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Understanding the effects of different review features on purchase probability

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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. Building on dual-process models of persuasion, 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, we investigate the financial impact of online product reviews on purchase decisions. The results demonstrate the persuasive power of different review features that are derived from dual-process models of information processing. Managerial implications on how advertisers and companies should design and manage online product reviews are offered.

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eWOM; online product reviews; dual-process model; heuristic-systematic model; purchase behavior

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 and Mayzlin 2006; Liu 2006; Maslowska, Malthouse, and Bernritter 2017; Maslowska, Malthouse, and Viswanathan 2017). A recent report from 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.

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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 et al. 2007; Doh and Hwang 2009; Floyd et al. 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 reviews with their actual purchases. The majority of previous studies have focused on psychological variables such as attitudes (see Purnawirawan et al. 2015, for a review) or used proxy measures such as sales rank, but research studying actual sales at an individual level is limited (see Floyd et al. 2014, for a review). This study uses online product reviews and individual-level 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 and Schuff 2010; Quaschning, Pandelaere, and Vermeir 2015; Schindler and Bickart 2012; Willemsen et al. 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, 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 advertisers can use reviews and 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 and 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 are 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 lead us to use the dual-process models of persuasion such as the Elaboration Likelihood Model (ELM) (Petty and 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.

The ELM has been widely used as a framework to explain the ways in which consumers process information in online product reviews (Cheng and Ho 2015; Cheung, Sia, and Kuan 2012; Park, Lee, and 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 and Watts 2008). Unlike the ELM, which assumes that individuals take either the central or peripheral route to persuasion, the HSM posits that the heuristic and systematic processing may occur independently or concurringly, allowing us to investigate the simultaneous impact of heuristic and systematic processing (Bohner, Chaiken, and 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 discuss the persuasive effects of online product reviews. Similar to the approach taken by Zhang et al. (2014), we consider that both content-related characteristics and non-content cues affect review readers' purchase decisions 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). Table 1 summarizes extant research that applied the dual-process models to online product reviews. As shown in Table 1, previous research has treated argument quality as an important element in systematic processing. 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 online product reviews. We divide these characteristics into message content and message source (i.e. reviewer) characteristics.

Table 1. Summary of existing literature on eWOM that applied dual-processing models.

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 positively affected attitude, which fully mediated its effect on purchase intentions
Cheng and 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 credibility exert a larger influence than argument quality
Cheung et al. (2008)	ELM	Survey	Argument quality Source credibility		Information usefulness Information adoption	Argument quality (reliance, 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, Sia, and Kuan (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 and 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 and 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, particularly high-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
Kim, Brubaker, and Seo (2015)	Dual-process models	Experiment	Perceived authority Perceived bandwagon Perceived	Credibility	Product attitude Webpage attitude Purchase intention	Expert reviews have a greater impact on attitudes toward product review websites, and this effect was moderated by star ratings. Star ratings have a strong positive effect on users' attitudes toward the product, attitudes toward the

(continued)

Table 1. (*Continued*)

Author(s)	Theory	Method	Predictor(s)	Mediator or moderator	Outcome(s)	Findings
			objectivity Social plugins Star ratings			website, and their purchase intention. Presence of sharing applications also had positive effects on attitudes toward the product. Credibility mediates the relationship between heuristic cues and product evaluation
Park, Lee, and Han (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 and 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 and 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. Low-skepticism consumers adopt the peripheral route in forming attitudes
Zhang and 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

