Understanding the Role of Different Review Features in Purchase Probability

Under second round review, International Journal of Advertising

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Understanding the Role of Different Review Features in Predicting Purchase Probability

Abstract

The role of electronic word-of-mouth (eWOM) has been recognized by marketers and academics, but little research has examined the impact of eWOM on purchase behavior. This study aims to disentangle the effect of different online review features (i.e., argument quality, review valence, review helpfulness, message sidedness, source credibility and reviewer recommendation). Using product reviews and purchase data from an online retailer website, this study investigates the financial impact of online product reviews on purchase decision. This study found that most review or reviewer characteristics influence purchase probability. The results provide insights to dual-process models of persuasion. Managerial implications on how companies should design and manage their online review system are offered.

Keywords: eWOM, online product reviews, heuristic-systematic model, purchase behavior

Understanding the Role of Different Review Features in Predicting Purchase Probability

With the emergence of digital and social media, electronic word-of-mouth (eWOM) has become a powerful source of information influencing purchase decisions. Consumers have constant access to online product reviews from online retailers, brand websites, brand community blogs, and third-party review platforms where consumers can participate and engage in discussions about their consumption experience. Among various forms of eWOM, this study focuses on online product reviews because they are written by consumers who presumably have experience with a product and are actively sought by potential consumers, thereby affecting review readers' purchase decisions more directly. A growing number of studies have identified various effects of online product reviews on consumer attitudes and behaviors (Chevalier & Mayzlin, 2006; Liu, 2006; Maslowska, Malthouse, & Bernritter, 2017). A recent report from the Nielsen Company (The Nielsen Company, 2015) finds that consumers trust recommendations or opinions from other consumers more than traditional forms of advertising such as commercials or product placements on mass media, showing the persuasive power of online product reviews.

Several features of online product reviews have been a subject of scholarly investigation including review quality, valence, mode (e.g., textual, visual, or multi-modal), platform (e.g., company-provided vs. third-party provided), or reviewer characteristics (e.g., experts vs. non-experts). Many studies have examined how the aforementioned online review features influence the level of usefulness or helpfulness of reviews. Some have investigated how a single or combination of these features affect psychological variables such as brand attitudes or trust, or behavioral variables such as purchase intention (Dhanasobhon, Chen, Smith, & Chen, 2007; Doh & Hwang, 2009; Floyd, Freling, Alhoqail, Cho, & Freling, 2014).

The purpose of this study is as follows: First, it extends previous scholarly efforts on

understanding the influence of online product reviews and examines the effects of different review features by testing multiple review characteristics in a single model. In doing so, we also test a possible curvilinear relationship and interaction effects of review features to advance our understanding of the relationship among review characteristics.

Second, this study estimates the monetary impact of online product reviews by linking individual consumers' exposure to them with their actual purchases. The majority of previous studies have focused on psychological variables such as attitudes (see Purnawirawan, Eisend, De Pelsmacker, & Dens, 2015, for a review) or used proxy measures such as sales rank, but research studying actual sales at an individual level is limited (seeFloyd et al., 2014, for a review). This study uses online product reviews and sales data, which enables us to provide empirical evidence of the impact of online product reviews on actual sales. While many existing studies treat review helpfulness (often referred to as usefulness) as a dependent variable (e.g., Mudambi & Schuff, 2010; Quaschning, Pandelaere, & Vermeir, 2015; Schindler & Bickart, 2012; Willemsen, Neijens, Bronner, & de Ridder, 2011), this study considers helpfulness as one of the predictor variables to find out its role in making a purchase decision.

Finally, in contrast to previous research that has focused on experiential goods from Amazon.com, TripAdvisor or Yelp, this study uses data from one of the largest online retailers, which sells various types of search goods (e.g., household items, beauty products, or over-the-counter medicine). This gives us an opportunity to investigate which elements of reviews (review content and/or non-content cues) would matter more when it comes to purchasing everyday products.

In sum, this study looks at the association of different online product review features (i.e., review valence, length, pros and cons, helpfulness, authorship, and product recommendation)

with purchase probabilities. By investigating these features, this study offers theoretical contributions to the literature on information processing as well as managerial insights regarding how firms should manage their online recommendation systems to better serve existing and potential consumers.

Literature Review

Online Product Reviews and the Dual-process Models of Persuasion

Online product reviews can be described in terms of quantitative and qualitative features (Sridhar & Srinivasan, 2012). Quantitative aspects of reviews are often expressed as numerical summaries such as average star ratings and number of reviews. Qualitative aspects present consumers' assessment of a product or a service such as review content. Because quantitative aspects are often displayed above or next to a product description, they can be read by customers without them perusing the textual portion of reviews. Qualitative aspects, on the other hand, require customers to either click on a 'review tab' or scroll down a web page in order to find and comprehend a text. Usually qualitative review features require additional attention and/or action from customers compared to quantitative review features.

This distinction of quantitative and qualitative aspects of online product reviews and the differential levels of attention and motivation required to process them leads us to use the dual-process models of persuasion such as the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986) or the Heuristic Systematic Model (HSM) (Chaiken, 1980) as our conceptual framework to understand the persuasiveness of different online review features. These models are based on the premise that there are two distinctive routes of information processing. Central route or systematic processing assumes that individuals have the ability and motivation to process messages, which results in deeper information processing and lasting attitudinal changes.

In contrast, peripheral route or heuristic processing is associated with using simple decision rules and cues, leading to superficial information processing and temporary attitudinal changes. Table 1 summarizes extant research that applied the dual-process models to online product reviews.

