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The Impact of Social Influence on the Perceived Helpfulness of Online Consumer

Reviews

Hans Risselada, Lisette de Vries, Mariska Verstappen

forthcoming in European Journal of Marketing

Introduction

Electronic word-of-mouth (eWOM), or providing information about goods, services, brands, or companies to other consumers through the internet, noticeably shapes consumers' perceptions and preferences (Chen et al., 2011; Godes and Mayzlin, 2004; Jang et al., 2012).¹ An increasingly important element of eWOM is online consumer reviews² (Babic et al., 2016; Chen and Xie, 2008; Chevalier and Mayzlin, 2006), and trade publications state that at present roughly half of internet shoppers always or at least most of the time check online reviews before making a purchase (eMarketer, 2016). Academic studies also show that online reviews play an important role in consumer decision making, since consumers consider content generated by their peers to be more credible and trustworthy than marketer-generated information (Gilly et al., 1998; Schindler and Bickart, 2012). As a result, online reviews affect firm performance (Floyd et al., 2014; You et al., 2015).

With the enormous number of online reviews available—in 2014, Amazon.com contained about 140 million product reviews (McAuley, 2016), with single products having thousands of reviews—consumers have to choose which ones to read. Consumers are not able to process all reviews available, and therefore they try to distinguish among them. One way to do so is to consider the review's helpfulness (Lee, 2013). Consumers vote on reviews that are helpful, and these reviews are therefore better able to guide consumers in their decision

¹ This definition of eWOM is from the first two sentences of the paper by Babic-Rosario et al. (2016).

² To facilitate readability we use the terms “reviews” and “online reviews” interchangeably.

making process and have a larger impact on the formation of consumers' attitudes toward the reviewed product (Purnawirawan et al., 2012).

The literature on review helpfulness identifies content presentation characteristics, such as structure and spelling errors, as important drivers (e.g., Li et al., 2013; Mudambi and Schuff, 2010; Willemsen et al., 2011). These content presentation factors affect how consumers process the information in the reviews and thus influence the perceived helpfulness of the reviews. Surprisingly, although online reviews are consumer-to-consumer interactions in which social influence plays an important role (e.g., Katona et al., 2011; Racherla and Friske, 2012; Risselada et al., 2014), research examining the impact of social influence on perceived review helpfulness is limited. Previous studies show that when writing reviews or forming their evaluation of reviews, consumers are swayed by others and by previously posted ratings (Lee et al., 2015; Moe and Schweidel, 2012; Muchnik et al., 2013; Sridhar and Srinivasan, 2012).

Several studies report the impact of, for example, star ratings of a product on review helpfulness (Mudambi and Schuff, 2010; Singh et al., 2017; Yin et al., 2016). This labeling could be considered social influence in the sense that the opinions of others regarding the *product* may affect the perceived helpfulness of the *review*. However, for this study we define social influence more narrowly as the impact that existing votes about the review's helpfulness have on the perceived helpfulness of the review. That is, in our investigation, we assess the impact of existing votes on new votes.

Given that consumers use helpfulness votes to distinguish reviews, an important consideration is to what extent these votes reflect the actual helpfulness of the information in the review and to what extent they reflect previous helpfulness votes. When consumers think a review is helpful, they can vote positively, and if they consider the review unhelpful they

can vote negatively. The votes are regarded as a social signal and they can function as a heuristic that enables other consumers to more easily process all information in the review.

Observational learning states that a consumer's own judgment is less important in the presence of observed actions of others (Banerjee, 1992; Bikhchandani et al., 1992). Thus, when consumers note helpfulness votes they might simply follow the votes. In addition, the helpfulness votes of others can diminish the impact of the content presentation characteristics of online reviews (e.g., structure, spelling errors), because consumers might pay less attention to the content presentation factors.

In this study we investigate to what extent the helpfulness votes previous readers attach to a review (our social influence measure) affect a consumer's perceived helpfulness of that review. Furthermore, we assess to what extent this social influence measure moderates the relationships among several content presentation factors (i.e., spelling errors, review length, structure, position of the votes, and status of the reviewer) and perceived review helpfulness. In our examination, we use a choice-based conjoint experiment whereby respondents evaluate different reviews and choose the review they perceive as most helpful. In this way, we obtain insights into how consumers actually process online reviews and are able to determine the relative impact of and interactions between social influence (helpfulness votes previous readers attach to the review) and content presentation factors.

