable, and the relationships between variables are estimated using negative binomial regression (Fang et al. 2016).

A machine learning approach - Gradient Boosted Decision Tree (GBDT) - is applied to model the factors predicting helpfulness. GBDT is a promising approach that can deal with the non-linear responses and interactions among the predictors (Elith et al. 2008). Combining the advantages of decision trees and boosting, GBDT can provide better predictive performance than that in a single predicting model. It is suggested by recent papers that GBDT outperforms many other machine learning models (Li et al. 2007; Zheng et al. 2008). A brief introduction to the algorithms of GBDT is discussed as follows.

$f(x), x \in R^N$ is a basic regression tree which partitions the spaces of the joint explanatory variable values into disjoint regions $R_j, j = 1, 2, \dots, J$ that is linked with each of the terminal node of the tree. A constant predictor value γ_j is assigned to each regionR_j such that $f(x) = \gamma_j$. A complete tree is represented as a piecewise constant function:

$$T(x;\ \Theta) = \sum_{j=1}^{J} \gamma_j\, I(x \in R^N) \qquad (1)$$

where $\Theta = \{\mathrm{R_j}, \gamma_j\}_1^J$ and I is the indicator function. The parameter space delta is estimated by minimizing the total loss for a given loss function $\psi(y_i, \gamma_j)$:

$$\hat{\Theta} \ = \ \arg\min_{\Theta} \sum_{j=1}^{J} \sum_{x_i \in R_j} \psi(y_i, \gamma_j) \qquad (2)$$

To find disjoint regions and solve the above minimization problem, numerous heuristics are conducted.

Aggregating the trees described above forms a boosted tree $f_M(x)$ and each tree is calculated in sequential stages:

$$f_M(x) = \sum_{m=1}^{M} T\,(x; \Theta_m) \qquad (3)$$

where Θ_m at stage m is estimated to fit the residuals from the $m - 1th$ stage:

$$\hat{\Theta} = \arg\min_{\Theta} \sum_{i=1}^{N} \psi(y_i, f_{m-1}(x_i) + \gamma_{jm}) \qquad (4)$$

We apply the GBM package (Elith et al. 2008; Ridgeway 2007) in R (http://r-project.org) to conduct the analysis. The required parameters include 1) the loss function (distribution); 2) the number of iterations (number of trees); and 3) the model regularization (or shrinkage) parameter (Hastie et al. 2009). The shrinkage parameter scales the contribution of each additional tree. Smaller shrinkage values result in slower learning rates and need more iteration trees at the cost of more computation time.

Poisson distribution is set as the loss function for the target variable. The training and test sets were created by randomly splitting 70% training and 30% test sets from the sample. After testing a number of settings, the shrinkage value is to be 0.001 for calibration so that the best trade-off between computation time and predictive performance is attainted. The number of trees is set to be 9230, which is the optimal number of iteration estimated by the independent test set.

Results

Table 3 reports the descriptive statistics for the variables. The values of Variance Inflation Factor (VIF) range from 1.04 to 1.21 with a mean of 1.11 for experience goods, and from 1.01 to 1.05 with a mean of 1.03 for search goods. These factors are well below the threshold value of 10 (Ryan 1997). Moreover, the interaction terms are mean-centered to alleviate possible problems of multicollinearity and to enhance the interpretability of our results (Aiken et al. 1991).

Variables	**Experience Mean (SD)**	**Search Mean (SD)**
Review Helpfulness	35.6973 (175.0650)	4.8100(56.7584)
Review Subjectivity	4.6261 (3.6789)	4.4426 (4.3121)
Review Elaborateness	123.7696 (157.2457)	48.1328 (76.3005)
Rank No. of Reviewer (million)	3.9145 (10.2051)	4.9822 (11.0920)
Readability	5.7789 (3.6961)	4.7698 (3.4922)

Table 3. Descriptive Statistics

The regression analysis results are shown in Table 4. Model 1 includes only the independent variables and Model 2 includes both the independent variables and interaction terms. For both experience and search goods, review subjectivity and review elaborateness have significant positive influence on review helpfulness, while the rank number of reviewer shows significant negative association with review helpfulness. As shown in Model 2, the coefficients for subjectivity, elaborateness and rank number of reviewer are correspondingly 0.0349 ($p<0.05$), 0.0074 ($p<0.00$) and -0.0528 ($p<0.00$) for experience goods, and 0.0832 ($p<0.00$), 0.0123 ($p<0.00$) and -0.0235 ($p<0.00$) for search goods. Hence, H1, H2, H3 are supported.