Insert Table 1 about Here

The ELM has been widely used as a framework to explain the ways in which consumers process information provided by online product reviews (Cheng & Ho, 2015; Cheung, Sia, & Kuan, 2012; Park, Lee, & Han, 2007). However, this study takes the HSM as an overarching theoretical framework because of its flexibility in terms of applying the dual paths to persuasion (Zhang & Watts, 2008). Unlike the ELM, which assumes individuals take either the central or peripheral route to persuasion, the HSM posits that the heuristic and systematic processing may occur independently or simultaneously, allowing us to investigate the additive impact of heuristic and systematic processing (Bohner, Chaiken, & Hunyadi, 1994). The HSM specifies three motivations of information processing, namely, accuracy, defense, and impression motivation. Among these three, the accuracy motivation (i.e., the motivation to make objective judgements) is most closely aligned with the context of online product reviews. Todorov, Chaiken, and Henderson (2002) pointed out that both systematic and heuristic processing can lead to accuracy, urging the need to incorporate message or source characteristics related to the two processes. It is noteworthy that the purpose of this paper is not to test the conditions of how systematic and heuristic processes take place. Rather, we apply the dual-process framework of the HSM to identify antecedents of persuasion in the context of online product reviews. Similar to the approach taken by Zhang, Zhao, Cheung, and Lee (2014), we consider that both content-related characteristics and non-content cues affect review readers' purchase decision concurrently.

Online reviews can influence consumers via heuristic or systematic processing since they are composed of content-related characteristics (e.g., argument quality) as well as non-content cues (e.g., average star ratings). As shown in Table 1, previous research has treated argument quality as an important element in systematic processing, whereas other content-related or source-related features such as star ratings or source credibility have been regarded as heuristic cues. Consumers who read reviews can be influenced by a single feature or a combination of them. In addition to argument quality, star ratings, and source credibility, this study includes review helpfulness, message sidedness, and reviewer recommendation as other possible cues that consumers can use while they are processing reviews. We divide these characteristics into message content and message source (i.e., reviewer) characteristics.

Review Content Characteristics

Argument quality. One of the fundamental elements in online reviews is content. People who have the motivation and ability to read reviews (i.e., systematic processing) will pay careful attention to other consumers' opinions about a product that they consider purchasing. People who lack the motivation or ability to read reviews will glance over other cues that signal the quality of a message (i.e., heuristic processing). Previous studies have found that argument quality positively influences information adoption (Zhang & Watts, 2008) or purchase intention (Park et al., 2007; Zhang et al., 2014). For example, Zhang et al. (2014) found that argument quality (i.e., perceived informativeness and persuasiveness) is one of the key determinants of consumers' willingness to purchase products. Park et al. (2007) identified review quality (i.e., relevance, objectiveness, understandability, sufficiency) as one of the antecedents of purchase intention. In many studies, *length* of a message has been regarded as a proxy for information quality (Bosman, Boshoff, & van Rooyen, 2013; Cheng & Ho, 2015; Huang, Chen, Yen, & Tran,

2015; Mudambi & Schuff, 2010) with longer messages expected to provide high quality information on product features. Extant studies suggest a positive linear relationship between review length and its effect on review credibility, helpfulness, or purchase intention.

However, it is also possible that the effect of review length is nonlinear. The reasoning behind this is twofold. First, although longer messages may induce greater certainty than shorter ones, because they are perceived as more complete (Rucker, Tormala, Petty, & Briñol, 2014), previous research has observed that customers write long reviews to express their dissatisfaction (Vasa, Hoon, Mouzakis, & Noguchi, 2012). Second, individuals have a limited cognitive capacity and hence cannot attend to and process all available stimuli (Kahneman, 1973). Therefore, consumers may not be willing or able to comprehend a message that is too lengthy (Huang et al., 2015; Kuan, Kai-Lung, Prasarnphanich, & Hok-Yin, 2015) due to cognitive overload. This implies that the positive impact of review length will reach its maximum at a certain length and then decrease once the length passes this threshold. Thus, we hypothesize that review length has a curvilinear relationship with purchase decision, meaning that the positive effect increases until the length of a review reaches a threshold, and then diminishes.

H1: Review length has an inverted-U relationship with purchase probability.

Review valence. While the length of a message is an indicator of the quality of the message, the *valance* of a review is an indicator that implies the cognitive consequence of customers' attitudes toward a product (Liu, 2006). In an online review system, review valence is expressed in a form of star ratings, which serve as a heuristic cue reflecting the popularity and the quality of a product (Sundar, Oeldorf-Hirsch, & Xu, 2008). Extant literature is equivocal regarding the effects of ratings (King, Racherla, & Bush, 2014), but the majority of previous studies have found that a higher average star rating is associated with more favorable

impressions of products, which increases purchase intention (Chen, 2008; Kim, Brubaker, & Seo, 2015; Sundar et al., 2008). More specifically, a positive effect of star rating on sales (rank) has been found for such products as books, movies, cell phones or beer (Chevalier & Mayzlin, 2006; Chintagunta, Gopinath, & Venkataraman, 2010; Clemons, Gao, & Hitt, 2006; Gopinath, Thomas, & Krishnamurthi, 2014; Zhang & Dellarocas, 2006). In line with these studies, we expect that positive product reviews improve consumers' attitudes toward products and increase purchase intention, whereas negative ones exert the opposite impact.

Interaction between review valence and helpfulness. In addition to this positive impact of positive reviews and the negative impact of negative reviews, we expect that this association between valence and purchase probability is moderated by the level of review helpfulness. Previous research into online reviews has overwhelmingly focused on predicting helpfulness of online reviews, hence, treating it as an outcome measure. Therefore, we have some understanding of what makes reviews helpful, but we do not know what the role of helpfulness is in the purchase decision process. Scarce previous research suggests that more helpful reviews are more prevalent for top selling products (Otterbacher, 2009), and that helpfulness is a signal of other customers' endorsement of the review (Metzger, Flanagin, & Medders, 2010), which translates to a more positive attitude towards the reviewer and product (Walther, Liang, Ganster, Wohn, & Emington, 2012). Extant research also suggests that consumers perceive extreme reviews (i.e., very negative or very positive) more useful than moderate ratings (Park & Nicolau, 2015), suggesting a positive influence of helpful reviews from extremely positive reviews and a negative influence of helpful reviews from extremely negative reviews. Therefore, we pose the following hypothesis that predicts the moderating role of review helpfulness on the association between valence and purchase probability.