The results show that social influence indeed affects how consumers process the information in online reviews and thus consumers' perceived helpfulness of online reviews. Consumers perceive reviews as more (less) helpful in the presence of positive (negative) helpfulness votes of others. We also find that helpfulness votes of others diminish the positive impact of structure and the negative impact of spelling errors on perceived helpfulness, which is in line with observational learning theory. We thereby contribute to the literature by providing insights into how consumers process online reviews and by demonstrating that they

are influenced by others' opinions in evaluating reviews. Firms may influence these processes by displaying a helpfulness button to facilitate evaluation of reviews. Consumers prefer useful reviews and thus to satisfy consumers or visitors, firms should provide the option to vote. This option also provides firms with some influence on the effects of review characteristics on review helpfulness. However, for consumers the implications are less straightforward. The results imply that consumers may tend to follow other consumers' opinions without forming their own opinion. This tendency can be misused by firms in that they could hire people to vote on certain reviews that are not necessarily helpful for consumers but for the firm. More positive votes lead to higher perceived helpfulness of the review, which likely reinforces the biased effects of the helpfulness votes. This finding highlights the relevance of understanding the impact of social influence on the evaluation of online reviews.

How do consumers process online consumer reviews?

Consumers' motivation, opportunity, and ability all influence how consumers process information (MacInnis et al., 1991). Motivation is defined as goal-directed behavior, while opportunity is the extent to which the consumer is distracted from processing or has limited time. Ability is whether the consumer has enough skills to be able to process information. When consumers search for and read online reviews, their motivation and ability to do so are generally already high, and they are likely to engage in more effortful information processing (Lu et al., 2014). While motivation and ability are difficult for firms to influence, firms can influence opportunity to process by affecting the way the information in the review is presented (MacInnis et al., 1991).

For online consumer reviews, firms are able to shape the information in reviews to only a limited extent. However, firms can provide a spelling checker, guide the length of a review by mentioning the minimum or maximum number of words to be written, and provide a structured or unstructured format. Additionally, they can offer the option to indicate whether

the review is helpful or not. In supplying these features, firms are not affecting the actual content of the review, but are influencing how consumers process the information. Therefore, these factors are likely to influence the perceived helpfulness of online reviews.

Effects of content presentation factors and social influence on perceived review

helpfulness

Content presentation factors

Commonly studied content presentation factors directly link to the presentation of the information in the review. Therefore, these factors affect the opportunity to process the information and hence the perceived review helpfulness (Baek et al., 2012; Mudambi and Schuff, 2010; Schindler and Bickart, 2012; Willemsen et al., 2011). In Table 1, we provide an overview of the literature on review helpfulness and identify which variables affecting helpfulness other researchers have studied.

Of note in the table is that the product rating is the most studied independent variable related to review helpfulness. We show the rating in our experiment but do not manipulate it. We focus on the impact of the content presentation factors and the extent to which they are affected by social influence, and we do not expect those effects and interactions to depend on the rating. Regarding the content presentation factors, the table shows that length has been studied often, which is why we include it in our study. All other factors have been studied in a few papers, but no particular factors stand out. We decided to include structure and spelling errors because although structure does not appear as such in the table, the closely related concept of readability has been studied several times. Also, from a practical point of view, structure and spelling errors are important attributes since some platforms do impose a specific structure or spelling checkers. However, little is known about the potential impact of these choices on the helpfulness votes. For the same reason we include the position of the votes—above or below the review text. The table also shows that quite a few studies include

reviewer characteristics, but to keep our design feasible, we included only one broad reviewer characteristic—status—which covers some of the reviewer characteristics shown in the table. Most of these effects are well established in the literature. We therefore provide key references, but do not formulate hypotheses here.

<<<INCLUDE TABLE 1 ABOUT HERE>>>

Spelling errors. Spelling errors affect the readability of a message and thus make the processing of information less fluent. Spelling errors can cause misunderstanding, ambiguity, and difficulties in the comprehension of a message (Ghose and Ipeirotis, 2011; Sallis and Kassabova, 2000). Consumers perceive writers of grammatically correct email messages as more competent than writers of grammatically incorrect messages (Jessmer and Anderson, 2001). Other studies specifically show that spelling errors in reviews reduce the perceived helpfulness (Forman et al., 2008; Ghose and Ipeirotis, 2011; Schindler and Bickart, 2012).