Our regression analysis also indicates that, for both experience and search goods, readability significantly moderates the relationship between review subjectivity and review helpfulness. The coefficient for the interaction (review subjectivity × review helpfulness) is 0.0093 ($p<0.05$) for experience goods and 0.0111 ($p<0.01$) for search goods. Figure 2(A) and Figure 2(C) reveal that, for both types of products, reviews with high level of subjectivity get more helpful votes than reviews with low level of subjectivity, and such relationship is more positive when readability is high. Therefore, H4b is supported. Surprisingly, readability is found to significantly and negatively moderate the relationship between review elaborateness and review helpfulness for experience goods ($p<0.00$), such that the positive relationship between review elaborateness and review helpfulness is stronger when readability is low (see Figure 2(B)). Our results also show that there is no significant moderation effect of readability between review elaborateness and review helpfulness for search goods. Moreover, readability is not a significant moderator for the relationship between reviewer rank and review helpfulness for both product types.

Dependent Variable	Review Helpfulness			
Product Type	Experience		Search	
Independent Variables	Model 1	Model 2	Model 1	Model 2
Review Subjectivity	0.0295*	0.0349*	0.0750***	0.0832***
Review Elaborateness	0.0061***	0.0074***	0.0125***	0.0123***
Rank No. of Reviewer	-0.0554***	-0.0528***	-0.0220***	-0.0235***
Readability		0.0103		0.0389*
Interactions				
Review Subjectivity ×Readability		0.0093*		0.0111**
Review Elaborateness ×Readability		-0.0007***		-0.0002
Rank No. of Reviewer ×Readability		-0.0006		-0.0014
Observations	1,493	1,493	1,295	1,295
Pseudo R2	0.0341	0.0395	0.0791	0.0806