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 and Watts 2008) or purchase intention (Park, Lee, and Han 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, Lee, and Han (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, and van Rooyen 2013; Cheng and Ho 2015; Huang et al. 2015; Mudambi and 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 et al. 2014), previous research has observed that customers write long reviews to express their dissatisfaction (Vasa et al. 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 due to cognitive overload (Huang et al. 2015; Kuan et al. 2015). 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, and Xu 2008). Extant literature is equivocal regarding the effects of ratings (King, Racherla, and 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, and Seo 2015; Sundar, Oeldorf-Hirsch, and Xu 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 and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Clemons, Gao, and Hitt 2006; Gopinath, Thomas, and Krishnamurthi 2014; Zhang and 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, and Medders 2010), which translates to a more positive attitude towards the reviewer and product (Walther et al. 2012). Extant research also suggests that consumers perceive extreme reviews (i.e. very negative or very positive) more useful than moderately rated reviews (Park and Nicolau 2015). Taken together, this suggests that there will be an interaction between review valence and helpfulness in a way that positive reviews that are perceived more helpful will exert a more positive influence than positive reviews that are perceived less helpful. In case of negative reviews, the pattern will be the opposite: negative reviews with a higher level of helpfulness would have a more negative impact compared to negative reviews with a lower level of helpfulness. 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) pointed out that, in the case of online reviews, one-sided arguments can be considered more helpful and persuasive than two-sided ones unlike advertising messages. The aim of advertising is to sell a product and hence is not perceived as credible when one-sided arguments are provided. However, online reviews are not expected to be driven by persuasion motives, but motives to share opinions and help other consumers make an informed purchase decision, which makes one-sided arguments more persuasive. 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 ask whether two-sided messages (i.e. reviews presenting both pros and cons) have a different 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 in a review (i.e. a two-sided review)?

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 have the expertise on a topic, it is more likely that a message from the source is seen as more credible (Quaschning, Pandelaere, and Vermeir 2015; Sundar 2008). The trustworthiness and expertise of the source have been extensively studied as major dimensions of source credibility in advertising research (Dou et al. 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 et al. 2013; Riegner 2007).

However, consumers are aware that some firms can remove negative reviews or encourage positive reviews with some forms of rewards (Li and Hitt 2008). This can make consumers skeptical about the trustworthiness of reviews. To address such concerns, several online retailers, including Amazon.com, place a *verified buyer* badge to indicate whether a reviewer made a purchase. 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, and Daly 1975), consumers are more likely to follow information provided by other customers (Blazevic et al. 2013; Huang et al. 2015). Therefore, we hypothesize that reviews written by customers who are verified customers will have positive effect on purchases.

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

Reviewer recommendation

In addition to an indicator of verified purchase, reviews contain *recommendations* from those who create reviews (Park and 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, and 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, and 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 two 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).

We have information on browsing (click log table) and purchase activities (transaction table) for 14 weeks, starting from 29 June 2014 through 11 October 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 9838 products that have one review are selected for analyses. These products are displayed 420,334 times during the 14-week period. Our unit of