H2: The level of review helpfulness moderates the association between valence and purchase probability. In particular, there is a positive interaction effect between valence and the level of review helpfulness on purchase probability.

Review sidedness. While review valence provides an overall evaluation of a product from a negative to positive spectrum, *pros* and *cons* (i.e., a summary of pros and cons of a product) demonstrate whether a reviewer provides a summary of positive and negative aspects of a product. Some companies started asking reviewers to write down specific pros and cons or to choose them from a provided scroll-down menu, believing that the presence of pros and cons can make reviews more persuasive, which would be in line with advertising literature studying the effect of two-sided messages. However, in the context of eWOM, it may not be the case. Schlosser (2011) found that, in the case of online reviews, one-sided arguments can be considered more helpful and persuasive than two-sided ones. In contrast to advertising, which aims to sell a product and hence is not perceived as credible, online reviews are not expected to be driven by persuasion motives, but rather motives to share opinions and help other consumers make an informed purchase decision by signaling the quality of a product. Therefore, we hypothesize that the presence of pros will have a positive influence on purchase probability, whereas the presence of cons will have an opposite influence. Additionally, we ask whether there is an interaction between the presence of pros and cons. In other words, we wonder whether two-sided messages (i.e., reviews presenting both pros and cons) have any impact on purchase probability, compared to one-sided messages (i.e., reviews showing only pros or cons).

H3a: The presence of pros in a review is positively associated with purchase probability.

H3b: The presence of cons in a review is negatively associated with purchase probability.

RQ1: Is there an interaction between the presence of pros and cons (i.e., two-sided)?

Reviewer Characteristics

Source credibility. Source credibility has been recognized as an important element of persuasion. When a person perceives a source to be trustworthy or to have expertise on a topic, it is more likely that a message from the source is seen as more credible (Quaschning et al., 2015; Sundar, 2008). The trustworthiness and expertise of the source have been extensively studied as major dimensions of source credibility in advertising research (Dou, Walden, Lee, & Lee, 2012). In addition, as shown in Table 1, source credibility has been identified as a major heuristic cue in the dual-process models. Previous studies have found that reviews written by consumers are perceived as more believable and understandable than those written by experts or companies because they provide users with information based on their actual product experience (Li, Huang, Tan, & Wei, 2013; Riegner, 2007).

However, consumers are aware that some firms can remove negative reviews or encourage positive reviews with (financial) rewards (Li & Hitt, 2008). This can make consumers skeptical about the trustworthiness of reviews. To address such concerns, several online retailers, including Amazon.com, indicate whether a reviewer made a purchase with a *verified buyer* badge. For other consumers, this shows that the reviewer has the experience of using the product, which increases the level of expertise and trustworthiness. In addition, it suggests that the reviewer is a real consumer and not someone who was paid to write a review. Because people are more inclined to trust those similar to ourselves (McCroskey, Richmond, & Daly, 1975), consumers are more likely to follow information provided by other customers (Blazevic et al., 2013; Huang et al., 2015). Therefore, we can hypothesize that reviews written by customers who are verified customers will have positive effect on sales.

H4: The presence of a verified buyer badge is positively associated with purchase.

Reviewer recommendation. In addition to an indicator of verified purchase, reviews contain *recommendations* from those who create reviews (Park & Kim, 2008). Reviewers can indicate whether they would recommend a product to a friend. Unfortunately, previous research into the role of this review feature is scarce. This is surprising since, as Reichheld (2003) claims, a customer's propensity to recommend a product to others (i.e., referral value) is the most important success measure in business. In addition to star ratings, which signal an overall evaluation of product quality, reviewer's recommendation provides a measure of reviewers' willingness to recommend the product and constitutes another cue indicating the reviewer's satisfaction with the product (e.g., Finn, Wang, & Frank, 2009). As such, it can directly influence other consumers' purchase intention. We propose the following hypothesis.

H5: The intention of a reviewer to recommend a product to a friend is positively associated with purchase probability.

Method

Data

This study uses online product reviews and purchase data obtained from a large online retailer in the United States. The company provides health, beauty, and personal care items such as over-the-counter medicine, vitamins, cosmetics, and skin/hair products. Since the company only has an online presence, all purchases are recorded and can be linked to product reviews on the firm's website. The company provides an online review page that allows its users to post and read product reviews. Once customers find a product, they can browse the product page with the image, price, star ratings, the number of available reviews for the given item. More interested consumers can click a "Review" tab positioned below a brief product description and picture.

Once consumers click the Review tab, they can see more detailed review features. First,

they see a summary of reviews when there are more than 2 reviews for a given product. The aggregated information includes average star ratings (from 1 to 5 stars), the number of reviews available for the product, and the percentage of reviewers who said they would recommend the product to a friend. When there is a single review for a product, the summary section is not provided. Below the summary information is each review sorted from the newest to oldest by default. Figure 1 illustrates how each review is shown to the users and what elements are included in each review: (1) The date when the review was written; (2) under the date of post, a star rating is presented on a scale of 1 star from 5 stars; (3) then, the information on the reviewer is provided including the name (can be a real name or nickname) and a badge that shows whether the reviewer is a user who has a record of verified purchase from the retailer; (4) optionally reviewers can choose whether they list a list of pros, cons, and/or best uses of the product; (5) review text is presented; (6) optionally, reviewers can choose to answer to the question whether they would recommend the product to a friend; (7) finally, review-readers can vote whether they think the given review was helpful (Yes / No).

Insert Figure 1 about Here

We have information on browsing and purchase activities for 14 weeks, starting from June 29, 2014 through October 11, 2014. In addition, we have reviews data that include information on review and reviewer characteristics. However, the data do not allow us to track which specific reviews were read by a customer, the time spent reading reviews, or whether the customer changed the sort order. Rather, we are only able to know whether or not a customer clicked the Review tab for a specific product. Due to this constraint, we narrow down our analysis to products that have a single review to make sure that those who clicked on the Review

tab actually were exposed to the review. In sum, a total of 9,838 products that have one review are selected for analyses. These products are displayed 420,334 times during the 14-week period. Our unit of analysis is an exposure (i.e., display) of a product review to a consumer who clicked the Review tab on the retailer's website.