Review length. The literature suggests that review length may positively affect perceived helpfulness. Longer messages tend to increase processing opportunity and enhance comprehension (MacInnis et al., 1991). Longer reviews may be perceived as containing more information, which increases a consumer's confidence in the information (Tversky and Kahneman, 1974). Moreover, longer reviews may signal greater involvement of the review writer and thereby increase the perceived quality of the information (e.g., Pan and Zhang, 2011). However, review length may also negatively affect perceived helpfulness, because processing longer reviews requires more cognitive resources and the reviews may thus be perceived as more complex, reducing processing opportunity (Ghose and Ipeirotis, 2011). Since consumers who read online reviews are generally more motivated and able to process the information, we expect that the negative effect might be weakly present (e.g., Lu et al., 2014). Also, most empirical results to date provide support for the positive effect of review

length (e.g., Ghose and Ipeirotis, 2011; Mudambi and Schuff, 2010; Pan and Zhang, 2011; Schindler and Bickart, 2012; Willemsen et al., 2011).

Structure. Multiple studies show that the structure of a direct marketing message affects the response rate and level of interest (Hozier and Robles, 1985; Sherman et al., 1991). Structure in the form of spacing and clear headlines to texts can increase readability, and readability triggers processing attention (Macdonald-Ross, 1977). Structure may also reduce the required processing time, making a structured online review easier to comprehend than an unstructured online review (MacInnis et al., 1991). A commonly used technique to improve clarity and comprehensibility of texts is the use of bulleted lists, which is also related to spacing within a text. Studies in the charity donation literature provide indirect support for this effect by showing that using bulleted lists in fundraising letters increases donations (Goering et al., 2011). We assess the impact of structure by using a specific kind of bulleted list that is common on review websites, namely lists of pros and cons of a product. In line with the existing literature, we expect that a structured online review is more readable and comprehensible than an unstructured review and is therefore perceived as more helpful.

Position of the votes. Helpfulness votes are typically displayed above or below a review. As Table 2 shows that no research has examined this attribute, we include it as an exploratory characteristic. Given that consumers typically read from top to the bottom, votes above a review are more salient and thus more likely to be easily processed. Given this greater ease of processing, reviews with votes displayed on top may be perceived as more helpful. On the other hand, the votes are easy to see regardless of their position, because they are displayed separately and in a distinguishing way. This attribute may thus have a nonsignificant impact.

Status of the reviewer. Several web shops assign a certain status to reviewers who have written many reviews by designating them as “top-reviewer.” As this top-reviewer

badge is based on someone's actual writing behavior it implies something about a reviewer's reputation (Cheung et al., 2009). Prior research has shown that a higher reviewer activity level has a positive effect on the credibility and helpfulness of reviews (Baek et al., 2012; Cheung et al., 2009). For "expert status" we use two levels: no status and top reviewer.

Social influence: Helpfulness votes of others

A consumer's perceived helpfulness of a review may be affected by previous readers' perceptions of the review helpfulness. That is, the votes on reviews can help consumers to process the information more easily. Theory on observational learning supports this relationship. Observational learning is defined as "drawing quality from mere observation of peer choices" (Zhang, 2010, p. 315). Key in this definition is that in the case of observational learning, consumers do not know and use *the reasons* for the actions that are being observed—that is, why consumers bought a product. They only observe *the action*. Observational learning may cause herding behavior, where consumers no longer use their own information and judgment but simply follow the actions of others (Banerjee, 1992). This possibility suggests that when consumers see that others have found a review (not) helpful, they will also be more likely to perceive the review as (not) helpful. Herding is likely to occur when a clear and unambiguous signal is present. In the case of helpfulness votes, the signal would be either a clear majority of positive ("Yes, this review was useful") or a clear majority of negative votes ("No, this review was not useful"). The possible effects of observational learning lead us to expect that clearly valenced helpfulness votes of others affect perceived review helpfulness in the following ways:

H₁. A clear majority of positive (negative) helpfulness votes others attach to the review will positively (negatively) affect perceived review helpfulness as compared to a review with no votes.