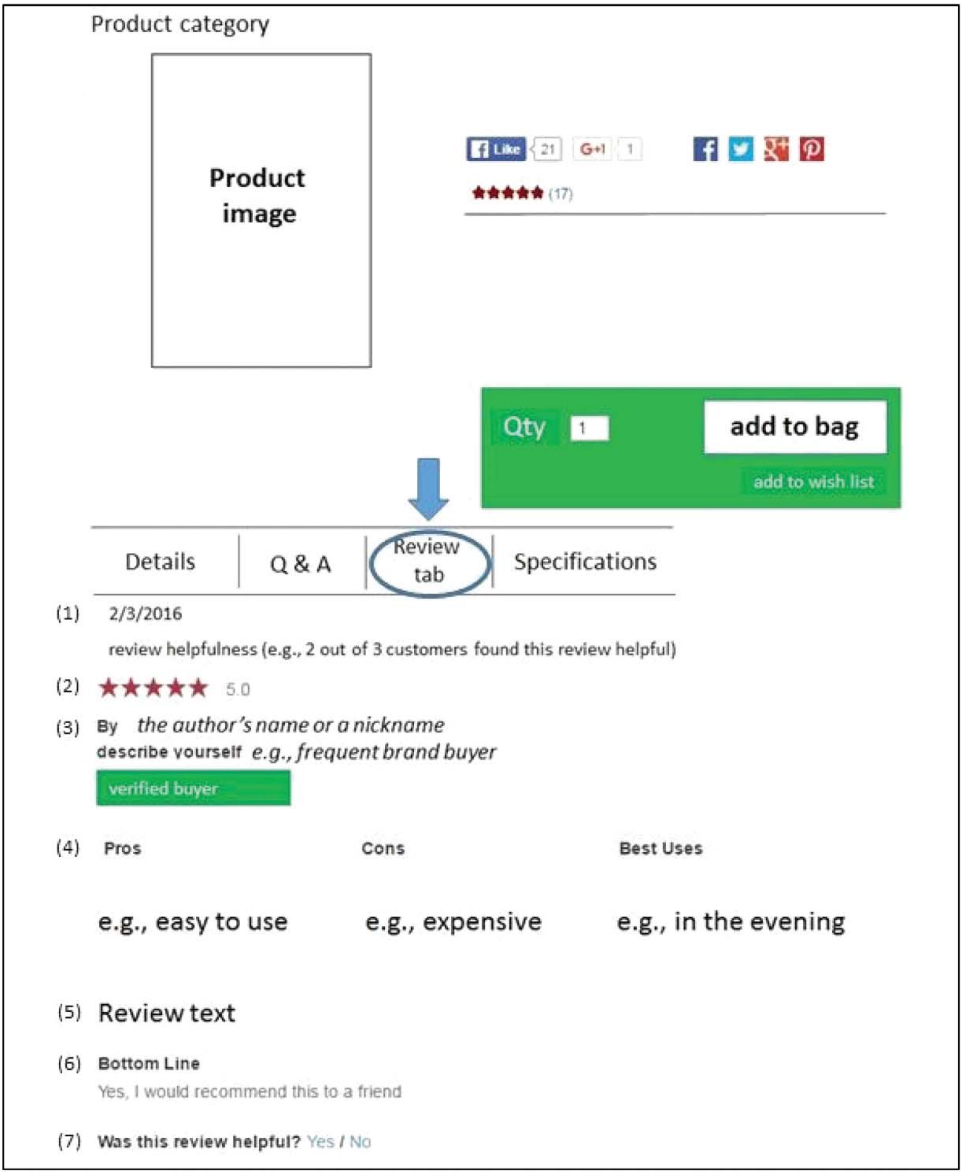

Figure 1. A modified screenshot of a review on the retailer website.

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 (Maslowska, Malthouse, and Viswanathan 2017). 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 exposed to when they process online product reviews systematically and/or heuristically. Regarding review content characteristics, *argument quality* is measured by review length (i.e. number of words in a review). 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 as indicated by other consumers. As shown in Figure 1, at the bottom of each review, review readers can vote whether it was helpful or not. We use the raw count of the response 'Yes' to the question as the measure of review helpfulness. Message sidedness is measured by using pros and cons variables. *Pros* and *cons* are two binary variables showing whether a review has a presence of pros or 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 is presented in Table 2.[1]

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

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 4249 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 having a skewed distribution are log-transformed before they are entered into the model.

We discuss the rationale for our model specification. The purpose of the paper is to study the effects of all the review stimuli on the purchase decision of a prospective buyer. We therefore include measures of all stimuli, since this is what the prospective customer sees. There will likely be correlations between some of the variables, because the different features of a review reflect the reviewer's experience with the product. For example, a reviewer who had a positive experience will likely give a large number of stars, be willing to recommend the product to a friend, and list pros, creating positive correlations between the variables. Dropping measures of certain stimuli from the model will create an omitted variable bias and overstate the effects of the remaining variables (Liu-Thompkins and Malthouse 2017). Measures of all customer stimuli must therefore be included in one model.

Results

A logistic regression analysis is conducted to estimate purchase probability using characteristics of review content and reviewers with n = 413,666. A test of the full model against a constant only model is statistically significant, showing that the independent variables as a set predict purchase behavior ($\chi^2_{25} = 178928.5 - 175207.9 = 3720.638$, $p < .0001$). Cox and Snell's R-squared equals 0.008954, Nagelkerke's R-squared equals 0.02550, and McFadden's R-squared equals 0.02079. While the primary objective of this model is not prediction,[2] the area under the receiver operating characteristics (ROC) curve (AUC) equals 0.615, with the ROC curve shown in Figure 2.