We acknowledge that this analytic approach limits our ability to generalize the findings. However, it gives us the ability to estimate the influence of specific review features on purchase probability more accurately. First, it allows us to link a review with purchases from those who read this specific review because this is the only review available to those who were interested in the product, which helps us better estimate the financial impact of individual reviews. Second, this analytic setting makes us certain that reviewers are taking either systematic or heuristic information processing or both. Since there is a single review for a product, consumers clicking the Review Tab will be exposed to both review content and other information cues. Following the accuracy motivation, those who are highly motivated to make an objective judgement about their product choice will go through systematic processing by reading the argument(s) in review content. Those who are less motivated simply scan through heuristic cues such as a reviewer badge or star ratings. It is also possible for customers to use both factors so that systematic and heuristic processing occur concurrently.

Measures

Predictor variables. The predictor variables are online review and reviewer characteristics that consumers are hypothesized to use when they process online product reviews systematically and/or heuristically. Regarding review content characteristics, argument quality is measured by review length measured by the number of words. We create a quadratic term of review length to see whether the relationship between review length and purchase probability is

an inverted-U shape, as stated in H1. Review valence refers to whether a review is negative, neutral, or positive. We categorize reviews into negative, neutral, and positive reviews with three stars as a cut-off value. Reviews with three stars are coded as neutral reviews and reviews below/above three stars as negative/positive reviews. The majority of the reviews were positive (77.5%), followed by negative (15.7%) and neutral ones (6.8%). Review helpfulness is operationalized as the level of helpfulness of a review perceived by consumers. As shown in Figure 1, at the bottom of each review, review readers can vote whether it was helpful or not. We used the raw count of the response "Yes" to the question as the measure of review helpfulness. Message sidedness was measured by using pros and cons variables. Pros and cons are binary variables showing whether a review has a presence of pros and cons of a product. Thus, if a review has at least one mention of pros, the value becomes 1, otherwise 0. The same applies to cons. Initially, we computed the count of pros and cons in each review. However, because there was a large number of missing values, pros and cons were dichotomized. Out of 420,334 exposures, 16% presented a list of pros, whereas 3% displayed a list of cons.

With regard to reviewer characteristics, we create two predictor variables: source credibility and reviewer recommendation. Source credibility is a binary variable indicating whether a reviewer is a "Verified Buyer," meaning that he/she purchased the item on the company's website. Out of 420,334 exposures, about half (52%) show that a review is written by a verified buyer, whereas the other half (48%) fall into a review written by an anonymous reviewer who is not a verified buyer. This does not necessarily mean that they have never purchased the product. It is possible that such reviewers have bought the product elsewhere. Reviewer recommendation is a categorical variable that shows whether a reviewer answered "Yes" to the question, "Would recommend this to a friend?", as shown in item (6) in Figure 1.

About 77% report they would recommend the product to a friend, 15.9% report they would not and 7% do not provide any answer.

Outcome variable. Our outcome variable is whether or not an item is purchased (i.e., conversion) after an exposure. Among the 420,334 exposures we analyzed, about 5.5% converted to purchases. A summary of descriptive statistics of the main variables are presented in Table 2.[1]

Insert Table 2 about Here

Analysis

To test our hypotheses and research question, we estimate a logistic regression predicting the probability of product purchase. We include characteristics of review content and review contributors as predictor variables. We also include review age (i.e., the number of days since the date when the review was written), product price, product category (i.e., broad product category presented on the retailer's website, for example, medicine & health, beauty, household items, baby & mom, etc.), and month of purchase (i.e., seasonality) in the model as control variables. Review age ranges from 2 days to 4,249 days (median = 575 days). About one third (35.1%) of exposures occurred in the beauty section of the website, followed by medicine & health (27.1%), personal care (14.9%), household, food, & pets (7.4%), sexual well-being (6.8%), baby & mom (4.4%), and others (4.2%). Predictor and control variables that are skewed are log-transformed before they are entered into the model.

Results

A logistic regression analysis is conducted to predict purchase probability using

characteristics of review content and reviewers. A test of the full model against a constant only model is statistically significant, showing that the independent variables as a set predicts purchase behavior ($|^2$= 3,720.6, df = 25, $p < .0001$).

Table 3 presents the logistic regression results. Concerning H1 (argument quality), we found that the association between review length and purchase probability shows an inverted-U shape. However, we only found directional evidence at the .10 level, thus failing to confirm H1. Figure 2 illustrates the quadratic effect of review length on purchase probability. Directionally, this suggests that the effect of review length is positive until it reaches its vertex (i.e., between 20 and 55 words) and then becomes negative when a review is too lengthy (i.e., above 55 words), showing that reviews that are perceived as too lengthy hurt purchase probability. Note that the horizontal axis is in log units. The top of the plot shows the original (unlogged) units.

Insert Figure 2 about Here

Concerning H2 (an interaction between review valence and helpfulness), the result shows that there is a positive interaction effect between review valence and review helpfulness on purchase probability, which confirms our prediction. Figure 3 shows that the helpfulness slope is steeper for negative reviews than for positive or neutral ones. As a negative review gathers more helpfulness votes the purchase likelihood decreases, while the effect of helpfulness votes for positive or neutral reviews is flatter. It is surprising that there is a negative association between helpfulness votes and purchase for positive and neutral reviews. This suggests that when individuals are exposed to reviews with positive valence and a higher number of helpfulness votes, they are less likely to make a purchase. Therefore, H2 is only partially confirmed.

Regarding H3, which concerns the influence of pros and cons, we predicted that the

presence of pros will increase purchase probability (H3a), whereas the presence of cons will do the opposite and decrease purchase probability (H3b). We did not find any influence of the presence of pros. However, we found a negative impact of the presence of cons. This implies that a heuristic cue signaling negative aspects of a product has a bigger influence than the one with positive aspects. H3 is partially confirmed. Regarding RQ1 (an interaction term between pros and cons), we did not find any significant effect between the presence of pros and cons.