In addition, other consumers may not unambiguously perceive a review as helpful or unhelpful, which is then reflected in mixed helpfulness votes. By mixed helpfulness votes, we mean that the review obtained an equal number of positive and negative votes from other consumers. The impact of mixed votes on helpfulness as compared to no votes is not possible to predict. Consumers may either be more motivated to process the information in the review or interpret the mixed votes in a confirmatory way. In the latter case, consumers that are a priori more negative may see the negative votes in the mix as a confirmation, and consumers that are a priori more positive may see the positive votes as a confirmation. We explore the differential impact of mixed votes and no votes, but do not formulate hypotheses on this impact.

Interactions among social influence and content presentation factors

No helpfulness votes might increase a consumer's motivation and opportunity to process the information in the review. Since consumers cannot infer from the votes whether the review is or is not helpful, they evaluate the helpfulness of a review on the basis of the content presentation factors. Therefore, we expect that the impact of the content presentation factors is greater in the case of no votes. That is, in the case of no helpfulness votes, consumers pay more attention to the content presentation factors than in the case with a majority of positive or negative votes. In addition, these clearly valenced votes enhance processing fluency and decrease processing time. Second, the theory of observational learning suggests that when the number of observed actions of others increases, the impact of a consumer's own information decreases (Cai et al., 2009; Zhang, 2010). Thus, in the presence of clearly valenced helpfulness votes of others (positive or negative), the contribution of an individual attribute to a consumer's overall evaluation of the review's helpfulness decreases. In other words, in the presence of a majority of positive or negative helpfulness votes as compared to the case with

no votes, consumers pay less attention to the content factors and thus the expected effects of content factors on perceived review helpfulness should become weaker. Thus:

H₂. The impact of content presentation factors (spelling errors, review length, structure, position, and reviewer status) is smaller in an absolute sense when positive or negative helpfulness votes of others are present than when no votes are present.

Research design

Choice-based conjoint analysis

To assess the impact of social influence relative to the impact of content presentation factors on perceived review helpfulness, we employ a choice-based conjoint (CBC) experiment. By using an experiment we avoid issues with observed data that are common in this research area, such as the winner circle and early bird biases (Li et al., 2013). The winner circle bias refers to the phenomenon that consumers pay more attention to reviews with more votes. By showing a small selection of reviews in our experiment, we avoid this attention problem. The early bird bias refers to the phenomenon that reviews that are posted earlier tend to receive more votes. In our experiment, we manipulate the number of votes while holding the posting date constant. CBC determines consumer preferences on the basis of utilities, by considering objects—here, reviews—as a set of attributes. The utility of an option is the sum of the utilities of the attribute levels of that option. The content—that is, the product and the information—is identical in all reviews; only the presentation method varies according to the defined attributes and levels. This approach allows us to compare the relative impact of all attributes and levels on the overall helpfulness of the review.

Data collection

Product. We use a high-involvement product for this study (tablet computers), because reviews are an important information source in the purchasing process of high-involvement products (Wang et al., 2013).

Attributes and levels. We include the helpfulness votes of others and several content presentation factors expected to influence perceived review helpfulness as attributes in the CBC analysis.

For the social factors, we operationalize the attribute “helpfulness votes of others” with four levels: no votes, 194 negative votes, mixed votes (97 negative and 97 positive votes), and 194 positive votes. We specifically use these numbers to have obvious opinions for positive versus negative votes. We choose numbers without zeros to distinguish the numbers more clearly from no votes.

For the attribute “spelling errors” we include either no spelling errors or three errors in the review. For the attribute “review length” we define two levels: short (70 words) and long (170 words). We base these numbers on the 33% and 66% percentile of the word-count distribution of a random sample of 15,000 reviews of the tablet review data (Wang, Mai, and Chiang, 2013). The information in the short and long review is kept constant. We used fillers to make the reviews longer. For the attribute “structure,” we define two levels. The unstructured review is a text without spacing and headlines, whereas the structured review reflects arguments divided into “pros” and “cons.”

The position of the helpfulness votes of others across websites is at either the top or the bottom of the reviews. Therefore, we position of the helpfulness votes either above the review text or below it.

Several web shops assign a certain status to reviewers who have written many reviews, designating them “top-reviewer.” This top-reviewer badge is based on someone’s actual writing behavior. For “reviewer status,” we use two levels: no status and top-reviewer.

On the basis of these attributes and levels, we created images resembling reviews of tablet computers (see Figure 1 for an example of such a review).