Table 3 presents the logistic regression results. Before discussing the parameter estimates, we assess and discuss multicollinearity. Multicollinearity is where the predictor

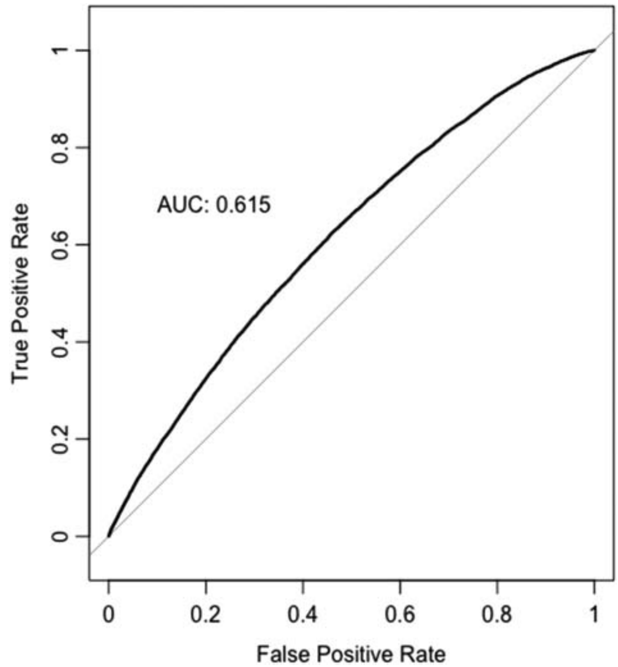

Figure 2. ROC curve of the fitted model.

variables are correlated with each other. The effect of multicollinearity is to increase the standard errors of the estimates, but multicollinearity does not affect other properties of the estimates, for example, they are still unbiased and the standard errors correctly reflect the reduced stability of the estimates. Liu-Thompkins and Malthouse (2017) suggest evaluating the correlations between predictors with variance inflation factor (VIFs), which quantify how much the variance (squared standard errors) of an estimated coefficient increases because of collinearity. When there are categorical predictors or polynomials, as we have here, then generalized VIFs (GVIF) can be used[3] (Fox and Monette 1992). GVIFs are provided in Table 3. The terms with an "X" indicate an interaction, where pros $\times$ cons has two dummy main effects and a product for the interaction. The valence $\times$ loghelp has two dummies for valence (neutral and positive), a slope for loghelp, and two interaction terms (loghelp $\times$ neutral and loghelp $\times$ positive), using a total of five degrees of freedom. Many of the GVIF values are substantial, with the largest equaling 6.05 for the valence $\times$ help interaction. Standard errors are also a function of sample size, where larger samples produce more reliable (lower standard error) estimates. While there is multicollinearity, inflating standard errors, our large sample sizes combat the variance inflation yielding small standard errors.

Concerning H1 (i.e. 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 3 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 (between 20 and 55 words) and then becomes negative when a review is too lengthy (i.e. above 55 words), showing

Table 3. Logistic regression predicting purchase probability.

Predictors	B	S.E.	Wald χ^2	GVIF(df)	Odds ratio
Intercept	1.7362***	0.488	12.655		
Review length				1.23(2)	
Log(Review length)	0.145	0.089	2.664		1.156
Log(Review length) squared	−0.021	0.011	3.400		0.979
Review valence					
Neutral	−2.118**	0.725	8.530		0.1203
Positive	−2.408***	0.460	27.437		0.0899
Negative (1–2 stars)	0	–	–		
Review helpfulness	−1.471***	0.188	61.053		0.2297
Review valence × helpfulness				6.05(5)	
Neutral × helpfulness	0.932**	0.305	9.357		2.540
Positive × helpfulness	1.153***	0.192	27.437		3.168
Review sidedness					
Pros (at least one)	0.017	0.022	0.577		1.017
Cons (at least one)	−0.152*	0.068	4.945		0.8590
Pros × Cons	0.054	0.102	0.272	1.66(3)	1.055
Verified buyer or not				1.17(1)	
Verified buyer	0.140***	0.015	88.507		1.150
Anonymous reviewer	0	–	–		
Recommendation to a friend				3.90(2)	
Yes	0.069*	0.030	5.355		1.072
No	−0.310***	0.046	46.004		0.733
No recommendation given	0	–	–		
Control variables					
Review age	−0.014	0.008	3.334	1.15(1)	0.986
Average price	−0.453***	0.017	724.422	1.08(1)	0.636
Product category				1.96(6)	
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
Other	0	–	–		
Seasonality				1.00(4)	
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
June 2014	0	–	–		

Notes. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

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.