With regard to reviewer characteristics, we found that displaying a review authored by a verified buyer has a positive influence on purchase probability, supporting previous findings on source expertise and credibility. When consumers are exposed to reviews written by a verified buyer, the odds of product purchase increase by 15%, compared to the case when they read reviews written by anonymous reviewers. H4 is confirmed.

Finally, reviewers' willingness to recommend a product to a friend also affects purchase probability. We found that compared to when such recommendations are not present, recommendation has a significant impact on purchase probability. Similar to pros and cons, we see a stronger influence of a negative reaction from a reviewer. When a reviewer would not want to recommend a product to a friend, the odds of purchase decrease by 26.7% compared to when a reviewer did not provide a recommendation. On the contrary, when a reviewer reports his or her willingness to recommend a product, the odds of purchase increase by 7% compared to no recommendation. Hence, H5 is confirmed.

Insert Table 3 about Here

Insert Figure 3 about Here

Discussion

Theoretical Implications

Customers trust online product reviews and hence increasingly consult them to make an informed purchase decision. While the literature on eWOM has been growing quickly, extant studies have focused on the role of review valence and volume and have not devoted much attention to other review features. There has not been much research that has tried to integrate relevant review or reviewer characteristic in a single model. Furthermore, review helpfulness has been overwhelmingly treated as an outcome variable in extant research. There is a dearth of empirical studies that have used individual-level sales data. Most research has focused on proxy measures such as sales rank, attitudes, or purchase intention. To fill these gaps in existing literature, this study applied the HSM and took a comprehensive approach by examining the impact of review and reviewer characteristics as well as possible interaction effects between review features on purchase decisions.

Overall, our findings show that most predictor variables grounded on the HSM significantly influence purchase probability. We found that argument quality (measured as review length) has an inverted-U shaped relationship with purchase probability. This suggests that the positive effect of review length reaches its maximum and diminishes if a review becomes too long. It also confirms recent studies that found a nonlinear effect of review length on outcome variables such as review helpfulness (Baek, Ahn, & Choi, 2012; Huang et al., 2015; Kuan et al., 2015). The persuasive effects of message length in an advertising context have shown mixed results. For example, Wells, Leavitt, and McConville (1971) showed that longer commercials presented more product usage illustrations, which increased viewers' opportunity to elaborate on the message. More elaboration leads to more counter-arguing, which ultimately

resulted in more negative attitudes toward the advertisement. However, Rethans, Swasy, and Marks (1986) did not find such an effect. There are several explanations for the inverted-U relationship between review length and purchase probability. First, consumers may experience cognitive overload when they perceive a review as lengthy although it is informative. Second, in line with Gossen's diminishing marginal utility law suggesting that the marginal utility of each unit decreases as the supply of unit increases, review readers may predict that a review exceeding a certain length will not provide additional information value, or even perceive them as less informative. Finally, following the ELM and a two-factor perspective (Cacioppo & Petty, 1980), longer reviews provide more opportunities for consumers to elaborate on the message and its arguments and enhance counter-arguing, which is detrimental to purchase decision.

Previous research has pointed out the role of star rating as a heuristic for popularity and quality (Sundar et al., 2008) and its positive impact on outcome variables. What we found in this study is a more complicated picture that shows a moderating impact of review helpfulness. In particular, negative reviews (i.e., with one or two stars) and a large number of helpfulness votes exert a strong negative influence on purchase probability. This may be attributable to the fact that negative reviews are scarce, thus when negative reviews receive a higher number of helpful votes, their credibility as information sources increases. The effects of positive and neutral reviews are quite flat, which suggests that the level of review helpfulness does not play an important role for positive and neutral reviews. Such results seem to be in line with the dual-processing theories. Since the majority of online reviews are positive and due to naive theories on the source of such positive information (i.e., self-presentation, competence signalling) (Chen & Lurie, 2014), consumers expect to see positive reviews and hence may process them rather peripherally. The moment they encounter a negative review, they may start processing

information more systematically, which will exert a stronger effect on attitudes and behaviors. In addition, when consumers process information systematically, they look for additional arguments such as star-rating or helpfulness votes. Other customers' agreement with the review expressed in helpfulness votes may make the review more credible and hence more persuasive. Negative star rating and many helpfulness votes will then negatively bias central processing (Chaiken & Maheswaran, 1994). This process may result in a negative evaluation of the product and hence lower purchase probability.

The results also suggest that the presence of pros does not have a significant impact, but that of cons does decrease purchase probability. This may be due to the positive bias of online reviews in general (Aral, 2014). Since the overall sentiment on the review system is positive, the inclusion of negative information attracts readers' attention (Willemsen et al., 2011) and may be expected to increase reviews' credibility, because negative information may seem more valuable and persuasive (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Indeed, some studies have shown that the number of positive online reviews is disproportionately high, which may cause customers to discount positive reviews as not reliable (Chevalier & Mayzlin, 2006). In line with this, the accessibility-diagnostic theory predicts that negative information exerts a stronger influence on judgements than positive information (Herr, Kardes, & Kim, 1991). Finally, the non-significance of the interaction term between pros and cons suggest that two-sided arguments may not be seen persuasive in online product reviews. This is consistent with Schlosser's (2011) argument that one-sided arguments may seem more persuasive and helpful when it comes to online reviews because the motivation of posting online reviews is to help other consumers' decision making by showing the quality of a product.

The results regarding reviewer characteristics suggest that people pay attention to the

nature of review source. Whether a reviewer actually bought and used a product mattered for purchase decision. Extant research shows that people form a more positive attitude toward a product and a website when reviews are written by other consumers than experts or companies (Park et al., 2007). Showing a badge that indicates a review is written by a consumer who has purchased and used the product increases purchase probability. In addition, a statement whether a reviewer is willing to recommend a product to his or her friend increases purchase probability compared to when there is no intention of recommendation. On the contrary, expressing unwillingness to recommend a product has a negative influence compared to not expressing any intention to recommend the product. The intention to share positive word-of-mouth about a product is a significant indicator of brand loyalty (Dick & Basu, 1994). Thus, the cue showing that a reviewer is willing to recommend a product can be crucial information that signals the quality of the product.