<<INSERT FIGURE 1 ABOUT HERE>>

CBC study design. We design the choice sets by means of the balanced overlap method, which is well suited for the estimation of interaction terms (Chrzan and Orme, 2000). In terms of the amount of overlap, or the number of duplicates in the attribute levels within choice sets, this method falls between the complete enumeration method and the random method. For more details on these design methods we refer to Chrzan and Orme (2000). In terms of the attributes and levels, the optimal design contains eight choice sets of three reviews each. Respondents receive these eight choice sets, and from among the three reviews they have to choose the review they perceive as the most helpful to them.

Often in CBC study designs a no-choice option is included where consumers can eschew making a choice (Carson et al., 1994). We do not include a no-choice option for several reasons. First, consumers might simply choose this no-choice option to avoid difficult choices. Second, consumers can become bored toward the end of the choice tasks and might choose the no-choice option for the remaining questions, which leads to biased results. Third, consumers might feel that certain attributes are missing, which can result in preferring the no-choice option (Gunasti and Ross, 2009). As it is essential for this research that consumers actually make trade-offs, we exclude the no-choice option.

The reviews in our experiment are all modifications of real reviews from Amazon about the Xoom tablet computer (Wang et al., 2013). In each set, the content of the reviews is the same, precluding participants from choosing a review on the basis of different preferences for product characteristics. Instead, they must base their decision on the social and/or content presentation factors. Each review has more positive than negative points. To emphasize the positive perception, each review has an evaluation of four out of five stars, so that the ratings

of reviews are uniform. We included the star rating in the reviews because in practice, almost all reviews contain a star rating and thus our reviews are a better representation of reality. Four stars are realistic since most reviews available are positive (Chevalier and Mayzlin, 2006), and the average rating for Amazon reviews is about 3.9 (Woolf, 2014).

Sample. We collected data via the Amazon Mechanical Turk platform from 211 USA- and Canada-based workers with at least 95% approval rates. We included an attention check at the end of the survey asking participants to indicate their zodiac sign, but within the text we requested that they write down their favorite sport instead. To notice this sentence, participants had to read the text carefully. One participant failed the attention check and is excluded from further analyses. Nine participants did not finish the survey and are also excluded from further analyses.

Our final sample of 201 participants includes 47.5% females and is on average 34.5 years old ($SD = 9.94$). Only 0.5% of the respondents have no education, 24.8% of the respondents went to high school, 26.7% went to college, 39.1% have a bachelor's, 6.9% a master's, and 2% a doctoral degree. The respondents regularly use the internet to purchase goods ("How often did you use the internet to purchase goods in the last six months?" (1 = Not at all - 7 = Quite often), $M = 5.45$, $SD = 1.45$, Median = 6).

We measured tablet product involvement of the participants in our survey using the four-item scale of Mittal (1989), where each item is measured on a seven-point Likert scale. The Cronbach's alpha (.073) is greater than 0.6, which indicates that internal consistency reliability of this scale is satisfactory (Malhotra, 2010, p. 319). Therefore, we take the mean of the four original items as our product involvement construct. The high mean ($M = 5.71$, $SD = 0.87$) indicates that the respondents are highly involved with the product category tablet, supporting our choice of this product as a high-involvement product.

Model specification

The utility (perceived helpfulness) of each online consumer review equals the sum of the utilities of each attribute level (helpfulness votes and content presentation factors) (Johnson, 1974). In the underlying multinomial choice model, the dependent variable is the review that respondents select from a choice set. Following convention in multinomial choice models, the utility of review i (U_i) is the sum of a systematic part (V_i) and a stochastic part (ϵ_i). So,

$$U_i = V_i + \epsilon_i$$

In line with standard choice-based conjoint studies, we estimate a multinomial logit model on the choice data. The systematic part of the utility model is defined as follows:

$$\begin{aligned} V_i = & \beta_1 \text{PosVotes}_i + \beta_2 \text{MixVotes}_i + \beta_3 \text{NegVotes}_i + \beta_4 \text{Errors}_i + \beta_5 \text{Long}_i + \beta_6 \text{Structure}_i \\ & + \beta_7 \text{TopReviewer}_i + \beta_8 \text{HighPosition}_i + \beta_9 (\text{Errors} \times \text{PosVotes})_i \\ & + \beta_{10} (\text{Errors} \times \text{MixVotes})_i + \beta_{11} (\text{Errors} \times \text{NegVotes})_i \\ & + \beta_{12} (\text{Long} \times \text{PosVotes})_i + \beta_{13} (\text{Long} \times \text{MixVotes})_i \\ & + \beta_{14} (\text{Long} \times \text{NegVotes})_i + \beta_{15} (\text{Structure} \times \text{PosVotes})_i \\ & + \beta_{16} (\text{Structure} \times \text{MixVotes})_i + \beta_{17} (\text{Structure} \times \text{NegVotes})_i \\ & + \beta_{18} (\text{TopReviewer} \times \text{PosVotes})_i + \beta_{19} (\text{TopReviewer} \times \text{MixVotes})_i \\ & + \beta_{20} (\text{TopReviewer} \times \text{NegVotes})_i + \beta_{21} (\text{HighPosition} \times \text{PosVotes})_i \\ & + \beta_{22} (\text{HighPosition} \times \text{MixVotes})_i + \beta_{23} (\text{HighPosition} \times \text{NegVotes})_i \end{aligned}$$

where the β s are the so-called part-worths. All variables are dummies that are equal to 1 if review i has that particular level for the attribute and 0 otherwise. From the multinomial logit specification, it follows that the probability of choosing review i in choice set J equals:

$$P[i|J] = \frac{\exp(V_i)}{\sum_{j=1}^m \exp(V_j)}, \text{ for } J = \{1, \dots, i, \dots, m\}$$

We use maximum likelihood estimation to obtain estimates for the part-worths using the mlogit R-package. We refer to standard texts on choice-based conjoint analysis for more details (Hair et al., 2010).

Results

Table 2 shows the part-worths of the estimated model. The log likelihood of the model is -1618.386.

<<INSERT TABLE 2 ABOUT HERE>>

The results on the simple effects of the helpfulness votes of previous readers support *H1*, indicating that consumers are indeed influenced by others in their judgments of review helpfulness. Consumers perceive reviews with negative votes of others as less helpful (-.465, $p = .063$) and reviews with positive votes of others as more helpful (.459, $p = 0.046$) than reviews with no votes. The part-worth of mixed votes is not significant (.095, $p = .686$), which implies that consumers do not perceive reviews with mixed votes as more or less helpful than reviews with no votes. The simple effects of spelling errors, length, and structure are in line with our expectations. Consumers perceive (1) reviews with errors as less helpful than reviews without errors (-.488, $p < .01$), (2) longer reviews as more helpful than shorter reviews (.552, $p < .01$), and (3) structured reviews as more helpful than unstructured reviews (.649, $p < .01$). The results show that consumers perceive reviews by top reviewers as more helpful than reviews by reviewers with no status (.265, $p = .040$) and the effect of position is not significant (.083, $p = .515$).

To test *H2*, we examine the interaction effects between the content presentation factors and the clearly valenced helpfulness votes. We find partial but limited support for this hypothesis. The results show a significant positive interaction effect between positive helpfulness votes and spelling errors (.538, $p < .01$), a marginally significant positive interaction between negative helpfulness votes and spelling errors (.346, $p = .072$), and a significant negative interaction effect of structure and positive helpfulness votes (-.381, $p = .036$). These three effects imply that the effects of those content presentation factors are

dampened in the presence of clearly valenced votes. However, all other interaction effects are not significant and thus not in line with *H2*.

Discussion

This study examines how consumers process online reviews and how social influence, in the form of the helpfulness votes others provide to reviews, affects the perceived helpfulness of online reviews. We show that the helpfulness votes of others indeed affect how consumers process the review and perceive the helpfulness of a review, whereby positive votes increase review helpfulness and negative votes decrease review helpfulness. Theory on observational learning can explain these effects, as it predicts that consumers will follow others' opinions (Banerjee, 1992; Bikhchandani et al., 1992; Kallgren et al., 2000).

Furthermore, we provide some evidence that our social influence measure—clearly valenced helpfulness votes of others—diminishes the impact of content presentation factors (e.g., spelling errors and structure) on perceived review helpfulness. This finding is in line with earlier analytical results showing that as the number of observed actions of others increases, the impact of a consumer's own information decreases (Cai et al., 2009; Zhang, 2010). However, we acknowledge that most of the interaction effects in our model are not significant and thus not in line with our key hypothesis that clearly valenced votes reduce the impact of content presentation factors in general.