Concerning H2 (i.e. 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 hypothesis. Figure 4 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 (i.e. message sidedness), we predicted that the presence of pros will increase purchase probability (H3a), whereas the presence of cons will do the opposite and

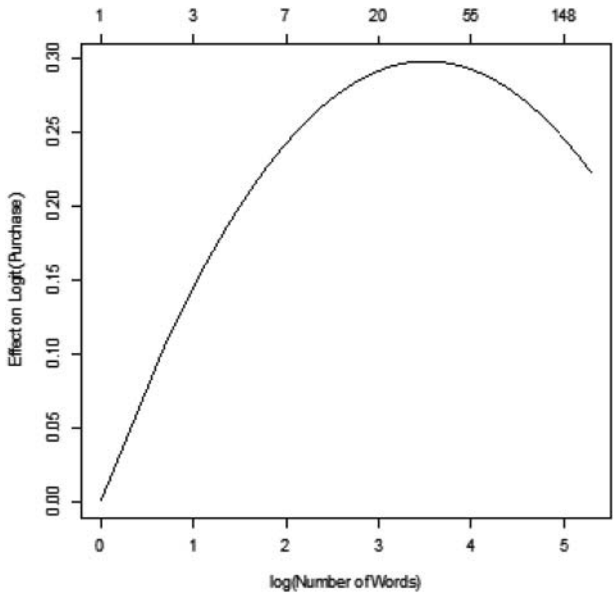

Figure 3. The effect of the number of words on the logit of purchase.

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 signalling negative aspects of a product has a bigger influence than the one with positive aspects. H3 is partially confirmed. Regarding RQ1 (i.e. an interaction between pros and cons), we did not find any significant effect between the presence of pros and cons.

With regard to H4 (i.e. source credibility), 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.

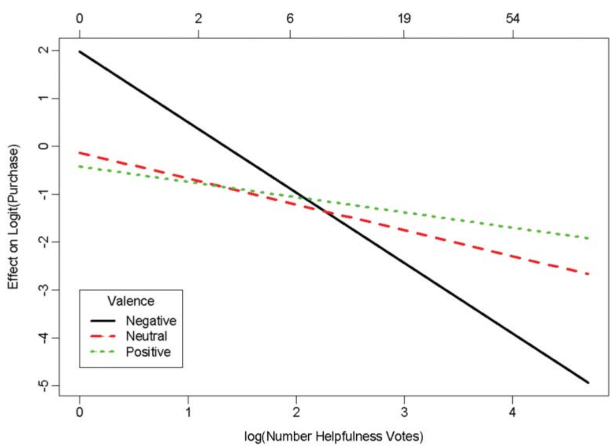

Figure 4. The interaction effect of valence and helpfulness on purchase.

Finally, regarding H5 (i.e. reviewer recommendation), reviewers' willingness to recommend a product to a friend affects purchase probability. We found that compared to when such recommendations are not present, recommendation has a significantly positive impact on purchase probability. Similar to pros and cons, we see a stronger influence of a negative reaction from a reviewer. When consumers see a review that contains 'No' to the question, 'Would you recommend this to a friend?', the odds of purchase decrease by 26.7% compared to when such answers are not provided at all. On the contrary, when a reviewer reports his/her willingness to recommend a product, the odds of purchase increase by 7% compared to no recommendation. Hence, H5 is confirmed.

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, volume, and/or source credibility, but have not devoted much attention to other review features. There has not been much research that has tried to integrate relevant review or reviewer characteristics 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 of review features on purchase decisions.

Overall, our findings show that most of the review features we examined 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, and 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 it as less informative. Finally, following the ELM and a two-factor perspective (Cacioppo and 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 decisions.

Previous research has pointed out the role of star rating as a heuristic for popularity and quality (Sundar, Oeldorf-Hirsch, and Xu 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 attributed to the fact that negative reviews are scarce, and 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. Since the majority of online reviews are positive and consumers expect to see positive reviews (Chen and Lurie 2013), they may process them rather peripherally. When they encounter negative reviews, such reviews are in contrast to the majority of other reviews, which may trigger more system processing of information and lead to a stronger effect of reviews 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. Following the bias hypothesis of the HSM, negative star rating and many helpfulness votes will then negatively bias central processing (Chaiken and 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. Related to the discussion above, this could be again 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 et al. 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 and 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, and Kim 1991). Finally, the non-significance of the interaction term between pros and cons suggests 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 seem more persuasive and helpful particularly for online reviews because the motivation of posting online reviews is to help other consumers by telling them 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, Lee, and Han 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/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 (WOM) about a product is a significant indicator of brand loyalty (Dick and 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. This also has an important implication for the design of the websites and reviewing requests sent to customers. First, longer reviews generally provide more information, but they may want to limit the length of each review by finding an optimal review length. Website designers may want to prime customers with the average number of words other customers wrote, for example. 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 (Askalidis, Kim, and Malthouse 2017). 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 by for example indicating where they got the product from is a good way to potentially increase the overall trustworthiness of reviews.