Practical Implications

From a managerial perspective, the findings of this study suggest that companies should consider which aspects of reviews must be taken more seriously. First, longer reviews generally provide more information, but they may want to limit the length of each review by finding an optimal review length. Second, when companies notice clearly negative heuristics, for instance, negative star ratings, a list of cons, or a "No" to the question whether they are willing to recommend a product to a friend, they should find a way to intervene and identify where the cause of dissatisfaction lies. Hence, companies should consider engaging in conversations with customers through webcare. Third, companies should actively solicit reviewers from customers who actually purchased and used a product. The problem of verified purchase is that it only recognizes consumers who bought an item from a particular retailer that provides the online

review system. For consumers who made a purchase elsewhere, there is no way that they can visually show that they are verified users. Thus, giving an option to reviewers to show that they have a real experience of using a product is a good way to potentially increase the overall trustworthiness of reviews.

From an advertising perspective, WOM has been considered as a key to advertising effectiveness (Keller & Fay, 2012), so is eWOM in the era of Web 2.0. When it comes to eWOM, customers often have difficulty evaluating credibility of messages (Levy & Gvili, 2015). There have been debates in the advertising discipline regarding whether brands should encourage consumers to post a product review, if so, which type of platform would be the most effective. Advertisers sometimes compensate consumers for posting a product review on their personal blogs believing that the review is perceived more reliable. Previous research shows that brand- and consumer-generated website are considered equally persuasive when consumers read positive reviews (Xue & Phelps, 2004). Alternatively, a study by Lee and Youn (2009) finds that customers are more likely to recommend a product after reading a positive review on a brand-generated website than consumer-generated one (i.e., a blog), suggesting that consumers are suspicious about reviews in consumer-generated websites. This perspective seems to be supported by the results showing that information whether a reviewer actually bought and used a product is important for customers' purchase decision. This finding is relevant considering that perceived source trustworthiness positively affects eWOM's influence on decision making (Lopez & Sicilia, 2014). In sum, we think that advertisers should stimulate customers' participation in eWOM while providing transparent information about the reviewing process.

Limitations and Suggestions for Future Research

Although this study provides insights regarding how each characteristic of online product

reviews influences purchase probability, a few limitations should be noted and addressed in future research. First, as we mentioned in the method section, we had to limit our sample to products with one review due to the way the data were collected. This reduces our ability to generalize the findings, but allows us to link consumers' exposure to reviews with purchase behavior. Second, argument quality was measured as review length, a proxy variable. Without a content analysis of argument strength in each review, this study was not able to test the effect of the level of argument quality on purchase decision. Third, this study used data from a single online retailer that mostly sells search goods and consumer packaged goods. Consumers' interest in reviews and their persuasive power may depend on product categories (Allsop, Bassett, & Hoskins, 2007). Finally, due to the nature of a secondary analysis of existing data, we did not have all the variables we hoped to include in the regression model such as personal characteristics, consumption history, WOM activities, or brands' marketing efforts.

Future research should investigate other content and source characteristics that are not observed in this study. In particular, in-depth analyses of review content – its readability, relevance, or informativeness – can provide further insights regarding the financial impact of review content (Mackiewicz & Yeats, 2014; Park & Nicolau, 2015). To better understand how consumers process online reviews, future studies should include content analysis and categorize different types of arguments presented in reviews. Also, many studies investigating online reviews (including our study) build on dual-process theories to establish their theoretical framework. Future research may want to go one step further and actually test dual-processes theories in the eWOM context (e.g., Zhang et al., 2014). This would require a controlled experimental design, which was beyond the scope of this paper. In addition, the role of aggregated information of reviews for a single product (i.e., summary section) should also be

investigated. It is possible that consumers may not read individual reviews, but read a summary section presented at the top of the Review tab. Whether a summary section exerts a bigger influence than individual reviews or whether there is a condition under which a summary of all reviews and individual reviews have an interaction (for instance, high consistency) is an interesting question that remains to be investigated. With regards to reviewer characteristics, how reviewers' disclosure of their personal information as well as the similarity between reviewers and review readers influence purchase decision can provide interesting insights.

In sum, this study contributes to the literature on online product reviews and consumer-generated advertising by looking at the effect of different review features on purchase decision. It confirms the effects of review characteristics that are identified based on the HSM approach (e.g., Cheung & Thadani, 2012). Some findings may seem intuitive, for instance, the positive effect of a verified buyer badge or the presence of cons. However, we also have unexpected findings, for example, the moderating effect of review helpfulness or the curvilinear effect of review length, require further investigation. With follow-up experiments that corroborate the findings from this research and research that examines the effects of reviews in other product or service categories.

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Footnote

[1] We assessed multicollinearity using generalized variance inflation factors (GVIF) proposed by Fox and Monette (1992). GVIFs are an appropriate way to assess multicollinearity in models with categorical predictors and polynomials. Many suggest that VIF > 10 indicate strong multicollinearity (e.g., Neter, Kutner, Wasserman, & Nachtsheim, 1996, p. 387). None of the VIF values exceed 6.06 in our case.