*p<0.05, **p<0.01, *** p<0.00

Table 4. Regression Results

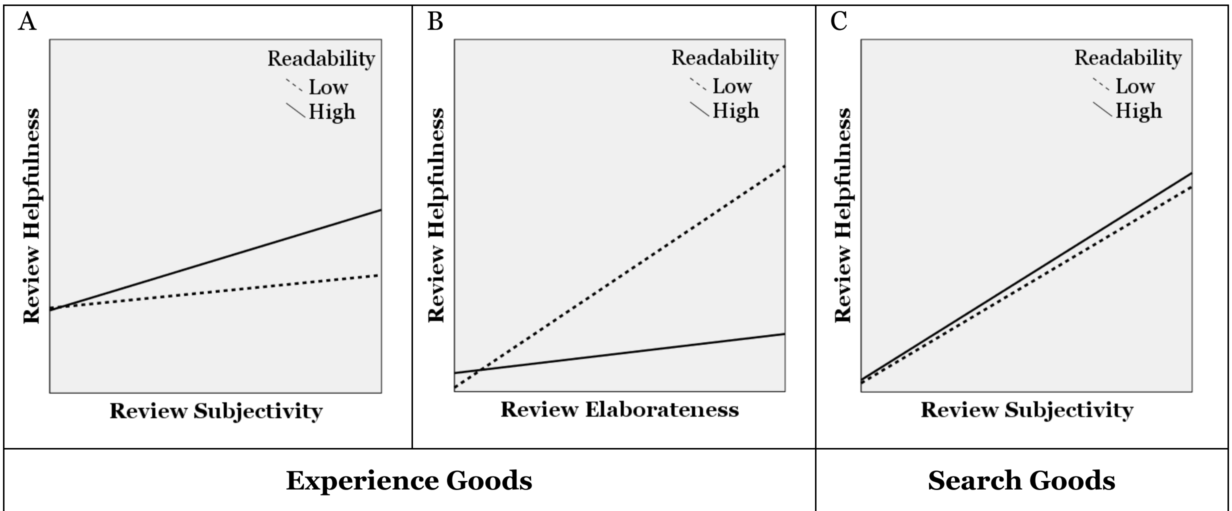

Figure 2. Moderating Effects of Readability

GBDT is run to further understand the relative influences of variables in predicting review helpfulness, and the results are shown in Table 5. The area under the receiver operating characteristic curve (AUC) of the models are 0.4993 for experience goods and 0.4759 for search goods, indicating that both prediction models have relatively good performances. High relative influence value indicates high importance in prediction. For experience goods, reviewer rank is the dominant predictor of review helpfulness, review elaborateness has the second highest contribution to prediction, and their interactions with readability are the third and fourth influential predictors correspondingly. Review subjectivity ranked the fifth, followed by readability and their interaction. For search goods, the interaction between readability and review elaborateness is the most important predictor of review helpfulness. Review elaborateness and reviewer rank are found to be the second and third most influential predictors, followed by the interaction between readability and reviewer rank. Readability, review subjectivity and their interactions are not as important as the other predictors, and are ranked as the sixth, seventh and fifth correspondingly.

Variable	Influence Rank (Relative Influence%)	
	Experience Goods	Search Goods
Review Subjectivity	5 (0.1963)	7 (0.0036)
Review Elaborateness	2 (17.2015)	2 (24.6894)
Rank No. of Reviewer	1 (73.5045)	3 (19.1014)
Readability	6 (0.1017)	6 (0.0193)
Readability×Review Subjectivity	7 (0.0659)	5 (0.0243)
Readability×Review Elaborateness	4 (2.6672)	1 (55.8955)
Readability×Rank No. of Reviewer	3 (6.2629)	4 (0.2666)

Table 5. GBDT Results

Discussion

In prior literature, researchers have considered readability as a message characteristic influencing the perceived review usefulness (Liu and Park 2015), but its potential moderating role in relationships between online review factors and review helpfulness may be overlooked (Korfiatis et al. 2012; O'Mahony and Smyth 2010). In this study, we have tested the moderating effects of readability on central and peripheral routes respectively. The results indicate that the text readability would influence the central route. As proposed, the influence of review subjectivity on helpfulness is positively moderated by readability. The positive correlation between subjectivity and review helpfulness is conformed to prior literature suggesting that personal opinion and experience are perceived to be persuasion evidence (Dillard and Shen 2013). When there is higher level of readability, readers can comprehend review content with personal opinions more easily. Otherwise, the perceived helpfulness of personal opinions may be alleviated as the content is not understandable.

When comes to review elaborateness, the moderating effect of readability turns out to be negative for experience goods only. This can be explained by previous findings on possible trade-offs between reading difficulty and review helpfulness (O'Mahony and Smyth 2010). Low readability means more contextualized and complex phrases which offer more technical and professional information related to the products compared to high readability with simple words. In that case, the influences of elaborateness can be strengthened by complexity of the text. Unlike experience goods, the technical and professional words used in reviews about search goods can be similar to the product information on website (Ghose and Ipeirotis 2011), and therefore word complexity may not offer additional insights.

In addition, there is no evidence showing the moderating effect of readability on peripheral routes in this study. One possible explanation can be that in the online environment where people are provided with bunch of reviews, low readability may not offer enough incentives for people to refer to the information source for help even though it requires less cognitive efforts. Instead, potential customers could switch to other piece of reviews to gain insights. In terms of the inconsistent findings with ELM, future research can further explore the way ELM works in online context.

The results from GBDT show that the relative importance of variables in predicting review helpfulness can be different between experience and search goods. In terms of experience goods, the most important predictor is reviewer rank, while for search goods the interaction effect between review elaborateness and readability comes at the first place. This is consistent with findings about the distinguishing characteristics of experience and search goods. For experience goods, opinions shared can be highly personalized, thus customers can be more motivated to verify the credibility of source from which the opinion is provided. Hence, reviewer rank as an indicator of reviewer's source credibility appears to be more important than clearly written and elaborated reviews for experience goods in the prediction (Ghose and Ipeirotis 2011). In contrast, search goods have clearly identifiable features that can be fully checked before consumption. Comments about the product features in the reviews can provide potential buyers with insights to enhance their evaluation about any purchase under consideration. Hence, the elaborated reviews with appropriate level of readability turns out to be the dominant factor in predicting helpfulness for search goods. Besides, although the subjectivity itself is a less important predictor for review helpfulness compared to reviewer rank and review elaborateness, there is still slight difference in ranking between experience and search goods. Subjectivity is relatively more important in prediction for the experience goods. Nevertheless, the second important factor remains the same for both types of products-the review elaborateness. It shows that the amount of information contributes considerably to the prediction of review helpfulness. This is consistent with the prior literature which highlights the role of sufficient information (Mudambi and Schuff 2010).