The aforementioned point about source credibility provides further insights to advertising scholars and practitioners. WOM has been considered as a key to advertising effectiveness (Keller and 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 and Gvili 2015). There have been debates in the advertising discipline regarding whether brands should encourage consumers to post a product review, and, 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 websites are considered equally persuasive when consumers read positive reviews (Xue and 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. Perceived source trustworthiness positively affects eWOM's influence on decision-making (Lopez and Sicilia 2014). Hence, it is of paramount importance that consumers know that the reviewer is expressing his/her honest opinion. This is also supported by our results showing that information whether a reviewer actually bought and used a product is important for customers' purchase decision. In sum, we think that advertisers should stimulate customers' participation in eWOM while providing transparent information about the reviewing process to diminish consumers' suspicion.

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, and 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 and Yeats 2014; Park and 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 needs to go one step further and actually test dual-process theories in the eWOM context (e.g. Zhang et al. 2014). This would require a controlled experimental design. In addition, the role of aggregated information of reviews for a single product (i.e. a 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 regard to reviewer characteristics, how the similarity between reviewers and review readers influences 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 decisions. It confirms the effects of review characteristics that are identified based on the HSM approach (e.g. Cheung and Thadani 2012). Some findings may seem intuitive, for instance, the positive effect of a verified buyer badge or the presence of cons. We also have unexpected findings, for example, the moderating effect of review helpfulness or the curvilinear effect of review length, which requires further scholarly investigation.

Follow-up experiments that corroborate the findings from this research and studies that examine the effects of review features on purchase decisions in other product or service categories would help generalize the findings on different effects of various review features.

Notes

1. We assessed multicollinearity using GVIFs proposed by Fox and Monette (1992). GVIFs are an appropriate way to assess multicollinearity in models with categorical predictors and polynomials. When there is multicollinearity, slope estimates are unbiased but have inflated standard errors (i.e. the variance of the estimates is inflated), but standard errors are also determined by sample size, which is very large in our case.
2. The model does not overfit the data. Our logistic regression model is estimated on 413,666 observations and has 25 parameters. Perhaps, the greatest risk to overfitting comes from the dummy variables, but we have large samples (valence has 63,979, 28,253, and 322,434 values; review recommendation has 29,274, 64,170 and 320,222 values; category has 18,542, 145,620, 29,515, 112,842, 17,670, 62,341, and 27,136; seasonality has 8224, 142,476, 111,599, 108,494, and 43,873 observations). To make sure that we are not overfitting, we use five-fold cross validation by assigning a random value 1–5 to each case (Kuhn and Johnson 2013, 69–70). We then estimated our model five times, each time leaving out one part, and applied the model to the left-out part. The value of AUC was computed on the held-out values. The original AUC value was 0.6146. The five-fold CV value is 0.6138, which differs by 0.0008. We also tried 10-fold cross validation and got the same AUC value to four decimal places. Thus, there is no evidence for overfitting.
3. For a predictor having a single degree of freedom, GVIF equals VIF (equaling $1/(1 - R^2)$ from a model predicting X_j from the other predictors in the model). Let X_1 be a block of predictors (e.g. multiple dummies for a categorical predictor), X_2 be a block of the remaining predictors in the model, and X be all predictors (bind X_1 and X_2 to product X). Let R_1 be the correlation matrix of X_1, R_2 the correlation matrix for X_2 and R be the correlation matrix for X. Then, GVIF = $\det(R_1)^{*}\det(R_2)/\det(R)$. A benefit of GVIF is that it is invariant to the choice of the baseline value (e.g. negative for valence), or category (requiring six dummies).

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Disclosure statement

No potential conflict of interest was reported by the authors.

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