Theoretical and managerial implications

This study provides insights into how consumers actually process online reviews. We show that the well studied content presentation factors as well as social influence affect how consumers process online reviews and consequently how consumers perceive the helpfulness of these reviews. Reviews with positive or negative helpfulness votes are perceived as more and less helpful, respectively. The mechanism behind this perception is observational

learning, through which consumers pay less attention to the information in the review itself when they can observe actions of others (i.e., the helpfulness votes). With mixed and no votes this mechanism is not present, since the evaluation of the review may be ambiguous, and people seem to rely more on their own judgment and put more effort into information processing. Thus, our study contributes to the literature on the perceived helpfulness of online reviews and how consumers may actually process online reviews, which has only recently started to receive scholarly attention.

Our study has some important implications for managers of retail websites. Websites should include a button allowing consumers to indicate whether they find the review helpful, because reviews with votes of others are perceived as at least as helpful as reviews without votes unless a clear majority of the votes is negative. Providing helpful content to visitors of the site is likely to induce satisfaction with the site and thereby increase retention rates. In addition, firms might want to monitor whether the votes are positive or negative, since the positive votes in particular raise the perception that the review is more helpful and at the same time decrease the influence of some of the content presentation factors.

Since managers should not alter the content of reviews, this option provides firms with a relatively easy way to partially influence how consumers process and perceive reviews, and some the effects of the content presentation of the reviews are weakened.

As reviews increasingly become available, consumers filter reviews on the basis of certain characteristics since they are not able to read all reviews. Our research finds that sorting reviews on helpfulness votes is a suitable strategy from a consumer perspective as it helps consumers differentiate among reviews. However, although this approach simplifies consumers' decision making since they use the votes as a simple heuristic, it also implies that consumers tend to mainly follow other consumers' opinions without forming their own opinion. Firms could misuse this effect by paying people to vote on certain reviews that are

extremely positive about the firm's products. More positive votes lead to higher perceived helpfulness of the review, which likely reinforces the biased effects of the helpfulness votes. Hence, such activities will not help consumers.

Limitations and further research

Although the results of our study are interesting and reliable, our investigation has certain limitations. First, the current study is of an experimental nature. While the internal validity is high, in that we could study the impact of social influence on perceived review helpfulness in a controlled environment, as in any experiment the external validity is limited. This limitation may partially explain the lack of significant interactions in our model. Therefore, it would be interesting to replicate our findings using secondary data.

Second, we studied only one aspect of social influence in the context of online reviews, namely the impact of helpfulness votes of anonymous others. However, other social processes may be at play in real-life settings, such as reviews shared via social media by friends, or social influence through the reputation of the source of the review writer. Studying the impact of all of these factors was not feasible in the current conjoint design, but would be interesting to investigate in future work.

Third, we operationalize helpfulness votes as yes/no answers to the question "Was this review useful?" Other operationalizations are possible and observed in practice, such as the percentage of positive votes or a 1–5 scale indicating how useful the review was. Although we do not expect our results change, future research could assess these differences.

Fourth, because the difference in the number of positive arguments versus negative arguments is quite salient in the structure condition, it may be that the positive impact of structure may be partly driven by this difference. This imbalance, however, is consistent with the four-star rating. We leave the issue of the imbalance and the type of structure for future studies.

Fifth, we wanted to assess whether social influence affects the impact of content presentation characteristics. To study this aspect, we manipulated social influence by varying the number of helpfulness votes. To avoid the number of levels effect in our design and to keep the experiment simple, we could use only a limited number of levels. Therefore we decided to vary the valence (i.e., positive, negative, mixed, and no votes) and use only one version of each of those valence levels. To get a clearly valenced signal, we used a relatively high number of positive and/or negative votes and, as we mention earlier, we chose numbers without zeros to distinguish positive/negative votes more from no votes. Given our research design, we cannot assess how the level of the number of helpfulness votes would affect our results on social influence. The same holds for the length attribute. We used a limited number of levels and therefore we cannot assess how the impact of length differs for different values of the word count. Both issues would be interesting avenues for future research.

Finally, an intriguing future research idea would be to examine the consequences of more helpful reviews for both firms and consumers. For example, are consumers more satisfied with the choice process? Do consumers believe they make better decisions when using the helpfulness votes of others? Would that again lead to more satisfied customers and fewer returns? These research questions are beyond the scope of this research, but we encourage other researchers to pursue them.

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