Table 1. Summary of existing literature on dual-processing models in an eWOM context

Author(s)	Theory	Method	Predictor(s)	Mediator or Moderator	Outcome(s)	Findings
Baber et al. (2016)	HSM	Survey	Trustworthiness Expertise Experience WOM use	Attitude	Intention to purchase electronic products	E-WOM sources' levels of trustworthiness and experience positively influenced eWOM use. E-WOM use postively affected attitude, which fully mediated its effect on purchase intentions
Cheng & Ho (2015)	ELM	Secondary analysis of exiting reviews	Argument quality Source credibility		Review usefulness	Argument quality and source credibility all have a significant positive effect on the readers perception of the usefulness of reviews. The effects of source crebility exerts a larger influence than argument quality.
Cheung et al. (2008)	ELM	Survey	Argument quality Source credibility		Information usefulness Information adoption	Argument quality (releance, timeliness, accuracy, comprehensiveness) and source credibility (expertise, trustworthiness) both have a positive influence on information usefulness, which in turn has a positive effect on information adoption.
Cheung et al. (2012)	ELM	Survey	Argument quality Source credibility Review consistency Review sidedness	Recipients' expertise Recipients' involvement	Review credibility	Argument quality, source credibility, review consistency, and review sidedness all have a positive effect on review credibility. The effect of review sidedness on review credibility is stronger for recipients with lower levels of involvement.
Filieri & McLeay (2013)	ELM	Survey	Information quality Information quantity Product ranking		Information adoption	Some dimensions of information quality (timeliness, relevance, accuracy, value-added information) and product ranking have a positive influence on travelers' adoption of information from online reviews.
Gupta & Harris (2010)	HSM	Experiment	E-WOM argument strength Optimality of product choice	Need for cognition	Product choice Total time spent on the site Time spent considering recommended options	E-WOM recommendations on an experience product lead high NFC individuals to spend significantly more time analyzing their choices than do low NFC individuals. Low NFC consumers make suboptimal choices based on e-WOM recommendations, whereas high NFC consumers tend to use e-WOM recommendations, but follow the recommendation only if it is an optimal product. Consumers, particularlyhigh NFC consumers, are willing to move away from their existing preferences, given that e-WOM recommendations on an experience product are probably deemed valuable enough for them to sacrifice their own preferences.

Table 1 (continued)

Author(s)	Theory	Method	Predictor(s)	Mediator or Moderator	Outcome(s)	Findings
Kim et al. (2015)	Dual-process models	Experiment	Perceived authority Perceived bandwagon Perceived objectivity Social plugins Star ratings	Credibility	Product attitude Webpage attitude Purchase intention	Expert reviews have a greater impact on attitudes toward product review wbsites, and this effect was moderated by star ratings. Star ratings has a strong positive effect on users' attitudes toward the product, attitudes toward the website, and their purchase intention. Presence of sharing applications also had positive effects on attitudes toward the product. Credibility mediates the relationship between heurstic cues and product evaluation.
Park et al. (2007)	ELM	Experiment	Review quantity Review quality	Involvement	Purchase intention	The quality and quantity of online reviews positively affect consumers' purchase intention. Low-involvement consumers are affected by the quantity rather than the quality of reviews, whereas high-involvement consumers are affected by review quantity mainly when the review quality is high.
Park & Kim (2008)	ELM	Experiment	Expertise of review readers Types of reviews Number of reviews		Purchase intention	The effect of type of reviews (cognitive fit) on purchase intention is stronger for experts than for novices while the effect of the number of reviews on purchase intention is stronger for novices.
Sher & Lee (2009)	ELM	Experiment	Argument quality Source credibility	Skepticism	Purchase intention	High skepticism consumers do not take the central route, but tend to base their attitudes on intrinsic beliefs. Log skepticism consumers adopt the peripheral route in forming attitudes.
Zhang & Watts (2008)	HSM	Survey	Argument quality Source credibility	Level of disconfirming information focused search	Information adoption	Argument quality and source credibility can affect the adoption of online reviews in online communities. Disconfirming information had a moderating effect only in an online travel forum, not in a community of Computational Fluid Dynamics.
Zhang et al. (2014)	HSM	Survey	Argument quality Source credibility Perceived quantity of reviews		Behavioral intention	Argument quality, source credibility, and perceived quantity of reviews were key determinants of behavioral intention. The bias effects from source credibility and perceived quantity of reviews toward argument quality were also found.

Table 2. Summary of descriptive statistics of main variables (*N*=420,334)

	Mean	S.D.
Review content characteristics		
Review length (# of words)	54.64	53.51
Review age (days)	656.91	495.44
Review helpfulness (votes)	1.42	2.98
Product characteristics	0.66	0.47
Price (dollars)	16.63	21.05

Table 3. Logistic regression predicting purchase probability

Predictors	B	S.E.	Waldχ^2	Odds ratio
Intercept	1.7362***	0.488	12.655	
Review Characteristics				
Review length[a]	0.145	0.089	2.664	1.156
Review length squared[a]	-0.021	0.011	3.400	0.979
Review valence[b]				
Neutral	-2.118**	0.725	8.530	
Positive	-2.408***	0.460	27.437	
Review helpfulness[a]	-1.471***	0.188	61.053	
Review valence*helpfulness[a]				
Neutral*helpfulness[a]	0.932**	0.305	9.357	
Positve*helpfulness[a]	1.153***	0.192	27.437	
Pros[c]	0.017	0.022	0.577	
Cons[c]	-0.152*	0.068	4.945	
Pros*Cons	0.054	0.102	0.272	
Reviewer characteristics				
Verified buyer[d]	0.140***	0.015	88.507	1.150
Recommendation to a friend[e]				
Yes	0.069*	0.030	5.355	1.072
No	-0.310***	0.046	46.004	0.733
Control variables				
Review age[a]	-0.014	0.008	3.334	0.986
Average price[a]	-0.453***	0.017	724.422	0.636
Product category[f]				
Baby & Mom	0.222***	0.043	26.592	1.249
Beauty	-0.300***	0.035	74.010	0.741
Household, Food, & Pets	0.387***	0.039	99.107	1.472
Medicine & Health	0.068	0.036	3.477	1.070
Personal Care	0.091*	0.036	6.238	1.095
Sexual Well-Being	-0.246***	0.048	26.829	0.782
Seasonality[g]				
July	-0.136**	0.047	8.470	0.873
August	-0.184***	0.047	15.277	0.832
September	-0.171***	0.047	13.136	0.843
October	-0.103*	0.050	4.329	0.902