Conclusion, Implication and Future Research

This paper adopts ELM to investigate the roles of readability, review subjectivity, review elaborateness and reviewer rank in influencing review helpfulness, and compares the predictive importance of variables under different product types. We find that readability positively moderates the relationship between review subjectivity and review helpfulness for both search and experience goods, while it negatively moderates between review elaborateness and review helpfulness only for experience goods. Moreover, reviewer rank is found to be the most important predictor for experience goods, whereas the interaction of readability and review elaborateness has the dominant importance in predicting review helpfulness for search goods.

This paper has the following contributions to the theory. First, we conceptualize factors influencing online review helpfulness from persuasion theory perspective. While previous literature on online review has referred to persuasion studies, little has adopted persuasion theory into the conceptualization (Zhang et al. 2010). In this paper, we propose a theoretical framework with review subjectivity and elaborateness as central cues, and reviewer rank as peripheral cues based on ELM. Moreover, review helpfulness is an aggregate evaluation on online review. Therefore, instead of using personal involvement or expertise as the moderator that influences the persuasion effectiveness of the central and peripheral routes, we bring up readability of text. Readability of text tends to influence readers' motivation and ability to process arguments. The framework developed from traditional ELM is tested in online context and the results are compared between different product types. The results confirm that the moderating role of readability should not be overlooked. Next, apart from testing the significance of correlations between factors and review helpfulness, we also investigate the comparative importance of variables in predicting helpfulness along with the comparison between search and experience goods. While prior literature has highlighted the importance of textual and reviewer features of online review, little is known about the predictive power of variables and across product types (Fang et al. 2016; Mudambi and Schuff 2010). The prediction results complement the regression results and allow scholars to understand review helpfulness more comprehensively. Methodologically, to get more insights on how factors influence review helpfulness, this paper applies the machine learning technique-GBDT based on real world data together with regression analysis.

This paper also has managerial implications. Findings from this paper can assist practitioners to understand how factors influence review helpfulness and help practitioners encourage valuable and high quality reviews. First, this paper clarifies the effectiveness of factors for the practitioners. For example, the positive effects of review subjectivity and review elaborateness on review helpfulness imply that practitioners should offer consumers incentives to write long reviews that disclose their own experiences and opinions. Moreover, practitioners should try to attract customer with high rank and good reputation to purchase the product and write customer review. Second, results of this study indicate that practitioners should tailor their strategies in encouraging valuable consumer feedbacks based on product types. For example, for both types of products, customers should be encouraged to write highly readable reviews that are highly subjective. However, for experience goods such as books, because readability has negative moderation effects between review elaborateness and helpfulness, practitioners should promote long and complex reviews. Third, our findings can further assist practitioners to effectively predict potential helpful reviews for their own product type and then adjust their strategies accordingly. For experience goods, the ranks of reviewers should be considered as the prior predictor of review helpfulness, while for search goods, practitioners should focus more on the length of reviews and their readability when predicting review helpfulness. If the review predicted to receive high helpful votes is negative, practitioners can alleviate potential negative influences by dealing with the complaints in time. They can also prepare for an increase in sales and distribute resources more appropriately beforehand if the review is positive.

Future research can extend this paper in the following perspectives. First, this paper selects books and cards as representative experience and search goods. Future research can increase the variety of products under each product type to further verify the results. Second, online reviews from third-party review websites like Yelp.com may function differently from those listed in online shopping platform, for example, the reviewer characteristics including reviewer rank may be shown more directly on the website. Future research can thus apply ELM to investigate reviews helpfulness in third-party review websites to further explore the way ELM works in online context. In addition, people from different cultural backgrounds are likely to perceive e-commerce platforms differently. While this paper focuses on western online marketplace, future research can investigate different cultural contexts and include cultural factors into the research framework.

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