Notes. * p < .05, ** p < .01, *** p < .001

[a] log-transformed

[b] Reference category = negative valence (1 - 2 stars)

[c] 0 = no pros/cons; 1 = at least one pro/con

[d] 0 = Anonymous reviewer; 1 = Verified reviewer

[e] Reference category = No recommendation (N/A)

[f] Reference category = Miscellaneous (i.e., "Others" category)

[g] Reference category = June 2014

Figure 1. A modified screenshot of a review on the retailer website

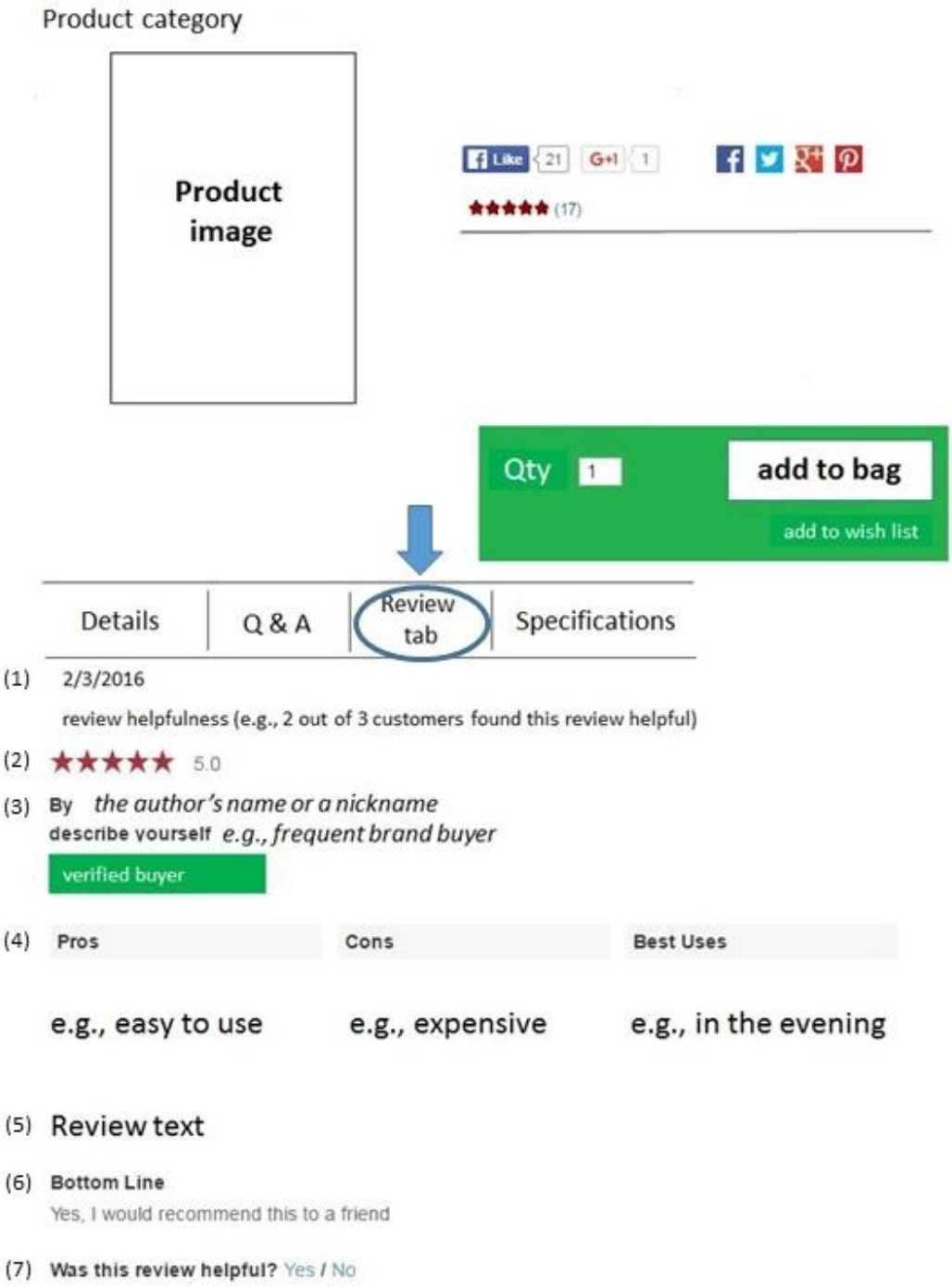

Figure 2. The effect of the number of words on the logit of purchasing

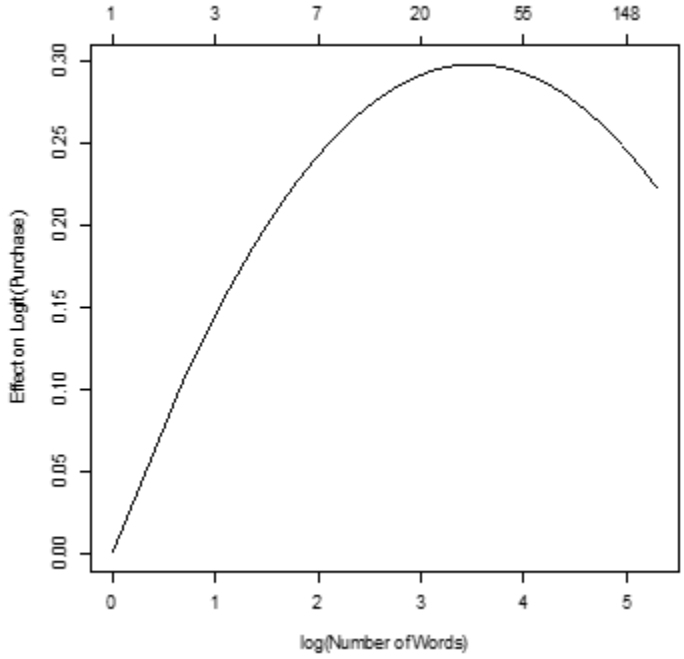

Figure 3: The interaction effect of valence and helpfulness on purchase